MEDICAL IMAGING APPLIED TO TEACHING AND MEAT SCIENCE

Pau Xiberta i Armengol

Universitat de Girona

DOCTORAL THESIS

Medical imaging applied to teaching and meat science

Pau XIBERTA I ARMENGOL

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La Dra. Imma Boada i el Dr. Anton Bardera, de la Universitat de Girona,

DECLAREM:

Que el treball titulat *Medical imaging applied to teaching and meat science*, que presenta el Sr. Pau Xiberta i Armengol per a l'obtenció del títol de doctor, ha estat realitzat sota la nostra direcció i que compleix els requisits per poder optar a Menció Internacional.

I, perquè així consti i tingui els efectes oportuns, signem aquest document.

Signatura

IMMA BOADA

ANTON BARDERA

Girona, 2 de febrer del 2018

Agraïments

Malgrat no m'allunyi del tòpic, no em veig capaç de començar aquest apartat d'altra manera que no sigui mostrant un profund agraïment a la meva directora, l'Imma Boada. Podria destacar, sense sorprendre massa a ningú, la seva total dedicació, disponibilitat i empenta en aquest projecte, però llavors em sabria greu que es restés importància a la seva capacitat humana, a les seves virtuts per convertir l'espai de treball en un indret tan agradable com qualsevol afició particular. Al seu costat, i des de ja fa uns quants anys, tinc la sensació d'haver treballat i après molt, i d'haver gaudit fent-ho.

Un agraïment semblant podria fer al meu codirector, i ara també amic, Anton Bardera. Disposat a escoltar sempre qualsevol proposta, a resoldre qualsevol dubte, i a plantejar noves idees, ha sigut també una peça imprescindible per completar aquesta etapa.

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Suposo, doncs, que aquest és el petit moment reservat a totes aquelles persones que, en major o menor mesura, de manera conscient o no tant, han ajudat a conduir aquest projecte des del principi fins al final. Tanmateix, considero que la culminació d'aquesta etapa, precisament d'aquesta, bé mereix també fer extensiu aquest agraïment de manera molt sincera a les persones que hi són d'abans i de sempre, les quals m'han empès no tan sols a arribar fins aquí, sinó també a veure els obstacles amb optimisme.

Als meus pares, per tant, no puc sinó mostrar-los gratitud eterna, perquè els ho dec tot. Confiança cega i suport constant sota qualssevol circumstàncies, i el bastó on recolzar-me quan les cames fan figa. Sense pressió i amb gran modèstia, han vetllat sempre per un recorregut acadèmic, el meu, que no tingués més dificultats que les que ja en són inherents, fins i tot en aquesta etapa culminant. Amb tot, han aconseguit molt més que això; amb el seu exemple de generositat i compromís, d'integritat i perseverança, han aconseguit que la meva ambició sigui valorar només allò que realment valgui la pena, el nucli més que la pell.

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Though here at journey's end I lie
in darkness buried deep,
beyond all towers strong and high,
beyond all mountains steep,
above all shadows rides the Sun
and Stars for ever dwell:
I will not say the Day is done,
nor bid the Stars farewell.

—J.R.R. Tolkien

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Aquells que no tenen la voluntat d'ensenyar-nos
és de qui més acostumem a aprendre

Als meus pares,
perquè em sé llavor
i fruit del seu esforç

List of publications

This thesis is presented as a compendium of the following research articles:

- Pau Xiberta and Imma Boada. *A new e-learning platform for radiology education (RadEd)*. Computer Methods and Programs in Biomedicine, vol. 126, pages 63–75, April 2016, doi: 10.1016/j.cmpb.2015.12.022.

  ⇒ JCR Impact Factor (2016): 2.503 (Quartile 1)

- Pau Xiberta, Imma Boada, Santiago Thió-Henestrosa, Pedro Ortuño and Salvador Pedraza. *Measuring the acceptance of e-learning in continuing education courses for medical staff: the experience of a thorax radiology course*. Submitted to Computerized Medical Imaging and Graphics.

  ⇒ JCR Impact Factor (2016): 1.738 (Quartile 3)

- Pau Xiberta and Imma Boada. *IVET, an Interactive Veterinary Education Tool*. Submitted to PLOS ONE.

  ⇒ JCR Impact Factor (2016): 2.806 (Quartile 1)

- Pau Xiberta, Anton Bardera, Imma Boada, Marina Gispert, Albert Brun and Maria Font-i-Furnols. *Evaluation of an automatic lean meat percentage quantification method based on a partial volume model from computed tomography scans*. Submitted to Computers and Electronics in Agriculture.

  ⇒ JCR Impact Factor (2016): 2.201 (Quartile 1)

- Pau Xiberta, Imma Boada, Anton Bardera and Maria Font-i-Furnols. *A semi-automatic and an automatic segmentation algorithm to remove the internal organs from live pig CT images*. Computers and Electronics in Agriculture, vol. 140, pages 290–302, August 2017, doi: 10.1016/j.compag.2017.06.003.

  ⇒ JCR Impact Factor (2016): 2.201 (Quartile 1)

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Abstract

Medical imaging has greatly progressed to become a mature technology which is essential in current clinical processes, either to diagnose, plan operations or follow up the evolution and treatment of pathologies. However, advances in diagnostic imaging have not been applied to the same extent to other fields such as education and meat science.

In the context of education, there is a lack of teaching environments which allow the students to take advantage and interact with medical images. Besides, if these environments are online and web-based, the removal of time and place restrictions stimulates the students' participation and, consequently, the learning process is improved. Regarding the teachers, these e-learning image-based tools have to be easy to manage so that the content creation process is fast and efficient. In the medical field, a new e-learning platform is proposed which is useful both for undergraduate students and medical professionals who want to enrol in continuing education courses. In the veterinary field, an interactive e-learning tool is described which not only incorporates the previous advantages, but it also supports new graphical resources, considering that they are scarcer in this field. A manual segmentation process to generate new three-dimensional models from computed tomography scans is also described.

In the context of meat science, medical image processing has several applications. One of the most important ones is the quality classification process of animals depending on their tissue composition; namely, the higher the amount of lean meat, the better the animal quality. Therefore, an automatic, fast and accurate method is proposed to compute the lean meat percentage of an animal carcass, and a partial volume effect model is used to make it robust to data variability which may exist either between different scanners or different images of the same scanner. When the objective is to classify the quality of live animals, the need for using medical image processing techniques is more evident, since they are non-invasive and the animals are not harmed. In this case, however, a new problem arises, since the internal organs from the medical images have to be removed because they are not needed to compute the lean meat percentage. To tackle this problem, two segmentation algorithms are proposed.

Medical imaging is, without a doubt, very useful in diagnostic processes, and this thesis has the purpose to demonstrate that it is also useful in the fields of education and meat science. Hence, improvements in teaching methodologies and solutions to image processing problems are presented, always having medical imaging as the main focus.

Resum

La imatge mèdica ha progressat a bastament per convertir-se en una tecnologia madura que és imprescindible en els processos clínics actuals, ja sigui per diagnosticar, planificar operacions o seguir l'evolució i el tractament de patologies. Tanmateix, els avenços en la imatge per al diagnòstic no s'han aprofitat de la mateixa manera en altres camps com ara l'educació o la ciència de la carn.

En el context de l'educació, hi ha una manca d'entorns de docència que permetin als estudiants aprofitar els avantatges i interaccionar amb les imatges mèdiques. A més a més, si aquests entorns són en línia i accessibles des del web, la supressió de les restriccions de temps i espai estimula la participació dels estudiants i, conseqüentment, es millora el procés d'aprenentatge. Pel que fa als professors, aquestes eines d'aprenentatge en línia basades en la imatge han de ser senzilles de gestionar, de manera que el procés de creació de contingut sigui ràpid i eficient. En el camp de la medicina, es proposa una nova plataforma d'aprenentatge en línia que és útil tant per estudiants de grau com per professionals de l'àmbit mèdic que vulguin matricular-se en cursos de formació contínua. En el camp de la veterinària, es descriu una eina interactiva d'aprenentatge en línia que no només incorpora els avantatges anteriors, sinó que també admet nous recursos gràfics, tenint en compte que són escassos en aquest àmbit. També es descriu un procés de segmentació manual per generar nous models tridimensionals a partir d'imatges de tomografia computada.

En el context de la ciència de la carn, el processament d'imatge mèdica té diverses aplicacions. Una de les més importants és el procés de classificació de la qualitat dels animals depenent de la composició dels seus teixits; és a dir, com més gran és la quantitat de carn magra, millor és la qualitat de l'animal. Així, es proposa un mètode automàtic, ràpid i precís per calcular el percentatge de carn magra de la canal d'un animal, i s'utilitza un model d'efecte de volum parcial per fer-lo robust a la variació de dades que pot existir entre diferents escàners, o bé entre diferents imatges del mateix escàner. Quan l'objectiu és classificar la qualitat d'animals vius, la necessitat d'utilitzar tècniques de processament d'imatge mèdica és més evident, ja que són tècniques no invasives i els animals no en surten perjudicats. No obstant això, en aquest cas apareix un nou problema, i és que els òrgans interns de les imatges mèdiques s'han d'eliminar perquè no són necessaris per al càlcul del percentatge de carn magra. Per afrontar aquest problema, es proposen dos algorismes de segmentació.

La imatge mèdica és, sens dubte, molt útil en processos de diagnòstic, i aquesta tesi pretén demostrar que també ho és en els camps de l'educació i la ciència de la carn. Així doncs, es presenten millores en les tecnologies docents i solucions a problemes de processament d'imatge, sempre mantenint la imatge mèdica com a eix vertebrador.

Resumen

La imagen médica ha progresado enormemente para convertirse en una tecnología madura que es imprescindible en los procesos clínicos actuales, ya sea para diagnosticar, planificar operaciones o seguir la evolución y el tratamiento de patologías. Sin embargo, los avances en la imagen para el diagnóstico no se han aprovechado en la misma medida en otros campos como la educación o la ciencia de la carne.

En el contexto de la educación, hay una falta de entornos docentes que permitan a los estudiantes aprovechar las ventajas y interactuar con las imágenes médicas. Además, si estos entornos son en línea y accesibles desde la web, la supresión de las restricciones de tiempo y espacio estimula la participación de los estudiantes y, por consiguiente, se mejora el proceso de aprendizaje. Referente a los profesores, estas herramientas de aprendizaje en línea basadas en la imagen deben ser sencillas de gestionar, de modo que el proceso de creación de contenido sea rápido y eficiente. En el campo de la medicina, se propone una nueva plataforma de aprendizaje en línea que es útil tanto para estudiantes de grado como para profesionales del ámbito médico que quieran matricularse en cursos de formación continua. En el campo de la veterinaria, se describe una herramienta interactiva de aprendizaje en línea que no sólo incorpora las ventajas anteriores, sino que también admite nuevos recursos gráficos, dado que son escasos en este ámbito. También se describe un proceso de segmentación manual para generar nuevos modelos tridimensionales a partir de imágenes de tomografía computarizada.

En el contexto de la ciencia de la carne, el procesamiento de imagen médica tiene diversas aplicaciones. Una de las más importantes es el proceso de clasificación de la calidad de los animales dependiendo de la composición de sus tejidos; es decir, cuanto más grande es la cantidad de carne magra, mejor es la calidad del animal. Así, se propone un método automático, rápido y preciso para calcular el porcentaje de carne magra de la canal de un animal, y se utiliza un modelo de efecto de volumen parcial para hacerlo robusto a la variación de datos que puede existir bien entre diferentes escáneres, bien entre diferentes imágenes del mismo escáner. Cuando el objetivo es clasificar la calidad de animales vivos, la necesidad de utilizar técnicas de procesamiento de imagen médica es más evidente, ya que son no invasivas y los animales no son dañados. No obstante, en este caso aparece un nuevo problema, y es que los órganos internos de las imágenes médicas deben eliminarse porque no son necesarios para el cálculo del porcentaje de carne magra. Para abordar este problema, se proponen dos algoritmos de segmentación.

La imagen médica es, sin duda, muy útil en procesos de diagnóstico, y esta tesis pretende demostrar que también lo es en los campos de la educación y la ciencia de la carne. Así pues, se presentan mejoras en las tecnologías docentes y soluciones a problemas de procesamiento de imágenes, siempre manteniendo la imagen médica como eje vertebrador.

CHAPTER 1

Introduction

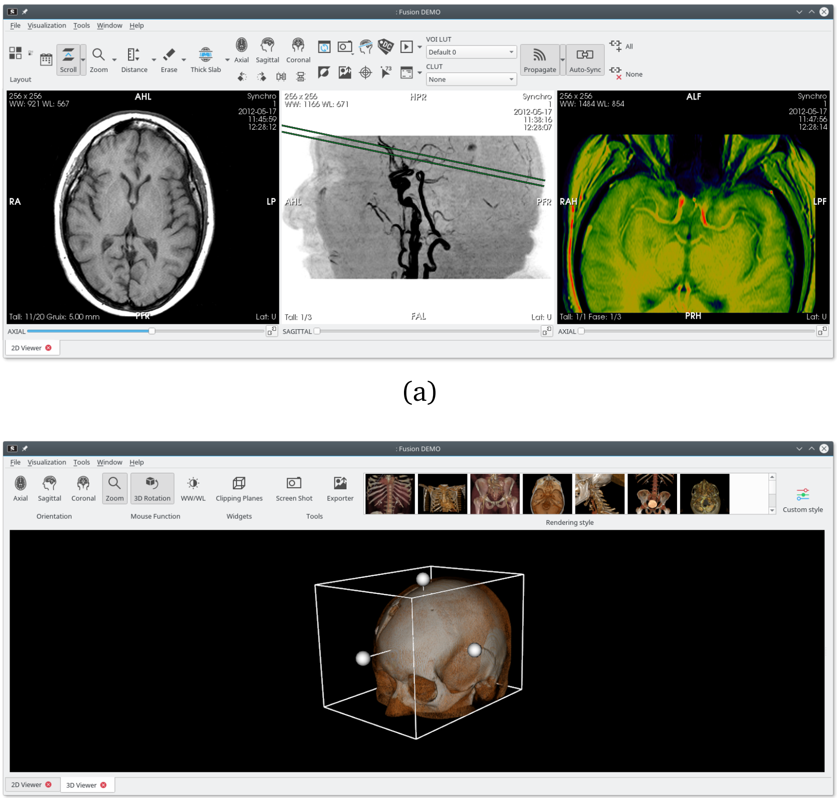
Since the discovery of X-rays at the end of the nineteenth century [Röntgen 1896], medical imaging has vastly evolved to become indispensable in current clinical practices [Doi 2006]. Indeed, the consolidation of X-ray imaging and the emergence of digital technologies and new imaging modalities have favoured the introduction of multiple diagnostic imaging techniques over the last few years [Doi 2007]. Some of these imaging modalities are computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound [Ganguly 2010].

Current medical imaging devices are able to obtain information from the internal parts of the body, and represent it as images. From these images, and applying specialised visualisation techniques, the body can be virtually reconstructed. These reconstructions are essential in the patient diagnosis and treatment, and have become a key element in hospitals, since they can be used, amongst other applications, to diagnose, plan operations and follow up the evolution of pathologies. To assist experts in these processes, medical imaging viewers are used (see Figure 1.1 for some visualisation examples). A medical imaging viewer is a software specifically designed to visualise medical imaging data with functionalities to explore and analyse it. Currently, there is a wide variety of both proprietary and open-source viewers [Haak 2016]. Their functionalities range from simple two-dimensional (2D) visualisations to advanced rendering techniques, including image processing tools to measure the volume of lesions and fuse information from different image modalities.

Considering that medical imaging is fundamental in the majority of clinical processes and related fields, many areas of research such as visualisation and image processing have focused on how to improve medical imaging applications and diagnostic processes. Fortunately, as illustrated in Figure 1.2, advances in these areas are also applicable to other fields, as diverse as education and meat science. The interest of this thesis has been centred on how to exploit and adapt these advances in both fields, with the purpose of improving some of their applications.

Medical imaging in education

In the context of education, the incorporation of new technologies in the teaching field has led to a change in the teaching methodologies [Garrison 2011, Soler 2012, Han 2013, Linaker 2015]. However, there is a lack of environments which allow the integration of medical imaging data. The current, more modern educational model pushes for the incorporation of such new technologies in the new teaching environments [Kasprzak 2016], but specialised methods to adapt and reuse the contents are required.



(a)

(b)

Figure 1.1. Visualisation examples from the in-house Starviewer[1] medical imaging viewer, showing (a) 2D representations and (b) a 3D model.

Graphical representations and images are key elements to present information in medical education (see Figure 1.3 for a diagram concerning the optimal features of an e-learning course). Generally, images are drawn freehand, obtained from atlases, or extracted from virtual environments capable to reproduce body information. Some current tools allow the visualisation of three-dimensional (3D) models and other medical imaging functionalities, but they are still far from the interactive capabilities of the medical imaging viewers, including the web-based ones such as Papaya[2], BrainBrowser[3] and Slice:Drop[4]. The content offered to the students has to be interactive and image-based, so that they can not only determine how to interpret images, but have enough motivation to learn by capturing their attention [Gunderman 2003]. In this sense, and taking into account both their economic and time cost, in some situations it may be interesting to virtually simulate practical classes to complement them, e.g. the practical classes using cadavers. In this context, interactivity is fundamental to achieve the goals of the simulation.

[1] https://github.com/starviewer-medical/starviewer [Accessed 5 April 2018]
[2] https://github.com/rii-mango/Papaya [Accessed 5 April 2018]
[3] https://github.com/aces/brainbrowser [Accessed 5 April 2018]
[4] https://github.com/slicedrop/slicedrop.github.com [Accessed 5 April 2018]

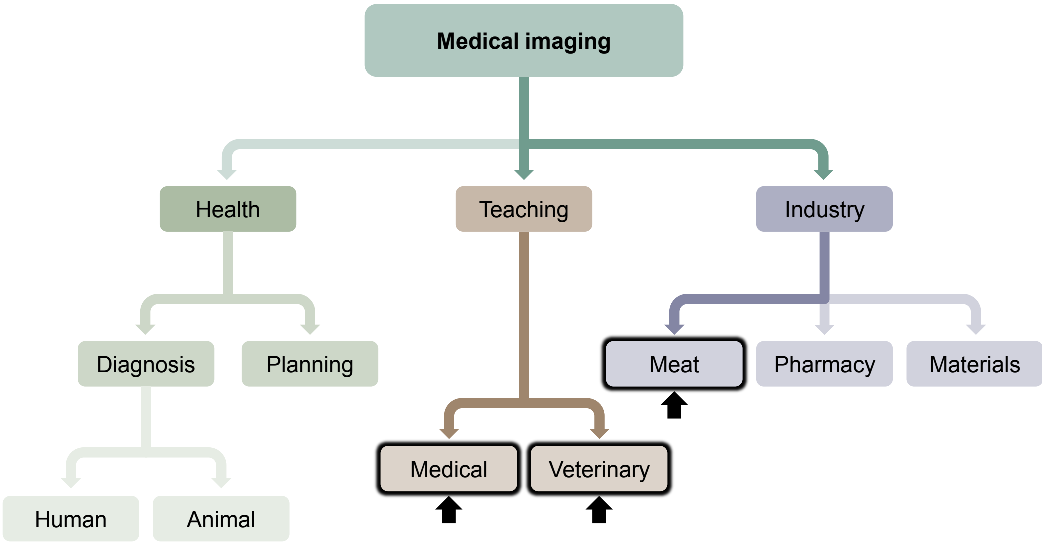


Figure 1.2. Some of the fields which can benefit from medical imaging visualisation and processing techniques, highlighting the fields this document will focus on.

Several application areas can benefit from the use of medical imaging techniques in their teaching methodologies. In this thesis, the medicine and the veterinary science fields have been studied.

Medicine

Focusing on medical education, there are some state-of-the-art frameworks which allow the exploration of medical images and models [Colucci 2015, Smit 2016], but they do not integrate functionalities to manage teaching tasks such as student evaluation. Furthermore, e-learning tools not only have to present the content to the students in a usable way, but also have to assist teachers in creating this content in a fast way, reusing current teaching material [Scarsbrook 2005]. The content creation tools provided to teachers, besides simplifying their work, have to let them present the content in an attractive and dynamic way for the students.

In the rise of e-learning during the last decades, and focusing on content creation and image interaction, several platforms have been proposed in the field of medical education [Bhargava 2013b, Bhargava 2013a, Zafar 2014]. Regarding the content creation and the reuse of contents, *MyPACS.net* [Weinberger 2002] is a web-based authoring tool to store and share teaching files, while the *Medical Imaging Resource Center* project (MIRC) [Roth 2005] and the *Key Image and Case Log Application* (KICLA) [Rowe 2014] provide similar features. As for the visualisation, *COMPARE Radiology* [Grunewald 2003] compares radiographs to analyse anatomical cases, and *RadStax* [Colucci 2015] includes image viewers which support region labels and multiplanar visualisation. With respect to image interaction, *USRC* [Burbridge 2015] provides some image manipulation features to interact with the teaching content. Focusing on

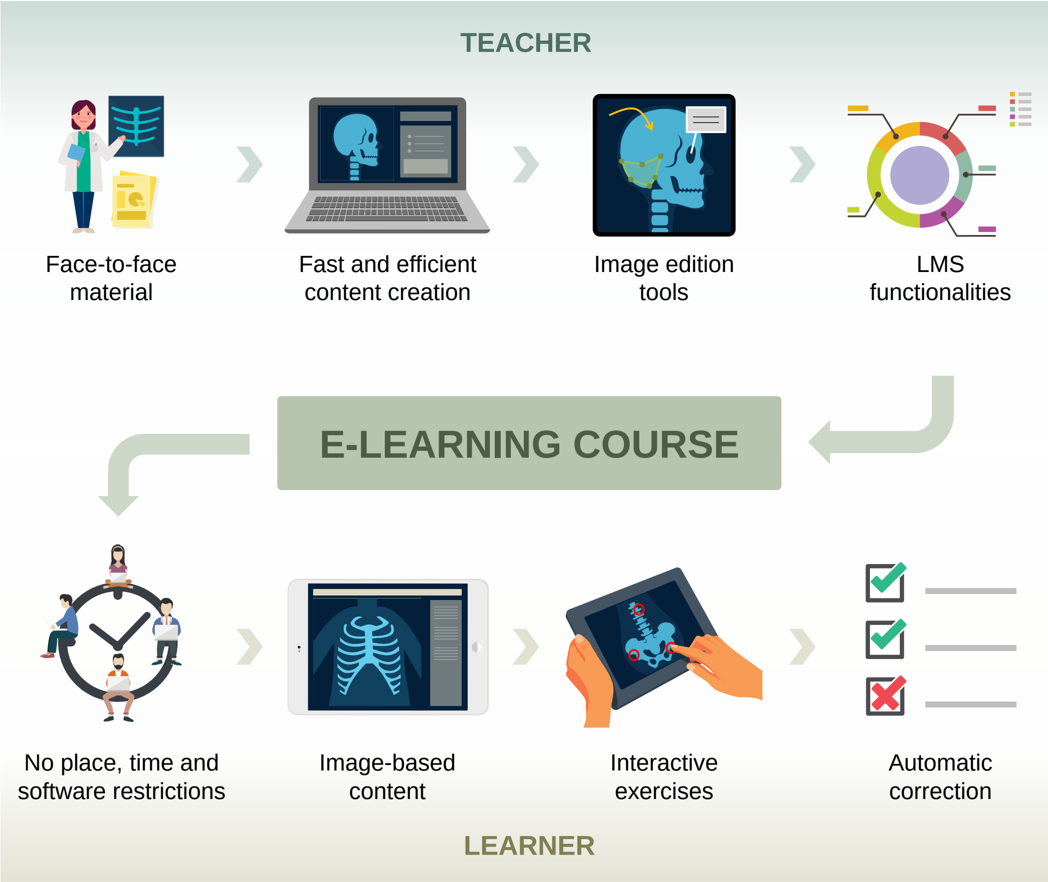


Figure 1.3. Optimal features of an e-learning course both from the teacher's side, using efficient and attractive content creation tools to transform the face-to-face material to an online course with learning management systems (LMS) functionalities, and the learner's side, removing the place, time and software restrictions (web-based environments) and offering image-based content and interactive exercises which are corrected automatically.

the exercises, the *E-Learning in Radiology* project (ELERA) [Grunewald 2004] allows the creation of image-based tests, and *Radiology ExamWeb* [Lewis 2013] allows teachers to create test exercises with feedback to the students. However, some of these platforms do not implement the notion of teacher and learner, or do not provide important features such as image interaction and automatic correction for the exercises.

Teaching with the help of medical imaging techniques is not important only in the undergraduate level [ESR 2011, Dmytriw 2015, den Harder 2016], where students can interact with radiological images and 3D models to learn particular medical concepts, but also in the field of continuing education [Laal 2012, Jones 2013], since many medical professionals enrol in recycling courses with the aim of maintaining their knowledge and learning about new advances in their field. Having an adequate knowledge and correctly interpreting medical images is useful to perform a better diagnosis and reduce costs in the hospitals [Smith-Bindman 2008, Ingraham 2016, Vijayasarathi 2016], although the participation of these medical professionals in the face-to-face courses which are offered is usually very low.

To encourage the medical professionals to participate in recycling courses, they need to find these courses interesting and dynamic [Collins 2004], and e-learning tools are an excellent means to achieve it, since place and time restrictions disappear, and many other interactive techniques not provided in face-to-face courses are allowed [Vilkonis 2013].

Veterinary science

The use of medical imaging and its interaction is starting to emerge as a fundamental tool for medical learning, but this process appears to be slower in the veterinary science field. For this reason, several authors advocate a modernisation process in this area [Short 2002, Simões 2010, Ozkadif 2012]. Although some studies prove that animal anatomy material can be taught by distance education methods [Bing 2011], and that simulation technologies should be encouraged [Valliyate 2012], there are very few veterinary e-learning tools, and few of them take advantage of medical imaging as a learning resource. Besides, the same shortcomings experienced by medical students with respect to e-learning tools which incorporate the interaction with medical images are also experienced by the veterinary science students, and generally by all the branches of science which make use of them.

Some of the proposed e-learning veterinary tools have been incorporated as part of e-learning programmes [Dale 2005, Ertmer 2007, Grizzle 2008], while other platforms are used as a teaching complement [Theodoropoulos 1994, Phillips 2001, Pop 2013]. Not all the frameworks are web-based, so students may be limited when they try to access them. It is also worth noting that some of them are only based on a particular species of animals, such as canine [Malinowski 2003, Linton 2005, Raffan 2017], equine [El Sharaby 2015] and sheep anatomy environments [Tawfiek 2011].

The availability of images and graphical resources is also scarcer in the context of veterinary science, notwithstanding that 3D models enhance students' learning [Lee 2010, Peterson 2016]. Image processing techniques allow the generation of new graphical resources such as efficient 3D models over which interaction can take place. However, this is a complex process, since multiple steps are required to build the geometry of the models. Segmentation, which aims to subdivide an image to its constituent regions or objects [Gonzalez 2002], is one of the key steps.

Hence, there is a need for veterinary e-learning platforms which can interact with radiological images and 3D models in order to enhance the learning process in veterinary science.

Medical imaging in meat science

When dealing with medical imaging applied to animals, another interesting application appears in the field of the meat industry. In this case, medical imaging is not only used to improve learning skills, but also as a tool to evaluate parameters which are useful for the industry, such as composition, curing and freezing parameters [Bertram 2004, Vidhya 2017].

To determine the quality of certain animals before their commercialisation, one of the most important parameters is the lean meat percentage (LMP) [Pomar 2009]. The tissues of an animal can be mainly divided in lean meat, fat and bone, and its commercial value is determined by the amount of the lean meat tissue (see Figure 1.4 for a diagram about different methods to compute the LMP value). Currently, the reference method to obtain this value is still the manual dissection, i.e. the animal carcass tissues have to be manually separated in order to calculate the LMP value and classify the quality of the animal. Although some techniques exist to simplify the manual dissection [EC 2008], so that it is only required to separate the tissues from certain parts of the carcass and extrapolate the result, the process is still considerably slow.

However, through the analysis and the processing of medical images, the LMP value can be accurately estimated without the need of carrying out a manual dissection. Furthermore, the process is much faster.

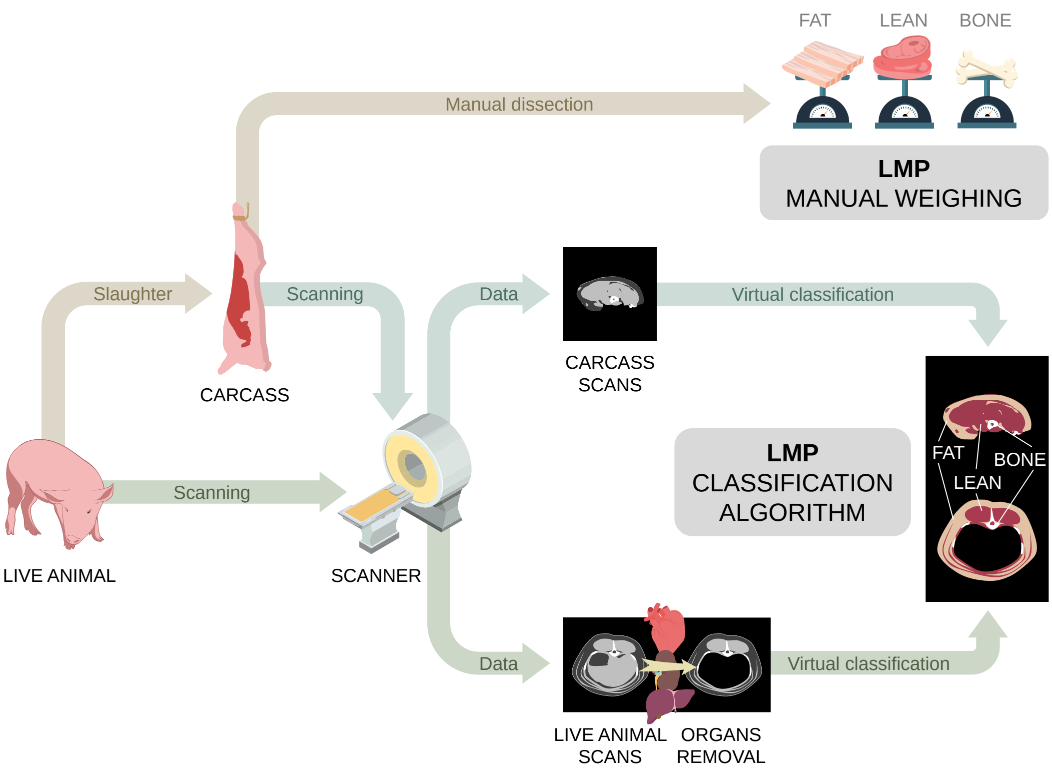


Figure 1.4. Different methods to compute the lean meat percentage (LMP), clearly distinguishing the manual dissection, which implies the slaughter of the animal and the manual classification by a trained butcher (including the manual internal organs removal), from the virtual classification, which uses classification algorithms over carcass or live animal scans, the latter including segmentation algorithms to remove the internal organs.

In a CT scan , the value of each pixel —or voxel, if working with a volume model— is usually expressed in Hounsfield Units (HU), which measure the attenuation coefficient of the animal tissues. Working with these values, image processing techniques such as segmentation are able to separate and classify the different tissues of the animal body, so that the lean meat percentage can then be computed over the total [Scholz 2015].

One of the industries which benefits most of these techniques is the pork industry, although they can be applied to other species such as sheep [Glasbey 1999]. Several methods have been proposed to analyse pig carcasses [Font-i-Furnols 2009, Vester-Christensen 2009, Picouet 2010, Bardera 2014] and live pigs [Luiting 1995, Kolstad 2001], and even the comparison between live pigs and their carcasses [Lambe 2013, Carabús 2015]. These methods include simple thresholding techniques, as well as the use of partial least squared regression [Dobrowolski 2004, Judas 2007, Font-i-Furnols 2009] and contextual Bayesian classification schemes [Vester-Christensen 2009].

However, the accurate classification of the animal tissues is not trivial, since the threshold value between two tissues is not obvious [Olsen 2017], and some tissues have very similar values, if not the same. The partial volume effect can also complicate the classification process [Tohka 2014]. Besides, images obtained from scanners of different vendors [Lamba 2014, Mackin 2015], or even from the same scanner in two different moments [Jacobsen 2016, Symons 2016], may present differences in the values, so that the thresholds which have worked well in a test, may not do so in other ones. Hence, the challenge is to develop lean meat quantification methods which are able to overcome these difficulties.

In some cases, it is important to evaluate the quality of the animals to monitor them [Carabús 2014, Font-i-Furnols 2015b], such as in the improvement of the quality depending on the diet. Therefore, the manual dissection is not possible because it implies the slaughter of the animal. In these circumstances, the advantage of using medical imaging data to determine the quality becomes much more evident, taking into account that it is a much less invasive technique.

Nonetheless, medical images from live animals present an additional problem. The internal organs are clearly represented in the images, but they are not required to compute the LMP value. Furthermore, the values of the image pixels or voxels of these organs are easily confused with the values of other tissues which are required for the computation. Hence, the internal organs removal implies another problem when computing the LMP value from live animals [Font-i-Furnols 2015a].

To summarise, medical imaging has certainly evolved to help medical professionals in the diagnosis process, but this knowledge has not been applied to the same extent to other fields such as the medical and veterinary science education, and the meat industry. The purpose of this thesis is to use medical imaging techniques to contribute to the research in these fields, either by improving methodologies or by proposing solutions to current problems.

1.1 Objectives

The development of this thesis responds to the need of taking advantage from medical imaging in fields where this technique is still not as widespread as in the field of diagnostic imaging, such as education and meat science. Based on this purpose, we can break down this aim into three main objectives:

- Apply medical image visualisation techniques to improve teaching in medicine.

  Medical imaging is an important technique in many branches of medical science, including anatomy and radiology. To learn its capability, medical students need proper methods to interact with radiological images, as well as having access to multiple data sets. However, current methodologies are mainly based on atlases or digital images which do not require an interaction between the student and the content. To improve students' comprehension and participation, images should take the main role in the learning process, and the use of interactive exercises should be encouraged. Moreover, teachers' efforts when creating the content should be minimised.

  > We want to design, build and evaluate in a real context a web-based medical imaging e-learning platform specifically devised for image-based and interactive content which is fast and easy to use for teachers, and motivating for learners.

- Apply medical image visualisation and segmentation techniques to improve teaching and increase the support for graphical resources in veterinary science.

  Unfortunately, the use of medical imaging in veterinary science teaching is even less significant than in the medical field. The amount of graphical resources is lower, and the adoption of atlases as the reference teaching method is more frequent. The analysis and exploration of medical images should be implanted as a common procedure to help students comprehend complex concepts. Furthermore, image processing techniques should be applied in order to create more graphical resources, such as 3D models. The creation of multiple and varied graphical resources, and the interaction with them, should be fostered for the students to take advantage from medical imaging in the learning process.

  > We want to design and build an interactive web-based veterinary e-learning tool which supports and promotes the use of graphical resources based on medical imaging, focusing on teachers' and learners' needs.

- Apply medical image processing techniques to improve the quality classification process of animals in the meat industry.

  Unlike the teaching methodologies, which mostly benefit from the medical image visualisation capabilities, the meat industry can take more advantage of the medical image processing techniques. The quantification of each animal tissue to compute the LMP value is a key process to determine the quality, and the standard method is still the manual dissection. Medical image analysis should be prioritised in order to automate the process and make it faster. Image processing techniques should also be used when dealing with live animals to avoid invasive procedures which may affect them.

> We want to propose an automatic, fast, robust and accurate approach to perform the animal tissue classification based on medical imaging processes, as well as some methods to achieve the same goal when classifying live animals.

1.2 Thesis outline

The contents of the thesis are structured in eight chapters. After the introduction and the definition of the objectives included in Chapter 1, the next five chapters describe the contributions made to achieve the main goals.

Chapter 2 presents a new web-based medical imaging e-learning platform to improve the teaching methodologies in medicine, whereas a study of its acceptance and an evaluation of the overall features of the platform in a real context are detailed in Chapter 3. In Chapter 4, the development of an interactive and web-based veterinary e-learning tool which supports new graphical resources in veterinary science is explained. Focusing on meat science, Chapter 5 proposes and evaluates an automatic, fast, accurate and robust tissue quantification method to determine the quality of animal carcasses from CT scans, and Chapter 6 presents two new segmentation methods to remove the internal organs from animal CT scans in order to facilitate the non-invasive quality classification of live animals.

Finally, the results and the discussion of all these contributions are summed up in Chapter 7, and the conclusions are given in Chapter 8, where a summary of the presented contributions is listed and some potential future directions of research are proposed for the topic of this thesis.

CHAPTER 2

A new e-learning platform for radiology education (RadEd)

The first main goal of this thesis is to apply medical imaging visualisation techniques to improve teaching in medicine. This chapter describes a new web-based medical imaging e-learning platform focused on radiology which provides image-based and interactive content to enhance the students' learning process and facilitates the content creation process for teachers.

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A new e-learning platform for radiology education (RadEd)

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ABSTRACT

One of the key elements of e-learning platforms is the content provided to the students. Content creation is a time demanding task that requires teachers to prepare material taking into account that it will be accessed on-line. Moreover, the teacher is restricted by the functionalities provided by the e-learning platforms. In contexts such as radiology where images have a key role, the required functionalities are still more specific and difficult to be provided by these platforms. Our purpose is to create a framework to make teacher's tasks easier, specially when he has to deal with contents where images have a main role. In this paper, we present RadEd, a new web-based teaching framework that integrates a smart editor to create case-based exercises that support image interaction such as changing the window width and the grey scale used to render the image, taking measurements on the image, attaching labels to images and selecting parts of the images, amongst others. It also provides functionalities to prepare courses with different topics, exercises and theory material, and also functionalities to control students' work. Different experts have used RadEd and all of them have considered it a very useful and valuable tool to prepare courses where radiological images are the main component. RadEd provides teachers functionalities to prepare more realistic cases and students the ability to make a more specific diagnosis.

1. Introduction

E-learning tools have become essential elements of teaching and learning methodologies. They provide functionalities that allow educators to improve communication and interaction between students, group development, personalised attention and access to material, amongst others. In addition, current technologies allow the creation of educational material that combines images, videos, text and sounds [1–4]. These materials can be interactively accessed by students providing feedback according to their actions. In this context, the student-centred methods where students have a more active role can benefit from e-learning tools and the large variety of activities that can be prepared. However, e-learning success depends not only on the functionalities provided by these new technologies but also on the provided contents. It is necessary that teachers prepare proper material for theory and practice to obtain the desired e-learning results. Content creation is a time demanding task that requires an extra effort by the teachers. We will focus our attention on content creation tools for topics that require a highly visual content such as radiology. Radiological images are essential not only for diagnosis but also for teaching and research. In radiology education, which

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occurs at the undergraduate, graduate, and postgraduate levels, students are exposed to a large number of radiological images to acquire and improve diagnosing skills [5,6]. In this context, the use of e-learning tools started twenty years ago [7–10] and it is an area of continuous development since it improves students' problem-solving ability [11–14]. Currently, throughout the European medical institutions, e-learning is involved in 70% of the time in radiology teaching [15]. For a review of e-learning work in radiology education see [16–18].

One of the key components of radiology education are the clinical cases used by teachers to introduce concepts and given to students to practice. Generally, these cases include radiological images, a description, and optionally questions for student assessment or self-study [19–27]. The case preparation requires collecting medical images from a PACS, extracting the informative tag attributes and denomination of the collected DICOM images, and presenting DICOM images in the proper format. The cases can be selected from personal collections or from common repositories. Focusing on the latter, there are websites created by official institutions such as the Radiological Society of North America (RSNA) or the European Society of Radiology (ESR) [28] which provide imaging databases and hypermedia documents with clinical cases. There are other websites such as *AuntMinnie* which provides radiologists and other professionals in the medical imaging industry a space to share and propose radiology cases, while offering some other functionalities such as a forum to communicate between the users related to the field of radiology [29]. Finally, there are more advanced websites that include functionalities for content creation. Some of them are presented in the following. *MyPACS.net* is a web-based authoring tool where radiologists can build on-line teaching file repositories to share and archive collections of images for using in slides or publications [24]. The *E-Learning in Radiology* project (ELERA) is a database of image-based teaching information with functionalities to create tests [30]. *COMPARE Radiology* is a web-based authoring software that provides anatomy cases with different levels of difficulty to students [25]. The *Medical Imaging Resource Center* (MIRC) project provides tools to share images and information for education, research, and clinical practice. It has an authoring tool to create radiology teaching files and other electronic documents in flexible formats with a common underlying structure [31]. *Radiology ExamWeb* is an application for teachers to create test exercises following a standardised format. Students can answer the tests obtaining feedback immediately [32]. The *Key Image and Case Log Application* (KICLA) is a software that works together with a PACS and allows users to store key images, image series and cine clips, in public or private folders that can be shared with other users [33]. *RadStax*, proposed by Colucci et al., is a web-based programme with an image viewer that allows the creation of labels on regions of interest of the images and also the introduction of information related to these labels. It also supports multiplanar visualisation and search functionalities [34]. In their work, they also defined the ideal resource for radiology teaching as the one that provides eight main features: (i) a fast and intuitive way to create labels for all anatomy of interest; (ii) the incorporation of basic information about each labelled region of interest; (iii)

Table 1 – Comparison of main web-based systems for radiology education including RadEd in the last column.

	MyPACS [24]	COMPARE [25]	ELERA [30]	ExamWeb [32]	KICLA [33]	RadStax [34]	RadEd
Content							
Focus of interest	Radiology	Radiology	Radiology	Radiology	Radiology	Anatomy	Radiology
Purpose	Theory	Theory	Practice	Practice	Theory	Theory	Practice
Cases search	Yes	No	Yes	Yes	Yes	No	Yes
External resources	No	No	No	No	No	No	Yes
External links	No	Yes	Yes	No	No	No	Yes
Learning functionalities							
Presentation-based	Yes	No	No	No	No	Yes	Yes
Types of exercises	Test	Guessing	Test	Test	No	Guessing	Test, location
Helping text for exercises	No	Yes	Yes	Yes	–	No	Yes
Exercise customisation	Medium	Low	Medium	Medium-high	–	Low	High
Assessment strategies	No	No	No	Yes	–	No	Yes
Image interaction							
Image importance	High	Medium-high	Medium	Low-medium	Medium	High	High
2D/3D/MPR	2D	2D	2D	2D	2D	2D &MPR	2D
Labels creation	Yes	No	No	No	No	Yes	Yes
Annotations creation	Yes	Yes	No	No	No	No	Yes
Basic operations (zoom, pan...)	Yes	Zoom	No	No	No	MPR Slices	Yes
General features							
Cross-browser	High	Low	High	Medium	Medium-high	Medium	High
Software dependency	Partially	No	Partially	No	Yes	No	No
Requires installation	No	No	No	No	Yes	No	No
Collaborative learning	Medium-high	Low	Low	Medium-high	High	Low	Low
User-friendly interface	Medium	Low-medium	Medium	Medium-high	Medium	High	High
Software knowledge	Medium	Low-medium	Low	Low	Low	Low	Low
Multilanguage	No	No	No	No	No	No	Yes

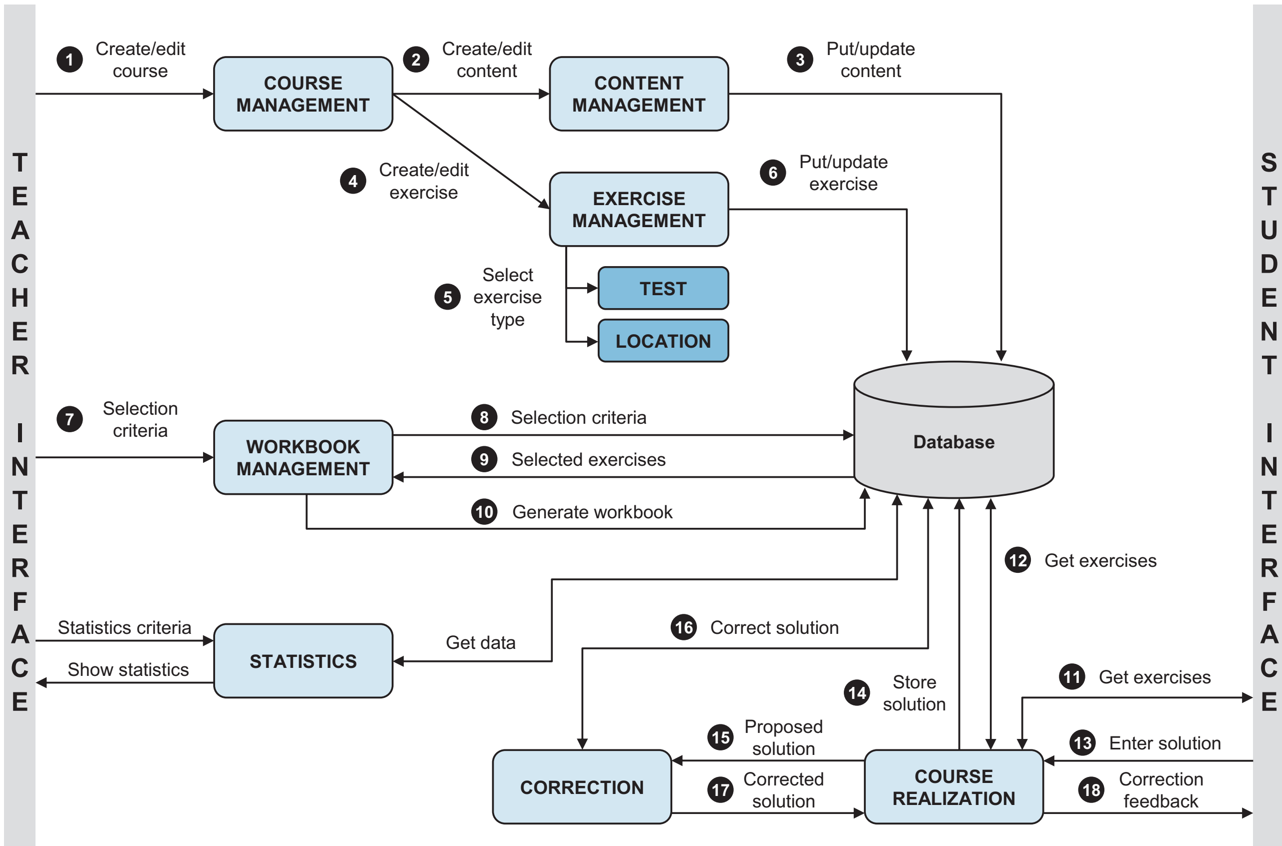

Fig. 1 – The main modules of the RadEd platform.

the ability to view all three planes of imaging simultaneously; (iv) a guide bar for localisation to facilitate three-dimensional understanding; (v) a search function; (vi) the ability to be easily incorporated into lectures; (vii) availability for independent study; and (viii) a means for self assessment. We agree with them that these are important features, but from our point of view, it is also important to make content creation as easy as possible.

In this paper, we present a new web-based teaching framework for Radiology Education denoted RadEd. RadEd integrates a smart editor to create case-based exercises that support image interaction such as changing the window width and the grey scale used to render the image, taking measurements on the image, attaching labels to images, and selecting parts of the images, amongst others. The ability to perform these actions allows teachers to prepare more realistic cases and students to make a more specific diagnosis. The proposed framework also provides functionalities to prepare courses with different topics, exercises and theory material, and also functionalities to control students' work. In Table 1, we compare our proposal with some of the previous described systems considering: *content creation functionalities* such as the focus of interest of the platform, the purpose for which has been created, the capability to search cases (categorisation), or the capability to support external resources and external links; *learning functionalities* such as the support to presentation-based cases, the types of exercises supported by the platform, the capability to support exercises with help messages for the students, the capability to modify exercises, or the support to assessment strategies; *image interaction functionalities* related to the operations that can be performed on an image such as 2D, 3D and multiplanar visualisations, the creation of labels and annotations, and basic operations; and *general features* such as the support to different browsers, or the dependency on a software, amongst others.

2. Design requirements

To define the requirements of our application, we analysed how teachers prepare the lecture sessions and also the practical classes of the Medicine Faculty of our university. We interviewed different teachers and we observed that most of them use slide presentations to show the cases to the students. In all the cases, images take a main role. We also analysed the teacher's actions when preparing a case. We defined as our main objective the integration of all these actions in a single editor that is the key element of our framework. Below we describe the main considerations that were taken into account to design this editor.

- First we considered that from each case we can create different exercises which always have an image. Then we considered the different actions that can be performed on these images. On the one hand, there are common actions provided by radiological viewers such as zooming and

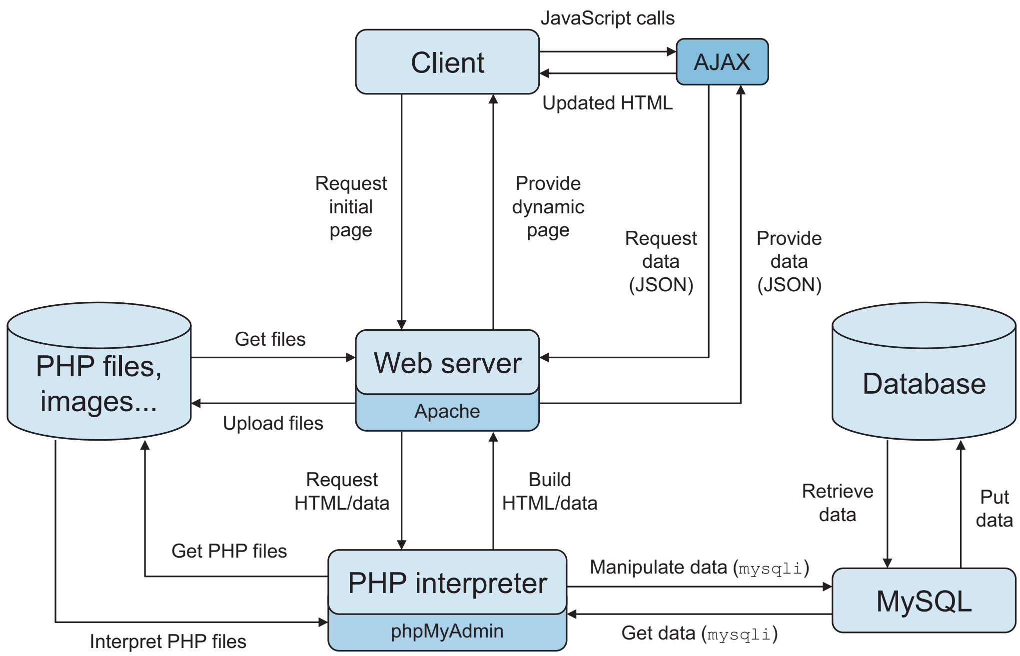

Fig. 2 – Client-server architecture of the RadEd platform.

panning. On the other hand, there are actions that can be performed to add information to the image. For instance, the definition of labels to highlight some parts of the image, the definition of regions of interest, or the representation of lines and other marks on the image. Our editor integrates a viewer with functionalities to support all these actions.

- A case or topic should have the description including the history of the anonymous patient, and the case exercises should have the following parameters: the image modality (computed tomography, magnetic resonance...), its speciality (neuroradiology, traumatology...), and the target users (medical students, radiology residents, post-graduates...). Our editor includes options to enter all this information.
- To start we considered three types of exercises: (i) test questions and (ii) multiple-choice questions, which are common to the majority of e-learning environments, and (iii) questions that require some interaction with the image such as selecting a region, placing a label or placing an icon. Our editor supports these types of exercises and combinations of them. In addition, once an exercise is created, the teacher can assign it a level of difficulty.
- Our framework has to support the automatic correction of exercises. We have to design strategies to automatically correct exercises and give instant feedback to the students. Feedback is crucial in the process of problem solving since learning is promoted when students are guided in their problem solving by appropriate feedback [35–37]. The editor provides functionalities to enter the correct solution of the exercises and also the feedback that has to be returned, as well as some help messages to guide the student to the solution.
- To automatically assess students, the teacher has to define the assessment criteria. We have introduced parameters to automatically assign marks. For instance, whether or not errors have to discount on the final mark. In addition, we have created templates to reproduce the assessment criteria.
- Our framework has to support the definition of time restrictions. Teacher has the chance to add time restrictions to the exercises such as deadlines, number of attempts and expiration time once the exercise has been accessed.

Note that no details about the image format have been given. For the sake of simplicity, in this first version of the platform we only support JPG/JPEG, PNG, GIF and BMP formats which are the most common. The support to DICOM files will be considered for the next version of the platform.

Once the editor requirements were defined, we considered a second group of requirements related to the course organisation. In this case, we considered functionalities to make the organisation of a course easier. These functionalities are common to the majority of e-learning platforms.

- Generally, exercises are related to different theory concepts. The teacher can consider exercises and then assign theory material to them, or can consider first theory and then assign exercises to it. We support both working modes. As theory material we consider the text introduced via menu or attached files.
- Focusing on the course management, we also provide functionalities to create groups of students, assign teachers to the groups, assign workbooks to the students and assign exercises to the workbooks. These actions are always performed by the responsible of the course.
- To follow up students' work, we register all their actions in a database. In this way, the teacher can track their work and also obtain different types of statistics.

As final considerations, our application has to be accessed via web, responsive and with support to different languages. In

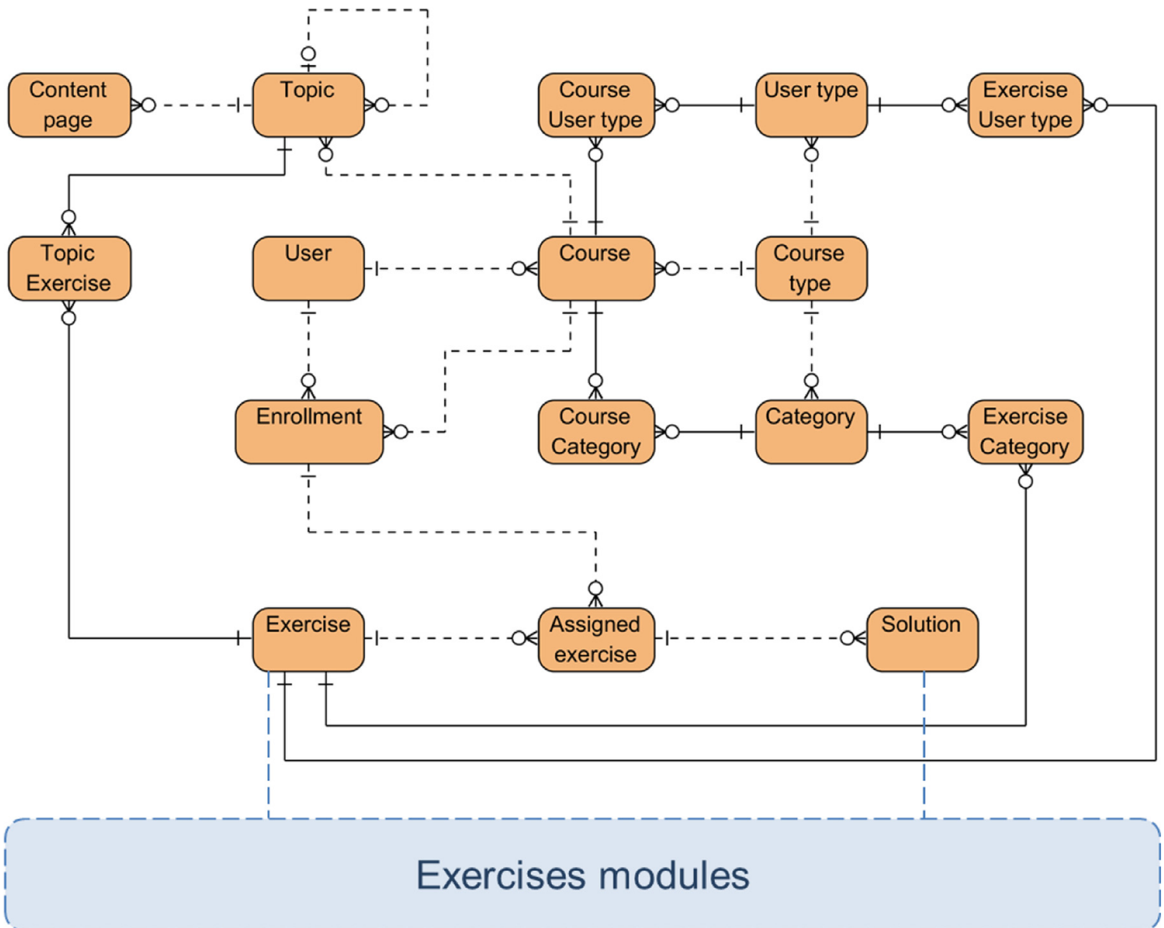

Fig. 3 – Database schema of the RadEd platform.

addition, its design has to be modular to allow the integration of new functionalities in an easy way completely transparent to the users.

3. System description

In this section, we present the architecture of the platform with its main modules and its functionalities (described in Fig. 1). The platform supports three user types: students, teachers and administrator. To enter into the system a username and a password is required. Students can be enrolled in different courses and for each course the teacher can assign them a workbook with different exercises. For each course, there are one or more cases or topics, and each case or topic can contain theoretical content and different exercises can be associated to it. The platform has a *database* that registers all the exercises and the theory material entered into the platform. All exercises are assigned a set of labels that identify: exercise title, speciality, application area, difficulty level, description and creation date. The system database also registers information related to students such as assigned exercises or students' solutions, and also information related to courses such as syllabus, material or exercises of each topic. Focusing on the platform modules, there is a *course management* module with the *content* and *exercise management* submodules used to enter

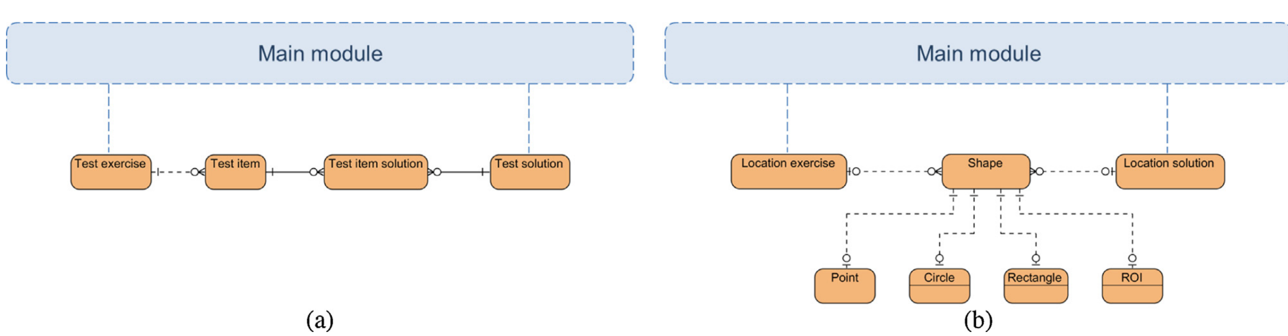

Fig. 4 – Database schema to maintain (a) test exercises and (b) location exercises in the RadEd platform.

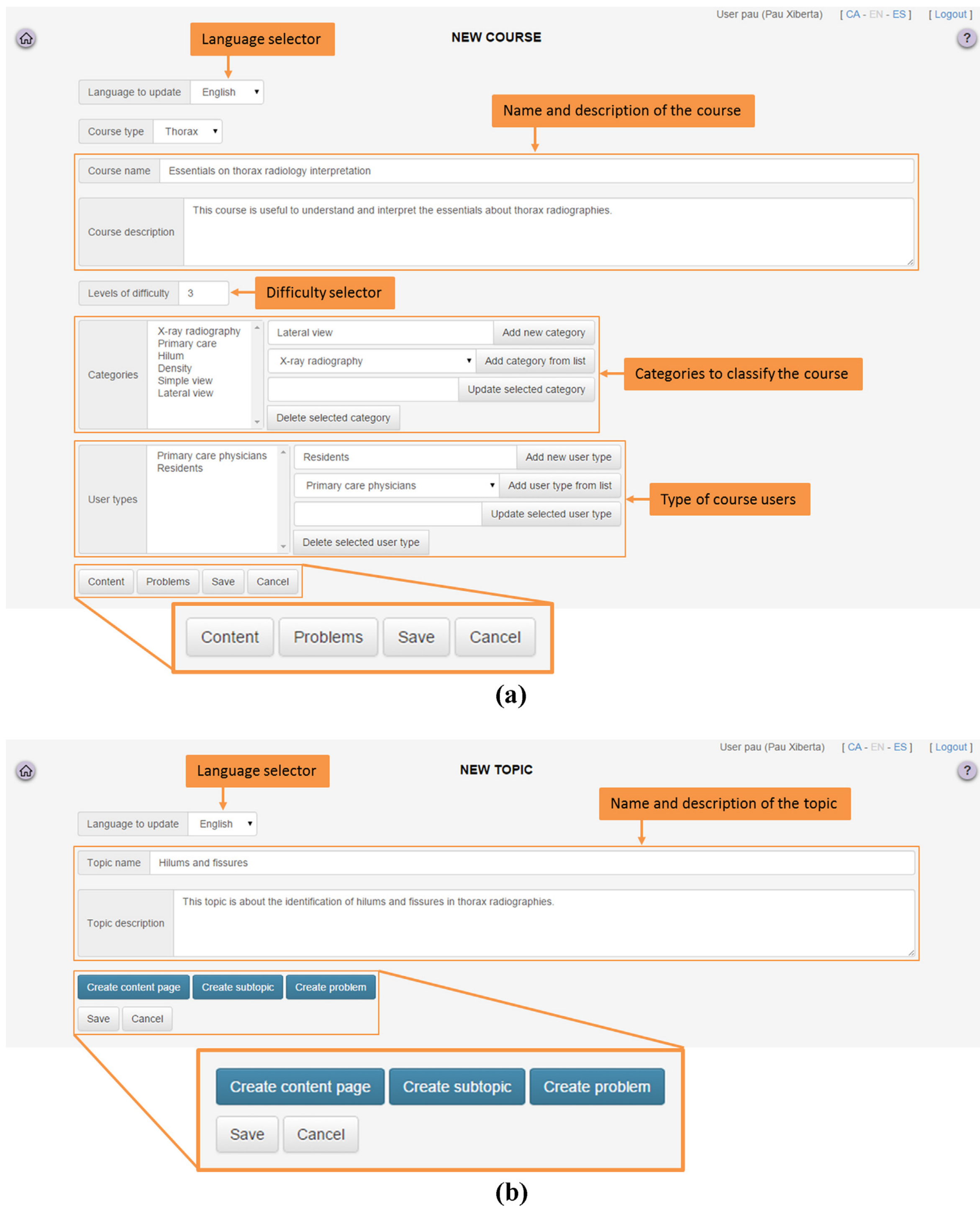

Fig. 5 – Some of the teacher interfaces designed to enter (a) the information of a new course, and (b) one of the topics of the course.

theory content and exercises into the system, respectively, and register them into the database. There is also a *workbook management* module used to create the students' workbooks. The exercises of the workbook are grouped by topics and can be added or removed at any moment. The *course realisation* module allows students the access to the workbook. For each exercise type, the platform provides a specific interface to enter a solution. This solution is registered into the system database and is sent to the *correction* module, which has a specific component for each exercise type. This module corrects on-line the proposed solution and provides immediate feedback about correction and, in case of errors, advises on how to correct them. Since all the information about exercises, solutions and corrections is stored in the system database, we designed a *statistics* module to query this database and extract information to follow students' progress. This

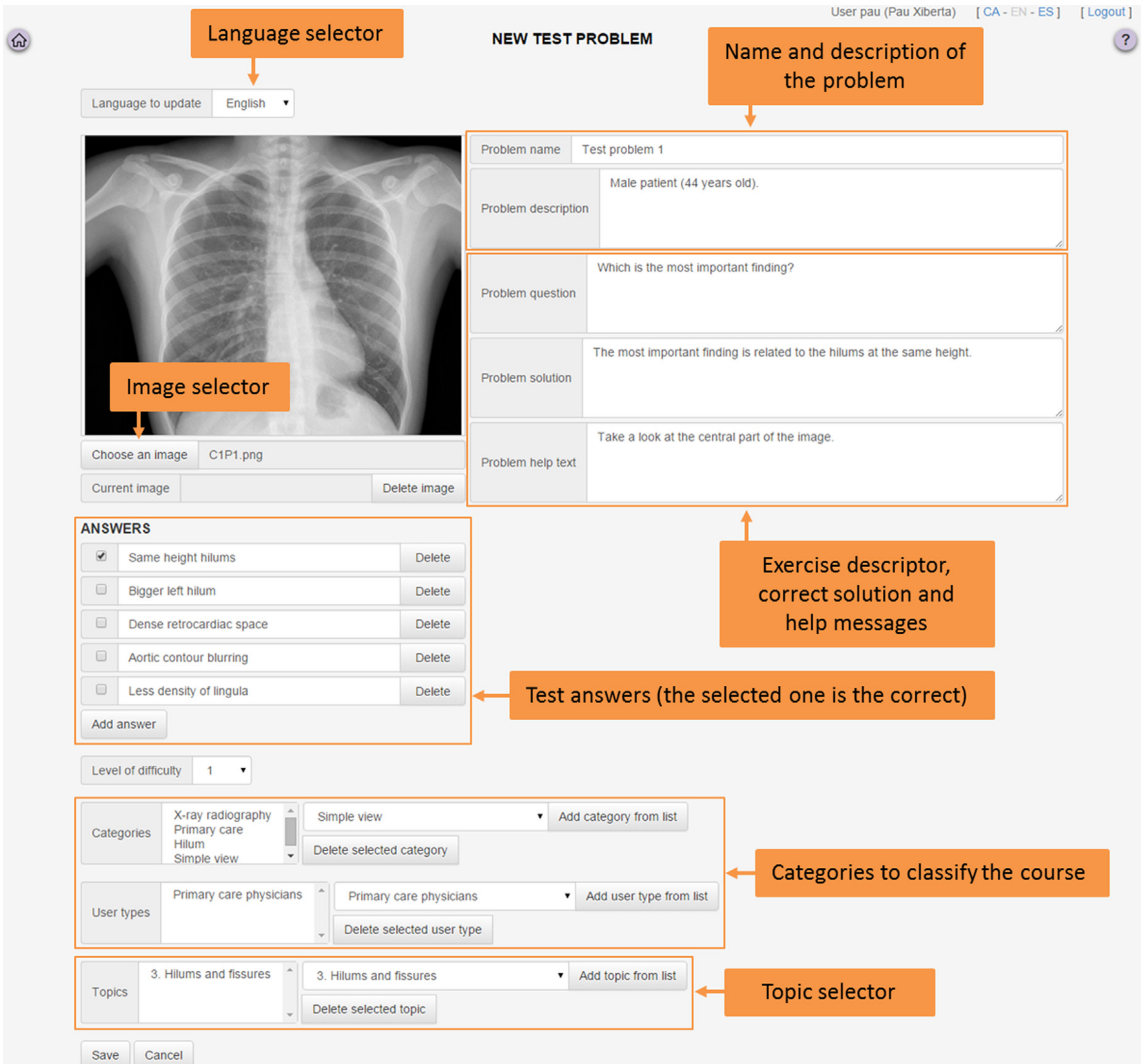

Fig. 6 – Interface to enter a test exercise.

information can be used to carry out continuous assessment. In this case, we collect from the database quantitative data about students' work such as number of errors, types of errors and time taken to complete the exercise. The teacher can use this information to control and monitor students' progress through their workbook. Note that, in the current version of the platform, there is no connection between the statistics module and workbook management or course management modules, and all the creation responsibilities are left up to the teacher. However, for the next version of the platform, we plan to establish a connection between these modules to exploit all the information stored in the system database. Such a connection will allow us to automatically determine the required course level for the student based on a short evaluation of the student's pre-existing knowledge and proficiency before starting the course; or modify the system so that difficulties encountered by the students during the course would be detected by the system, and further exercises to improve on this particular difficulty could be prepared by the teacher for such an eventuality, and presented to the student only if she/he begins to struggle with a particular concept within the course.

Our platform follows a client-server architecture. Fig. 2 shows a general view of this architecture, with its main elements and its communication strategies. It has an Apache web server, and a MySQL database management system to store our data. To implement the interfaces and the logic of the application we used HTML5 and JavaScript, respectively.

Finally, in Fig. 3, we present the schema of the database that has been designed to store all the required information. To describe it we are going to consider the main tables of this database. These are courses, users and exercises. Each course is assigned a type which is used to classify the course. For example, a thorax course belongs to the thorax type. Each course is assigned also a number of levels of difficulty, a set of categories, and a set of user types, features that are used to classify the exercises of the course. Courses are also assigned different topics, and these topics are assigned theory. Theory is represented as content pages or as links to external files stored in the topic and content page tables. Users are enrolled

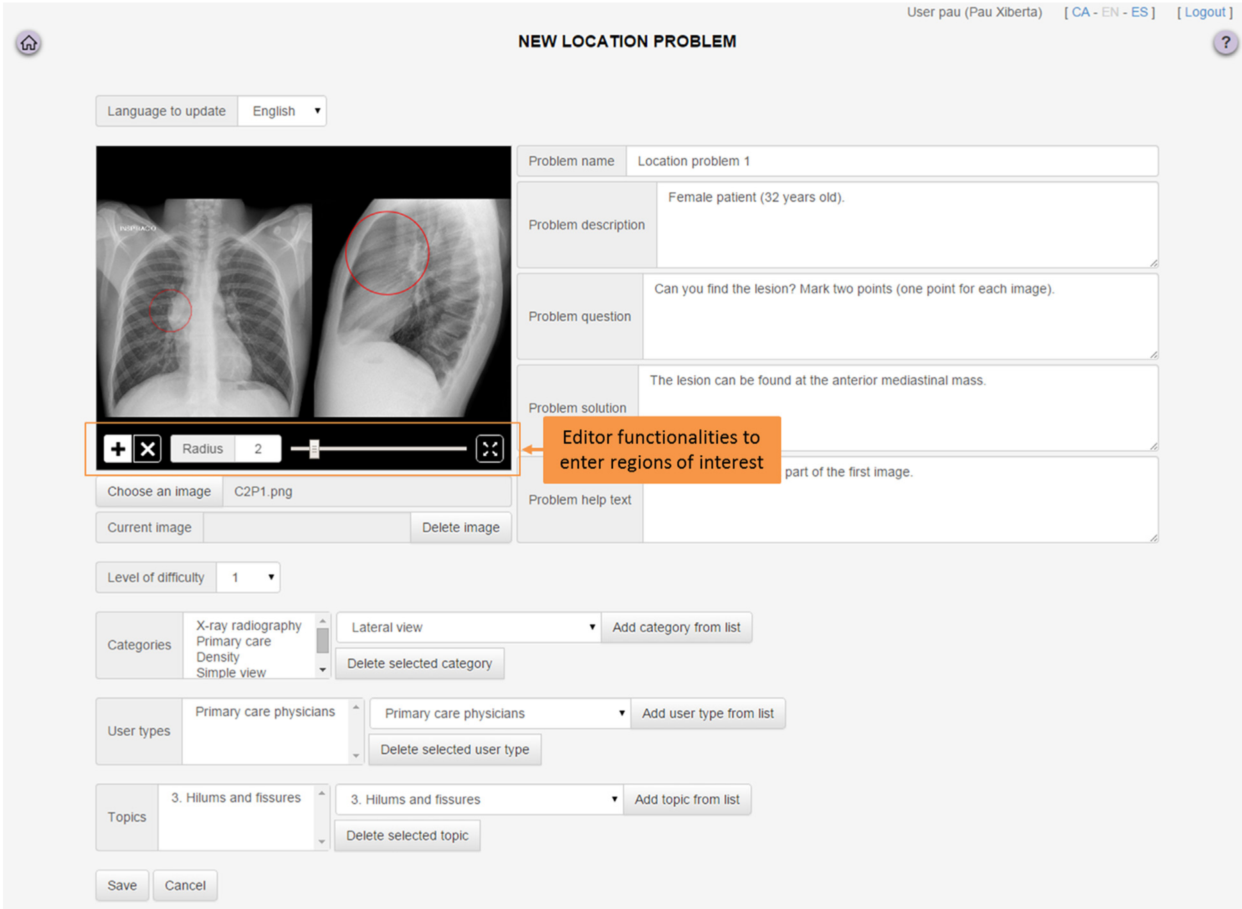

Fig. 7 – Interface to enter a location exercise.

in the courses and they are assigned some exercises. These exercises are assigned a topic that is also a topic of the course. Exercises are assigned to students. They will propose solutions to the exercises that will be stored in the solution table. This table also stores the correct solution of the exercise entered by the user that has created the exercise. Since the system supports different types of exercises, we have specific modules to store them and their solutions. In Fig. 4, the structure designed to maintain the test and location exercises is shown.

4. Results and discussion

In this section, we present some of the interfaces of the RadEd platform. The presented interfaces correspond to a course of essential topics on thorax radiology.

Fig. 5 shows the interfaces to enter the information of a course. As it can be seen in Fig. 5(a), to create the course the teacher has to enter, amongst other features, the language of the course, a functionality that is not supported by the other platforms analysed in this document. Similar to other platforms [25,30,32], the teacher also determines the number of levels of difficulty that the exercises from the course can take, and different keywords that are assigned to the course to filter information [24,30,32,33], such as categories and possible users. The course can be organised following topics and subtopics analogously to other platforms [24,33]. Fig. 5(b) corresponds to the interface designed to enter a new topic.

Fig. 6 shows the interface designed to create a test exercise. Aside from the common information related to an exercise, the teacher can also enter a help message that will appear when the student asks for help, as in other platforms [25,30,32]. When selecting the image, our platform only supports common image formats, such as JPG/JPEG, PNG, GIF and BMP, unlike other platforms which support more formats such as DICOM [24,33]. Regarding the answers section, our platform provides a high exercise customisation since the teachers can enter as many answers as they want, a feature that is not provided by any of the analysed platforms. The selector at the beginning of each possible answer is used to select the correct ones. Finally, the exercise is linked to one or more topics, another feature that only our platform provides.

Fig. 7 shows the interface designed to create a location exercise. The interface is similar to the test creation one presented in Fig. 6. The main difference is in the functionalities of the integrated editor. Since the exercise requires the identification of some regions of the image the teacher has to enter these regions defining a point and a radius. The selected regions will be used to automatically correct students' answers. Only regions contained in the teacher selected area will be considered as correct. All these features of the integrated editor are not included in any of the other analysed platforms.

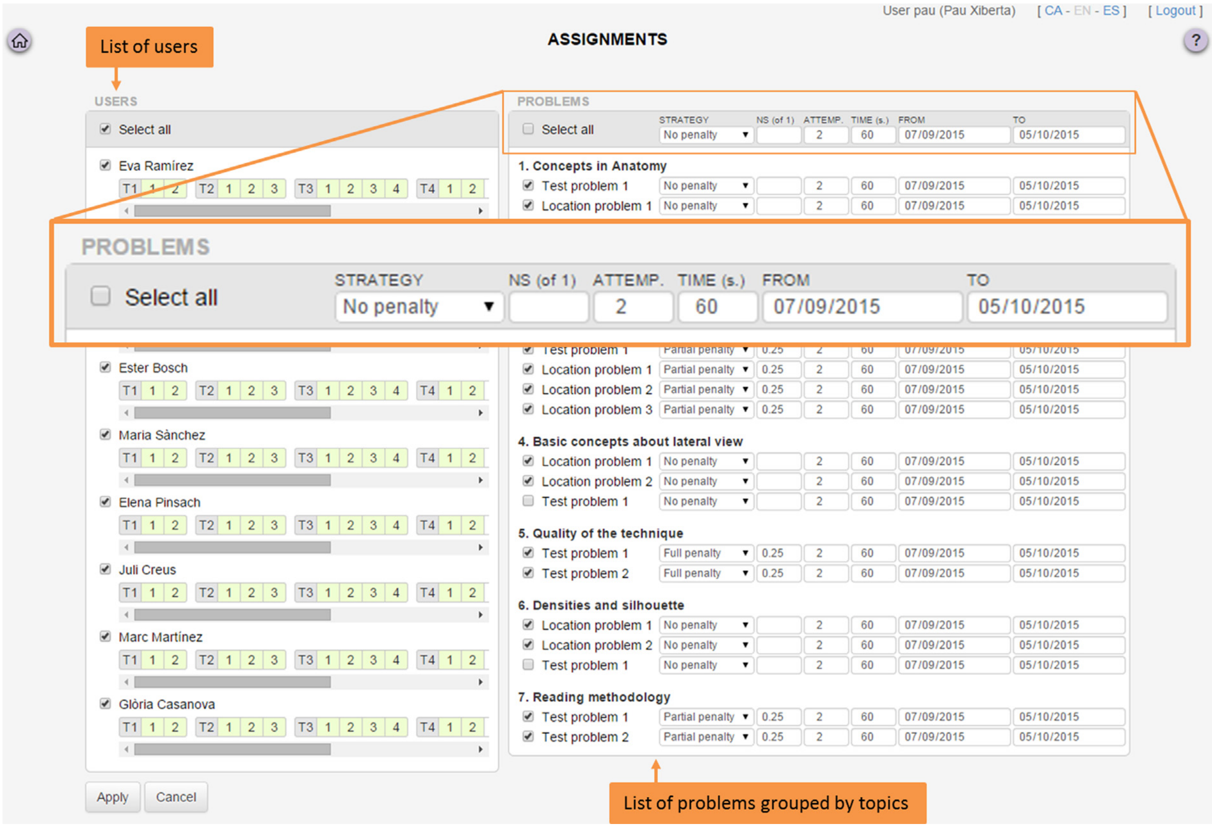

Fig. 8 – Interface to assign exercises to the students of a course.

Students are organised in courses and the teacher determines the exercises that each student has to solve. Only ExamWeb [32] is also able to do these assignments. Fig. 8 presents the interface created to assign exercises. For each student, we can see the exercises that have been assigned for each topic. To assign new exercises we have to select the students and the exercises. The high exercise customisation is made clear at this point, when the teacher has the possibility of determining the assessment strategy (no penalty, partial penalty of full penalty), the negative score (depending on the assessment strategy), the number of attempts the student can use to solve it, the time the student can spend once the exercise has been accessed, and the deadline. None of the analysed platforms offers this level of customisation, but some of them reach also a high level [24,30,32]. As for the assessment strategies, only ExamWeb [32] mentions them.

Fig. 9(a) is the screen designed for the teacher to enter theory material related to a topic. All the analysed platforms are able to include some theory material, but only three of them allow a structured layout as our platform does [24,25,33]. The content is structured in three different levels of information which determine how the information will be showed in the student screen, as it is illustrated in Fig. 9(b).

Fig. 10 presents the student interface for a location exercise. Our platform is the only one that provides both test and location exercises, and is designed in a way that other types of exercises are easy to integrate. All the exercises follow the same screen distribution, as stated by the labels on the figure. There are also four icons, from left to right, which represent the home button to return to the student's main page, the book icon to access the information related to the topic, the pen icon to solve the exercises, and the interrogation icon to obtain help about the interface options. At the bottom right there are the editor buttons to interact with the image. These buttons vary depending on the type of the exercise. In this case, it is a location exercise and we have the icon to mark regions on the image, a functionality that is new compared to other platforms.

Fig. 11 presents the student interface of a test exercise. In this case we present the screen once the exercise has been automatically corrected. Note that in the general information part we colour the exercises depending on their status. A filled box represents a solved exercise, and the green or red number represents an exercise correctly solved or not, respectively. The black boxes represent unsolved exercises. The figure shows the high importance that our platform gives to the images as do other platforms [24,25,34], and also the ability to perform basic operations such as zooming, panning or using the full screen tool, features that are only provided together by MyPACS [24]. However, our platform only supports 2D images visualisation, unlike RadStax [34] which also supports MPR visualisation.

4.1. *First user impressions*

Five different teachers tested the platform. Teachers 1 and 2 are from the Medical Faculty of our University. They teach in the Anatomy and Radiology subjects, respectively. They

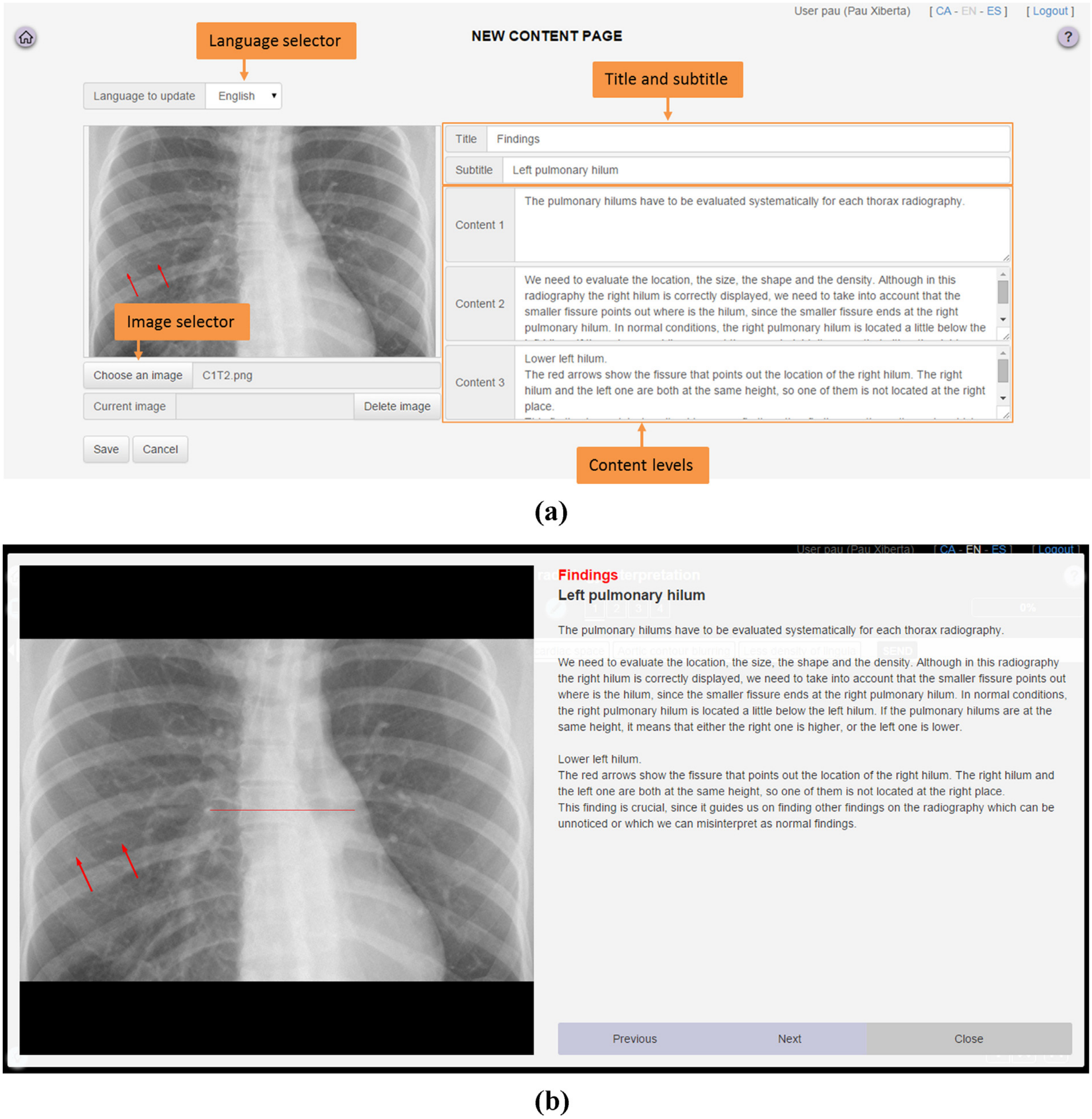

Fig. 9 – Interfaces related to the content of a topic. Screen (a) is the teacher interface and screen (b) how the student sees the entered content.

have been teaching for more than 30 years. Teachers 3 and 4 are from a private institution and teach Anatomy in Physiotherapy courses. Both have been teaching for more than 10 years. Teacher 5 is a radiologist who teaches resident physicians. He has more than 15 years of experience. All of them are familiar with e-learning environments. For their classes they use Microsoft PowerPoint (more than 80 per cent of the classes) and they have their own repository of cases that have been collected over the years. Generally, they do not use DICOM files for the classes; they work with common format images such as JPG/JPEG or PNG. When they want to work with DICOM files, they show the images using a radiological viewer. All the teachers use Moodle as the e-learning platform.

We introduced the platform to them in a 30 min session. We did not spend more time since we wanted to evaluate if menus and interfaces were clear enough for the teacher to prepare material. After this introductory session, we asked them to prepare one of the topics of their current classes using our platform. After preparing the classes we interviewed each teacher to collect their impressions about the platform. Our main interest was to know if the platform was useful and easy to use. All of them considered that RadEd was a very useful and valuable tool to prepare classes and that the main advantage of the platform was the editor. The possibility to create exercises that support user interaction was the most appreciated feature. They also considered that interfaces are user-friendly and they appreciated the support to different languages. They

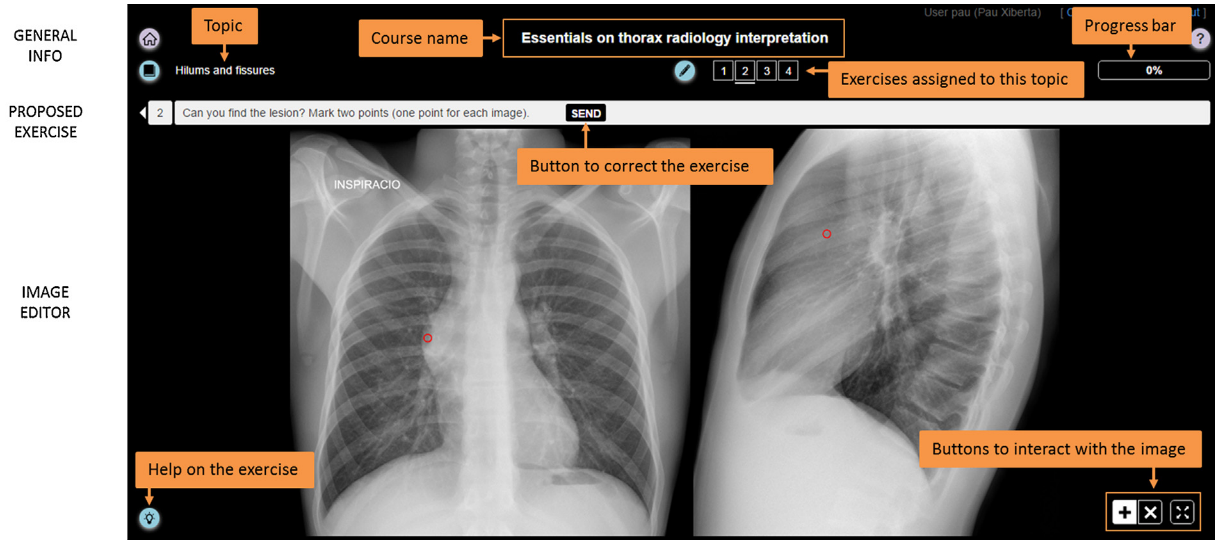

Fig. 10 – Student interface to solve a location exercise with the labels on the main parts of this interface.

also appreciated the flexibility of the platform to combine theory material with the exercises.

They proposed us the integration of new functionalities such as the preview of exercises once the teacher has created them and before assigning them to the students. We agree that this is a necessary functionality and we are programming it. They also suggested the integration of a multiplanar viewer and also a 3D viewer. Such a suggestion is also considered as a future work together with the support to DICOM files. They commented that the introduction of exercises requires an extra effort. However, all of them agree that once they have created the exercises, they very appreciate the possibility to access them at any moment. In this way, RadEd can be used to store their material. They were worried about the authorship of the exercises and they proposed us the possibility to integrate a public/private flag to determine if the teacher who has created the exercises wants to share the material or not. We did not consider this option, since our original idea was to have a collaborative platform. However, we are considering the possibility to support private cases as a strategy to obtain financing.

5. Limitations

Content creation is one of the most time demanding tasks of e-learning platforms. It requires teachers to prepare material taking into account that it will be accessed on-line,

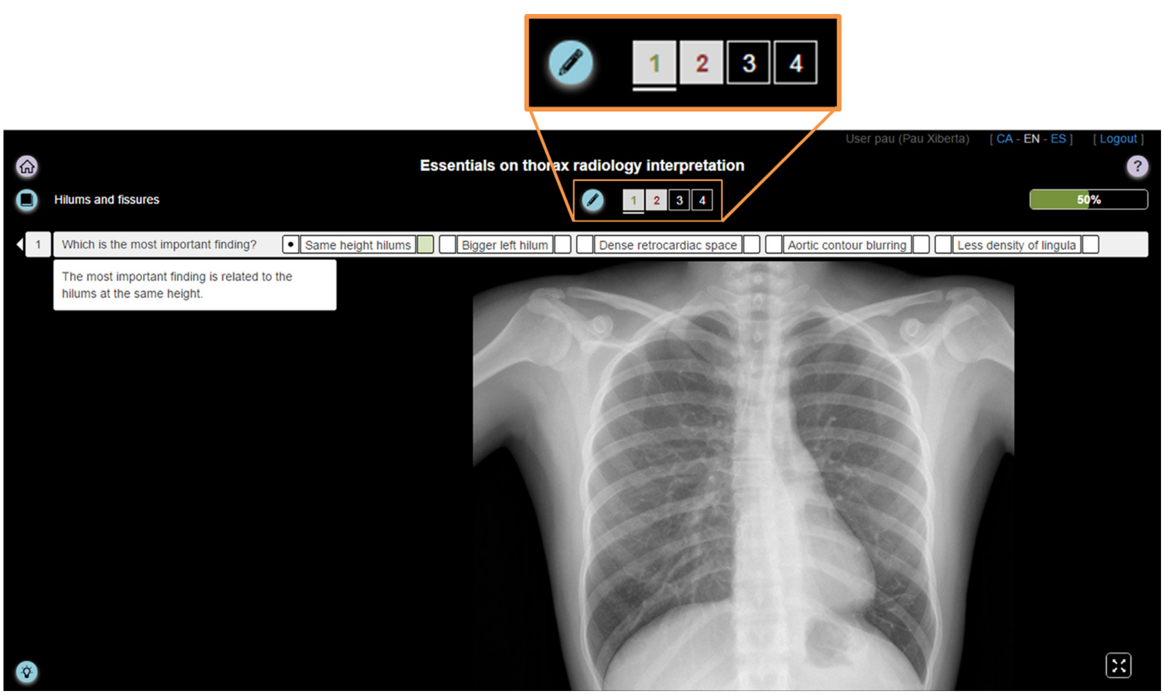

Fig. 11 – Student interface to solve a test exercise.

and this requires an extra effort to be presented in a more pedagogical way. Moreover, the teacher is restricted by the functionalities provided by the e-learning platforms. In addition, in contexts such as radiology where images have a key role, the required functionalities are still more specific and difficult to be provided by the platforms. The presented platform, RadEd, has been created to overcome some of these limitations. The platform has been constructed from scratch and considering the teacher as the main user to be satisfied. Although our first users have positively received the platform, we are conscious that it still presents several limitations that need further development. On the one hand, it requires more advanced visualisation techniques capable to reproduce the functionalities provided by radiological viewers. Although these functionalities can be easily integrated into the platform, the task that is going to require more programming time will be the support to DICOM files. In our opinion, as important as the visualisation methods is the possibility to access data directly from a PACS. This will considerably enrich the platform and will avoid teachers to extract images from the DICOM files. On the other hand, the platform can exploit all the information stored in the RadEd database such as the course organisation and student performance statistics. All this information can be used to automatically design courses and also to adapt contents to the different student profiles. Currently, the teacher does all these actions, but with the integration of intelligent tutoring systems functionalities most of them could be automated. Focusing on automation we can also improve all the assessment strategies and create templates that allow the reproduction among courses. With respect to the state of the art platforms, we consider that RadEd improves some of the current platforms as it can be seen in the comparison presented in Table 1. One of the main features is the provided editor that allows the creation of different types of exercises in an easy way. Finally, we want to remark the modular design of the platform that would allow us to easily adapt it to other contents, and create new types of exercises that could be included in the platform without further problems.

6. Conclusions and future work

In this article, we have presented RadEd, a web-based radiological education platform designed to complement teaching and learning of subjects that require the interaction with radiological images. Different to other e-learning platforms, RadEd has been designed to make content creation easier. With this purpose, it integrates a smart editor with advanced features to create customised exercises that support image interaction such as changing the window width and the grey scale used to render the image, taking measurements on the image, attaching labels to images, and selecting parts of the images, amongst others. The ability to perform these actions allows teachers to prepare more realistic cases and students to get a more interactive and efficient learning. The proposed framework also provides functionalities to prepare courses with different topics, exercises and theory material, and also functionalities to control students' work. Different teachers have tested the tool and considered RadEd a very useful and valuable tool.

Our future work will be centred on the creation of a new version of the platform that includes more advanced functionalities such as multiplanar reconstructions, 3D visualisations, support to DICOM files and new types of exercises. In addition, we plan to automate the course management and workbook generation processes by including information from the users stored in our database to provide intelligent tutoring systems functionalities. Finally, we want to extend our user study with a statistically significant sample of test users, both teachers and students.

Conflict of interest

There are no conflicts of interests.

Acknowledgements

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Chapter 3

Measuring the acceptance of e-learning in continuing education courses for medical staff: the experience of a thorax radiology course

The first main goal of this thesis expresses the need to find a proper method to improve teaching methodologies in medicine by motivating the students' participation. This chapter presents a study to evaluate in a real context the acceptance of a radiology course delivered through the e-learning platform described in Chapter 2.

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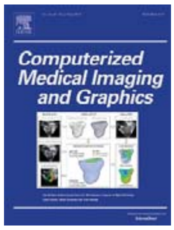

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Measuring the acceptance of e-learning in continuing education courses for medical staff: the experience of a thorax radiology course

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Abstract

We describe the experience of transforming a face-to-face course on thorax radiology to an online one. We evaluate the acceptance of the course and the features that make e-learning valuable to teachers and learners. A course on thorax radiology has been delivered to 249 participants. The experiment was carried out in two fases: Phase 1, as a pilot testing with 12 general practitioners (G1), and Phase 2, with 149 general practitioners (G2), 12 radiologists (G3) and 76 medical residents (G4). All participants evaluated the course design, the delivering e-learning platform, and the course contents using a five-point Likert scale (satisfaction level from 1 to 5). Collected data was analysed using t, Mann-Whitney U and Kruskal-Wallis tests. In Phase 1, the rounded scores of all questions except one surpassed 3.5. In Phase 2, all the rounded scores surpassed 4.0 indicating that a total agreement on all items was achieved. In the open questions, the participants valued the high interactivity of the platform, and the ability to overcome the place and time restrictions. All collected impressions indicate the high acceptance of the proposed methodology. To make radiology interpretation more widely available and accurate by generalists, the design of online courses based on e-learning platforms with functionalities that support image interaction and automatic content creation processes are very highly recommended, since they increase the learners' participation with respect to the face-to-face courses.

Keywords: E-learning, Continuing education learning, Content creation, Radiology

1. Introduction

Medical imaging has greatly evolved to become an indispensable tool for medical professionals in the diagnostic process. However, these advances have not been applied to the same extent to the field of medical education. Our purpose is to use medical imaging techniques to improve current teaching methodologies.

In this paper, we focus our interest on radiology courses for general practitioners and medical residents from a region of our country. Currently, there is a special interest in this audience not only to refresh and introduce radiology concepts, but also as a measure to reduce costs (Vijayasarathi et al., 2016). There is a need for strategies that ensure a proper and responsible use of medical imaging, and continuing education courses can contribute to it (Ingraham et al., 2016). With this purpose, medical teaching units of our region periodically propose courses of few hours (less than 10) focused on different aspects of radiology. Generally, the proposed courses are face-to-face and voluntary. Place and time restrictions are the main limitations to participate in the courses. Fortunately, most of these limitations can be overcome with e-learning technologies.

E-learning focuses on the use of computer and network technologies to enhance teaching and learning, while preserving or improving the interactivity of face-to-face learning. Over the last few years, it has gained great importance at all educational levels from primary school to universities (Garrison, 2011; Han et al., 2013; Islam, 2016). In radiology education, different e-learning tools have been proposed; for a review see Bhargava et al. (2013b,a) and Zafar et al. (2014). The challenge is how to design and implement courses that motivate teachers and learners to participate.

We will present the experience of transforming a face-to-face continuing education course on radiology for general practitioners and medical residents to a course carried out online and delivered using a platform specifically de-

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signed for this. We will describe the main decisions made, and we will measure the acceptance of the course participants. The presented experience highlights the challenges and steps needed to create the course.

2. Previous work

Radiology education is important in both undergraduate and residency medical education programs. Little radiology training is incorporated into non-radiology residencies and the majority of students believe that there should be more radiology teaching in medical school (Dmytriw et al., 2015). To tackle these problems, the Radiology Department of our region, supported by the medical teaching units, organise courses for non-radiologists and residents. The courses are face-to-face courses, compulsory for residents, and voluntary for general practitioners, the latter having low participation. In order to increase the number of participants and make radiology interpretation more widely available and accurate by generalists, we decided to take advantage from e-learning and transform a face-to-face course in an online one.

One of the main decisions when designing an online course is the selection of the e-learning platform. To select it, we have considered teachers and learners requirements with the purpose of increasing the learners' participation in the courses. In our context, course teachers are generally radiologists who are used to face-to-face classes. They prepare case-based classes either by using their own cases or by using examples from different image repositories. They consider practice fundamental to accumulate experience. Therefore, their main challenge is the translation of face-to-face material to online contents which can support user interaction in order to simulate practice (Gunderman et al., 2003). Focusing on learners, they require a large number of case studies, and an engaging way to interact with them and evaluate themselves (den Harder et al., 2016).

We evaluated some of the state-of-the-art e-learning platforms considering the support for content creation and image interaction as fundamental requirements. Since the target participants include medical residents, we were interested in platforms which can not only deliver material, but also track learners' work. *MyPACS.net* (Weinberger et al., 2002) and *KICLA* (Rowe et al., 2014) offer a limited image interaction, and they only allow entering clinical cases; they do not implement the notion of teacher/learner. By contrast, *ELERA* (Grunewald et al., 2004) and *Radiology ExamWeb* (Lewis et al., 2013) do provide exercises, but they are limited to multiple choice questions and no image interaction is offered; besides, the teacher cannot prepare a specific course with different topics. *COMPARE Radiology* (Grunewald et al., 2003) is limited to radiographs comparison, and it does not allow automatic correction for its exercises, since they consist in hiding and showing information to the user, and *RadStax* (Colucci et al., 2015) is a content-based tool which provides only a little quiz and requires the teacher to have knowledge about HTML/XML to enter new cases. Finally *USRC* (Burbridge et al., 2015) is a web application created and designed for use in an independent manner by medical students, but a Java applet has to be installed to run the image viewer; furthermore, although it provides a quiz and some functionalities to interact with the images, it does not support the automatic correction of exercises, nor does it control the learners' work. RadEd (Xiberta and Boada, 2016) provides functionalities to create theory material and exercises using images with which the user can interact. Moreover, it provides functionalities for automatic correction with feedback to the learner. To create and deliver the course, we considered RadEd as the most suitable platform.

3. Material and methods

3.1. The Radiological Education platform (RadEd)

RadEd (Xiberta and Boada, 2016) is a web-based e-learning platform designed to complement teaching and learning of subjects that require the interaction with radiological images. It is available for PC, tablets and smartphones and it is multilingual. It allows the creation of modules (or courses) grouped by topics which can contain different levels of sections and subsections. These items can contain theory and exercises. There are different types of exercises, such as test, identification of regions and labelling, which can be corrected online using the corresponding correction strategy integrated in the same platform. The platform provides specific editors for teachers to create theory material and exercises, and functionalities to control learners' work and visualise their progression with respect to other learners of the course, amongst others. For more details, see Xiberta and Boada (2016).

3.2. A course on thorax radiology

A radiologist with more than 20 years of experience both diagnosing and teaching prepared the online course. He used his own presentation slides and also a set of cases which he uses in his face-to-face classes. He translated all this material to online contents using the theory and exercise editors of the RadEd platform. By using the editor options, he assigned help messages and feedback to the exercises to guide the learners. It was not required to prepare the material from scratch. The course topics and some screenshots of the platform are presented in Table 1 and Fig. 1, respectively.

3.3. Participants

Test participants are 249 subjects classified in four groups: G1, with 12 general practitioners who participated only in the pilot testing; G2, with 149 general practitioners; G3, with 12 radiologists from the radiology department of the Hospital Josep Trueta of Girona; and G4, with 76 medical residents. The participants, recruited from different hospitals and medical residencies of our region, were

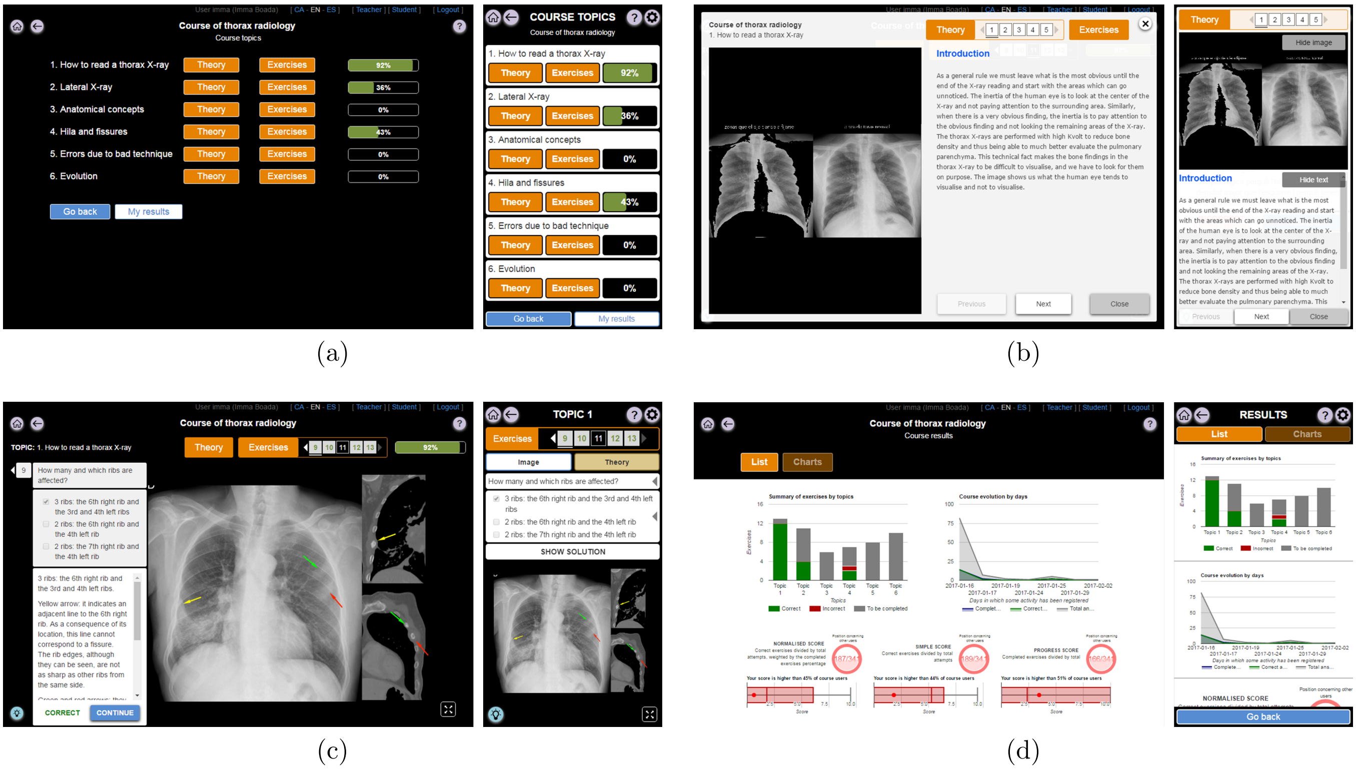

Fig. 1. Screenshots of the PC and smartphone versions of the course: (a) Course contents with the topics, the buttons to access theory and exercises, and the progress bar indicating the percentage of exercises that have been solved; (b) A theory page with the buttons to navigate to other pages and access the related exercises; (c) An example of one of the exercises of the course; and (d) Some statistics of learner progress such as number of exercises solved per day, number of correct exercises per topic, and position of the participant with respect to other members of the course.

Table 1
Topics of the thorax radiology course.

Topic	Theory pages	Exercises
How to read a thorax X-ray	5	13
Lateral X-ray	7	11
Anatomical concepts	10	6
Hila and fissures	4	7
Errors due to bad technique	3	8
Evolution	1	10

asked to perform the course voluntarily. Those who agreed were all accepted, so there were no exclusion criteria. The experiment in which they have participated has been conducted according to the Declaration of Helsinki principles.

3.4. Experimental design

Our experiment has been done in two phases (see Fig. 2). To test the course, Phase 1 was delivered to G1 members. They had access to the course for 15 days, and after completing 80% of the course they filled the questionnaire presented in Table 2. To answer, Likert scale (1 = total disagreement, to 5 = total agreement) was used (Likert, 1932). In this phase, some errors were detected and corrected. Afterwards, Phase 2 started with subjects from G2, G3 and G4. Again, participants had 15 days to access the course, and when 80% of it was completed they filled the same questionnaire.

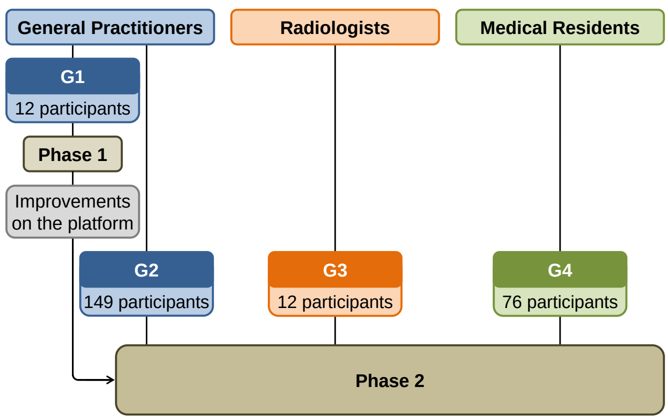

Fig. 2. Diagram of the participants divided by groups and phases.

3.5. Statistical analysis

To evaluate if the opinion of the course improved between Phase 1 and Phase 2 a Mann-Whitney U test has been performed. Using Phase 2 data, depending on the number of categories of independent variables, t-test and Kruskal-Wallis test were used to identify significant differences by gender, age, type of participant, attended online

Table 2
Participants questionnaire filled when 80% of the course was completed.

General Information
Age How many online courses have you participated in, aside from this one? [0, 1 to 3, > 3] Which device have you used preferentially to take the course? [Computer, Tablet, Others] Do you think that the smartphone version of the platform is useful? [Yes, No]
Global Evaluation (1 = Totally disagree, to 5 = Totally agree)
(Q01) Globally, I favourably evaluate the course (Q02) I would recommend this teaching methodology (type of course plus delivery platform) to my teammates
Usability (1 = Totally disagree, to 5 = Totally agree)
(Q03) It was easy for me to interact with images (Q04) It was easy for me to access and navigate through the content pages (Q05) It was easy for me to access and navigate through the exercises (Q06) It was easy for me to identify each icon with its function
Contents (1 = Totally disagree, to 5 = Totally agree)
(Q07) The topics in which the course was structured are appropriate (Q08) The course contents met my expectations (Q09) The balance between exercises and content was appropriate (Q10) Participating in this activity will allow me to improve elements of my daily work
Open questions
Aspects that you would suggest to improve this teaching methodology (type of course plus delivery platform) Positive aspects of this teaching methodology (type of course plus delivery platform) that you would emphasise Topics or issues on which I would like to take a course

courses and usefulness of the smartphone version of the platform. Age has been transformed to a 3-categorical variable (25 to 34, 35 to 49 and 50 to 64). In all stages, we used the software R (R Development Core Team, 2008) which is a free software environment for statistical computing and graphics.

4. Results

4.1. Participants profiles

Phase 1 of the experiment was performed by 12 voluntary participants with an average age of 42 years old and a standard deviation of 7.87. The characteristics of Phase 2 participants are shown in Table 3. We only considered those participants who answered the survey (184 out of 237), and from these ones, those who provided all the information, thus reducing the sample from 184 to 146 participants, since 38 participants did not provide their age. When analysing the usefulness of the smartphone version, and also the online courses previously attended by the participants, the sample is reduced to 145, since some participants did not provide this information. Note that approximately two thirds of Phase 2 participants are interested in the smartphone version of the platform (56% of general practitioners, 71% of medical residents, and 100% of radiologists). As it was expected, the non-interested group is the oldest one (Vilkonis et al., 2013). We can also observe that more than half of the subjects have participated in many online courses, while the rest is divided in those that have participated in none or few courses.

Table 3
Characteristics of Phase 2 participants.

		Age		
		mean	sd[a]	n[b]
Gender	Female	36.02	9.95	108
	Male	42.00	12.73	38
Type of participant	General pract.	44.19	9.23	84
	Medical resid.	28.14	5.32	57
	Radiologists	34.00	5.70	5
Usefulness of smartphone version	Yes	36.27	10.51	92
	No	40.09	11.49	53
Online courses previously attended	Many (> 3)	40.45	9.92	77
	None	30.00	6.55	36
	Few (1 to 3)	39.38	13.63	32

[a] Standard deviation.
[b] Number of participants.

4.2. Questionnaire results

Looking at Table 4, we can see that in Phase 1 the rounded scores of all questions of the test except Q03 surpassed 3.5 on a five-point Likert scale, while in Phase 2 all of them surpassed 4.0. Questions Q03 and Q05 have significant differences (p-value < 0.05), and Q02, Q07 and Q08 have nearly significant differences ($0.05 <$ p-value < 0.1). Therefore, the improvements introduced after Phase 1 have enhanced the course.

Table 4
Differences in the scores between Phase 1 and Phase 2, and p-values.

		mean	sd[a]	Mann-Whitney U
Q01	Phase 1	4.17	0.83	0.27
	Phase 2	4.42	0.69	
Q02	Phase 1	3.92	1.08	**0.07**
	Phase 2	4.43	0.73	
Q03	Phase 1	2.83	1.40	**0.005**
	Phase 2	3.95	1.04	
Q04	Phase 1	4.67	0.49	0.75
	Phase 2	4.68	0.54	
Q05	Phase 1	3.82	1.17	**0.03**
	Phase 2	4.49	0.75	
Q06	Phase 1	3.83	1.19	0.14
	Phase 2	4.30	0.82	
Q07	Phase 1	3.92	0.79	**0.07**
	Phase 2	4.31	0.77	
Q08	Phase 1	3.67	0.98	**0.07**
	Phase 2	4.16	0.85	
Q09	Phase 1	3.92	0.90	0.12
	Phase 2	4.28	0.83	
Q10	Phase 1	4.25	0.75	0.57
	Phase 2	4.34	0.80	

[a] Standard deviation.

Focusing on Phase 2 scores, represented in Table 5, we can see that there are no significant differences in the scores by gender, frequency of online courses previously attended, and usefulness of the smartphone version. This means that the course and the platform are suitable both for users who are used to participate in online courses and for participants who have never had such an experience before. Considering age and type of participant, only question Q03 presents significant differences (p-value < 0.05).

Regarding the open questions that participants filled in the last block of the questionnaire, we divided them in three groups:

1. *Aspects that they would suggest to improve the teaching methodology (type of course plus delivery platform).* Quite a few users said the course was too short, and that they expected more exercises. Other aspects they found improvable were the difficulty of the location exercises, the possibility to download the theory contents, the ability to organise the practical cases from less to high complexity, and informing about the length of the course. Related to the course contents, they wanted to delve into the patterns and differential diagnosis; they expected more paediatric images, a topic about lung parenchyma, and more practice in finding lesions over the images; and they suggested changing the order of the topics to study first the anatomy, while adding more radiographs to the first topic.
2. *Positive aspects of the teaching methodology (type of course plus delivery platform) that they would emphasise.* They highlighted the ability to take the course at any time and from anywhere; the interactivity and completeness of the platform; the easy, fast and intuitive interface and navigation; the value of the feedback after solving the exercises to help understanding where the user has made a mistake; the suitability of this platform for radiology courses; the good quality of the images and the well-structured information; the practical, image-based and light contents; the usefulness for the users' daily work; the good relationship between theory and exercises; and the fast learning and the maintenance of knowledge.
3. *Topics or issues on which they would like to take a course.* Participants requested and suggested many different topics, such as abdominal radiology, paediatric radiology, bone radiology, lumbar radiology, and ultrasound. However, a lot of participants requested the same course, but with more practical cases.

5. Discussion and conclusion

Radiology concerns almost all medical specialities and continuing radiological education is required to maintain competence and learn about new advances in this field. With this purpose, experts on the topic prepare courses which are usually delivered face-to-face. Due to limited resources related to time and teaching staff, special attention has to be paid when designing these courses (Gunderman et al., 2003; Scarsbrook et al., 2005). Amongst the different issues that need to be considered when preparing them, we have focused on two: (i) how to exploit technology capabilities and also the time and knowledge of the experts; and (ii) how to motivate learners' participation. We consider that both issues can be tackled from a technological perspective.

There are different applications and technologies that can be applied to prepare teaching material for radiology. In Kasprzak (2016), the uses of technology in the context of radiology education are presented, and in Bhargava et al. (2013b,a) multiple online radiology resources which offer case-based learning experiences are described. From

Table 5
Phase 2 scores taking into account gender, age, type of participant, frequency of online courses previously attended, and usefulness of smartphone version.

	Gender	Age	Type of participant	Online courses previously attended	Usefulness of smartphone version
	t-test	Kruskal-Wallis	Kruskal-Wallis	Kruskal-Wallis	t-test
Q01	0.65	0.96	0.20	0.99	0.19
Q02	0.59	0.98	0.62	0.93	0.21
Q03	0.42	**0.04**	**0.03**	0.70	0.34
Q04	0.54	0.68	0.82	0.88	0.38
Q05	0.45	0.16	0.22	0.40	0.09
Q06	0.12	0.08	0.34	0.61	0.08
Q07	0.91	0.76	0.12	0.60	0.55
Q08	0.44	0.39	0.06	0.68	0.40
Q09	0.68	0.60	0.07	0.71	0.69
Q10	0.86	0.51	0.19	0.56	0.34

our perspective, the majority of these applications seem to be designed to be used for experts and not for more general courses. Moreover, these applications do not consider important tasks of continuing education such as the control of learners' assignments or the learners' progress, especially in the case of medical residents. These functionalities are common of learning management systems and, in most of the situations, the radiological cases are integrated in other platforms such as Moodle. Such a combination makes content creation more difficult and this leads to an extra work for the teacher. For the sake of simplicity and to save time, we considered that a platform which integrates both the support to case-based problem creation and learning management systems functionalities would be better. Xiberta and Boada (2016) presented the RadEd platform which provides all these functionalities, so it has been used to perform this experiment, and it has been very well accepted. The time required for the teacher to prepare the course was less than what he expected since the majority of tasks that have to be done are repetitive, such as uploading images and copying the learning material from the face-to-face course, which is already prepared, and pasting it in the e-learning platform. Teachers are usually expert radiologists who have a great knowledge about the topic, but they do not know how to make the online experience attractive for students. From this experience, we have detected the importance of pedagogical support to guide teachers in questions such as the number of attempts that have to be assigned to an exercise, when to return feedback, and when to send help messages.

Focusing on learners' side, Collins (2004) evaluated education techniques for lifelong learning and described the application of ten principles of adult learning to radiological education. Amongst these principles, she remarks that adults learn best when they are active participants in the learning process and that they learn more effectively when appropriate feedback is given. Furthermore, adults tend to be problem-centred learners and learn best through practical applications of what they have learned. In the context of medical education, the impact of practical case-based methodologies has been very well studied and different studies demonstrated their positive impact on learners (Lim-Dunham et al., 2016; Yao et al., 2016; Gaupp et al., 2016). They have also been studied in the field of radiology, where case-based e-learning is pointed out as one of the most promising approaches (Maleck et al., 2001). Therefore, a good strategy would be the creation of online case-based courses which supports user interaction in order to simulate practice. We have designed such a course, focused on thorax radiology. The course has been very well accepted by both the experienced and non-experienced users. They specially appreciated the ease of use of the delivery platform as well as the possibility to interact with images. These results confirm Collins' principles. With respect to learners' motivation, we want to explore how gamification techniques can be used in our context to improve the results (de Marcos et al., 2016).

The course was also offered in a mobile version for smartphones and tablets, and despite the fact that most of the participants stated that this version would be useful, only 10 of them took advantage of it. Although the use of such technologies is widespread, even amongst the medical practitioners, and mainly amongst the residents (Korbage and Bedi, 2012a,b), they are not the preferred tool to diagnose due to the limitations they have regarding the screen size (Rodrigues et al., 2013; Al-Hasani et al., 2013). Some studies have demonstrated that they have some advantages with respect to the mobility, but when it comes to diagnosing they still cannot compete with a PC (Székely et al., 2013), and they are only kept for diagnosis during emergency (Aufferman et al., 2013; John et al., 2012). In Krupinski et al. (2007), the recommended requirements for diagnosis devices are defined, and smartphones and tablets do not meet them. In our case, then, this conclusion has been made clear.

From the results of the participants and the comments of the open questions, we consider that the proposed teaching methodology has successfully demonstrated to be effective in improving the participation of medical practitioners with regard to continuing medical education courses. Moreover, if we take into account the Kirkpatrick model (Kirkpatrick, 1994), we can clearly conclude that level 1 of this model has been achieved, since participants found the training favourable, engaging and relevant to their jobs. Indeed, from Q10 of the questionnaire (average score of 4.34), related to the improvement of the participants' daily work, we can consider that participants will apply what they learned during training when they are back on the job, so that levels 2 and 3 have also been achieved. With respect to level 4, related to the outcomes as a result of the training, it is difficult to measure in our context, since it requires a further evaluation where several parameters need to be considered, and not only the background on radiology. Judging by the scores of the participants, we also consider that the pilot testing of the experiment was useful to correct errors and improve the learners' e-learning experience.

As a limitation of our study, we consider some of the items of the questionnaire, such as Q03. For the sake of simplicity, we present short questions and this may lead to some confusion. Some users had problems with image identification due to the difficulty of the exercise, and they considered this as an image interaction problem. For the next test, we are going to rewrite these questions. Although the main objective of this study is the evaluation of the learners' participation and acceptance of the proposed teaching methodology compared to face-to-face courses, another limitation could be the missed opportunity to evaluate the knowledge of the participants before and after taking the course.

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CHAPTER 4

IVET, an Interactive Veterinary Education Tool

The second main goal of this thesis is to apply medical imaging visualisation and segmentation techniques to improve teaching and increase the support for graphical resources in veterinary science. This chapter describes a new interactive and web-based veterinary e-learning tool which supports the visualisation and interaction with multiple graphical resources based on medical imaging in order to strengthen the teaching and learning process. A manual segmentation process to obtain real 3D models from animal CT scans is also described.

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IVET, an Interactive Veterinary Education Tool

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Abstract

IVET (Interactive Veterinary Education Tool) is an e-learning web-based platform designed to support teaching and learning in veterinary science. To make content creation easier, it provides theory, exercise and image editors with functionalities to prepare exercises and theoretical content including 2D images and 3D models which can be manipulated by the users. It supports different types of exercises such as quizzes, 2D and 3D location exercises, and exercises based on multiplanar reconstructions from a set of animal scans. For each type of exercise, a correction strategy is defined to automatically correct the exercises and avoid the teacher to perform this process manually. All data is stored in a central repository, including the material prepared by the teacher and the solutions sent by the students, from which the system is able to compute some statistics, such as the evolution of the students and the final score of a course. By this way, teachers can use this information to carry out continuous assessment. All the resources such as 2D images, 3D models and animal scans are stored in the multimedia repository, included in the central one. To obtain real 3D models from animal scans, a manual segmentation process is also described.

Introduction

Current medical imaging devices, such as computed tomographies and magnetic resonances, are able to acquire precise information of body anatomy and function and represent it as images. These images are a key element not only for diagnosis and treatment but also for teaching purposes, especially in degrees such as medicine and veterinary science. In the context of medicine, many computer-assisted learning packages with interactive 3D anatomical models created from these images have been proposed [1–4]. Moreover, the benefits of interactive animation and virtual models to train spatial thinking have been presented [5], both in the medicine and the veterinary field [6, 7]. However, although the techniques used to create these packages and their corresponding models can also be applied in the context of veterinary science, the majority of tools have been proposed and are used only in the medical field.

Different studies confirmed the need of a modernisation process in veterinary education [8–11] and the benefits of e-learning environments [3, 12, 13]. Nonetheless, few environments have been proposed in this field, and most of them only deal with single parts of the animal body or with a particular species of animals [14–16]. To overcome this limitation, IVET (Interactive Veterinary Education Tool) is proposed, a new educational platform specifically designed to support teaching and learning in veterinary science.

The IVET platform has been created taking into account subjects such as anatomy and morphology, where image-based information is essential. The aim of the platform is to provide functionalities to satisfy both teachers' and learners' needs. Focusing on teachers, IVET should make content creation and students' follow-up as easy as possible. Focusing on learners, the platform should be attractive enough to motivate students to work. Therefore, functionalities to interact with the material, to explore images and models, and to obtain immediate feedback, amongst others, are crucial. The aim of this paper is to describe the IVET platform and compare it with state-of-the-art e-learning platforms for veterinary science.

To identify these platforms, a search was performed considering ScienceDirect, PubMed, Scopus and Google Scholar, and the following keywords: 'veterinary', 'e-learning', 'distance', 'learning', 'web', 'anatomy', 'animal', 'education', 'teaching', 'virtual', 'computer', 'internet', 'interactive', '3D', 'three-dimensional'. All the terms have been addressed in conjunction to increase the efficiency of possible outcomes. From this search, several results were obtained which were filtered considering only the ones related to anatomy teaching and veterinary education. The search results were reduced to the 46 most relevant publications. From these publications, a final selection of 11 was made, excluding the ones related to the human anatomy and the veterinary education overviews, and taking into account both the relationship with the veterinary field, and the presentation of an e-learning tool. The selected platforms are described below.

Theodoropoulos et al. [17] present a veterinary anatomy tutoring system covering gross anatomy, histology, and embryology, while Phillips et al. [18] develop a technology-mediated alternative to print-based external study of a postgraduate unit in veterinary diagnostic imaging. Focusing on distance learning courses, Dale et al. [19] explain their experience with a teaching and learning technology programme (TLTP) project called CLIVE (Computer-aided Learning in Veterinary Education), and Ertmer and Nour [20] describe a veterinary technology distance learning program based on instructional interactions in the context of two foundational physiology courses. Pop et al. [21], on the other hand, present three e-learning platforms in veterinary undergraduate and post-graduate education and training. Other platforms are used as additional tools to enhance learning, especially in the context of canine anatomy, such as the ones described by Malinowski [22], a multimedia project to assist veterinary technology students in learning canine skeletal anatomy in three dimensions; Linton et al. [23], a computer-based anatomy program to help students study the dissection, osteology, and radiology of the canine head; and Raffan et al. [16], a 3D interactive application about canine neuroanatomy for undergraduate veterinary education. However, other tools exist for the equine anatomy, such as the one developed by El Sharaby et al. [15], which consists in a computer-facilitated learning program which comprises two modules about horse anatomy, and for the sheep anatomy, such as the one presented by Tawfiek [14], a computer program about the virtual dissection of sheep including different parts of this animal's body. Finally, a more general tool for several farm animal species is described by Grizzle et al. [24], defining a virtual teaching laboratory for Animal Sciences students taking a course in Reproductive Physiology and Lactation.

Reviewed platforms are a good complement to veterinary education. However, their provided functionalities are still far from the ones provided by e-learning platforms used in other fields such as the medical one [2, 4, 25–27]. Generally, these include the possibility to control students' progress, and more advanced visualisation functionalities, inspired by radiological viewers, which allow users to prepare educational content, such as case-based studies, where images play a main role. Moreover, little attention is given to content creation functionalities, being the preparation of material a very time demanding task. The goal of this study is to design a new educational platform with more advanced functionalities which overcome these limitations.

Materials and methods

The architecture of the proposed platform with its main modules and its functionalities is illustrated in Fig 1 and described below.

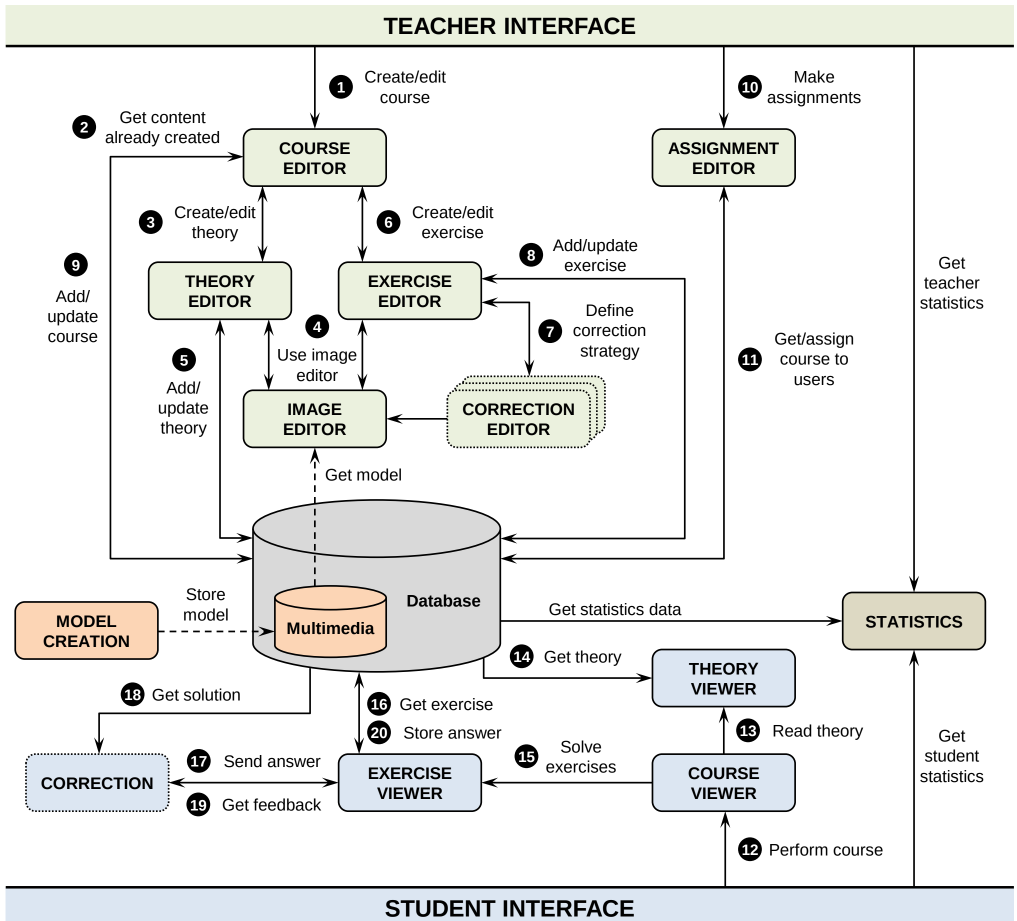


Fig 1. Architecture of the IVET platform. The main modules of the IVET platform and the functionalities provided to teachers and students.

Leaving the administrator aside, the platform supports two main user profiles: students and teachers. To log in to the platform, all the user profiles need a username and a password, and different interfaces are presented depending on each role. There is a central repository to store all the information such as the theoretical content, the exercises, and the solutions sent by the students, amongst others. Special attention is given to graphic information such as 2D images, 3D models and videos, which are stored in the multimedia repository.

Teacher functionalities

When teachers log in to the platform, they can create a new course or edit an existing one using the *course editor*, assign it to a group of students using the *assignment editor*, and obtain some information about the students' performance using the *statistics* module. As for the first functionality, once a course is created, the *theory editor* and the *exercise editor* can be used to fill the course with content. Both editors are connected to the *image editor*, which is the responsible of dealing with images and the interaction with them. The editors allow the creation of new material, but also the option of loading an existing one from the system *database* and update it, so that they avoid the creation from scratch. All the created material is stored in the system database, which also registers information related to students, such as the exercises assigned to them and the solutions they send. There is a *multimedia repository* where all the graphical material is registered.

In addition, the exercises of the platform are also assigned a set of labels which identify the difficulty level, the application area, the user type to which they are addressed, and the creation date, amongst others.

Student functionalities

When students log in to the platform, they enter the *course viewer*, from which theory and exercises of the course can be accessed. If an exercise is accessed, a specific interface to send the solution is provided. Once a solution is sent, the correction process starts. The *correction* module obtains the correction strategy linked to the exercise, performs the correction and returns feedback to the user. All the actions are stored in the system database, and used by the statistics module, which can build queries to get information about the students' progress, such as the number and type of errors for each exercise, and the time taken to complete them. This information can be used then to carry out continuous assessment.

Correction strategy

As represented in Fig 1, the exercise editor allows the creation of different types of exercises, each one having a specific corrector with the corresponding correction strategy (*correction editor*).

Currently, the platform supports test exercises, which set out a multiple-choice question to the students; 2D location exercises, which ask them to mark a specific point over a 2D image; 3D location exercises, which ask them to select one or more 3D models from the ones displayed in the 3D viewer; and multiplanar reconstruction (MPR) exercises, which load the scans of an animal and allow the students to move the basic anatomical planes (axial, sagittal and coronal) so that the intersection point of them is close to the point stated in the question.

Note that each type of exercise has a particular editor for the teacher to enter the correct solution, since the correction strategy is different. The platform has been implemented in a modular way, so that a new type of exercise can be added in the future without modifying the platform structure.

Multimedia repository

The multimedia repository stores all kind of graphic files, including 2D images, 3D models, and videos. As for the 2D images and the videos, they can usually be found in other resources, and it is not difficult to create new files. Regarding the 3D representations, they present more difficulties. On the one hand, to represent a DICOM file as a multiplanar reconstruction its slices have to be extracted and converted to 2D images, so that they can be displayed as 3D planes in the viewer. On the other hand, getting 3D surface models of a specific anatomical part can be more complicated. Most of the 3D models used in anatomy teaching are taken from general packages which are modelled following the information of the atlases, with no need of being fully realistic. However, if a 3D model is shown together with medical data, such as MRI and CT scans, as supported by the IVET platform, the 3D model has to match this data. To do so, the model has to be segmented using the scans as a reference.

The *model creation* module from Fig 1 represents this preparation process. In the examples presented in this paper, the CMISS software [28] was used to load the scans and perform the segmentation. Fig 2 shows the five steps required to segment a model: (a) get the medical data, which will be used as the guidelines for the segmentation, and in the example corresponds to a set of CT scans from a live pig with enough quality to avoid its pre-processing; (b) the model segmentation, using the CMISS software to add some nodes to the most representative scans to delimit the border of the model, and connecting them to create the exterior faces of a 3D surface model; (c) the conversion to a cubic model, transforming the current linear model (linear interpolation between nodes) to a cubic model (cubic Hermite interpolation, in this case), since the anatomy models needed are seldom linear, and their nodes are usually connected by curved lines to resemble real models; (d) the model post-processing, since although the linear to cubic conversion is properly handled by the CMISS software, sometimes the nodes have to be repositioned by loading the cubic model again and dynamically changing the position of the nodes (keeping the cubic interpolation), so that the edges of the faces can be fit to the scans; and (e) the conversion to the JavaScript Object Notation (JSON) format [29], using the functionalities of the CMISS software, so that the WebGL environment is able to load the model.

Moreover, CMISS has the option to add fields to the nodes, so that additional information can be obtained, such as computing the volume of the model, the area of its surface, and other mathematical functions.

Implementation details

The proposed platform has been implemented using HTML5, JavaScript and CSS3 for the user interfaces, and PHP and MySQL for the communication with the server and the database. A JavaScript library has also been used to work with the WebGL functionalities, which allows the visualisation of 3D models. Hence, the platform has been designed to be used in any web browser without the need for installing any plug-in [30].

First evaluation

A group of four different teachers recruited through personal contacts have performed a first evaluation of the platform. They are used to new technologies, and they use Microsoft PowerPoint to prepare the slides which support their lessons. The images they show in these slides are in common formats such as JPG/JPEG and PNG, including medical images; they seldom use DICOM files and medical imaging viewers to let the students practise. Some of them take advantage of 2D virtual atlases to complement their classes, but they almost never use 3D models or visualisation techniques higher than 2D. Furthermore, their students cannot perform online exercises because they have not found a proper e-learning tool.

The platform has been introduced to them individually, while describing the different features and its functioning. After the first introduction, they have been able to test the platform as much as they needed, and then their opinion about it has been

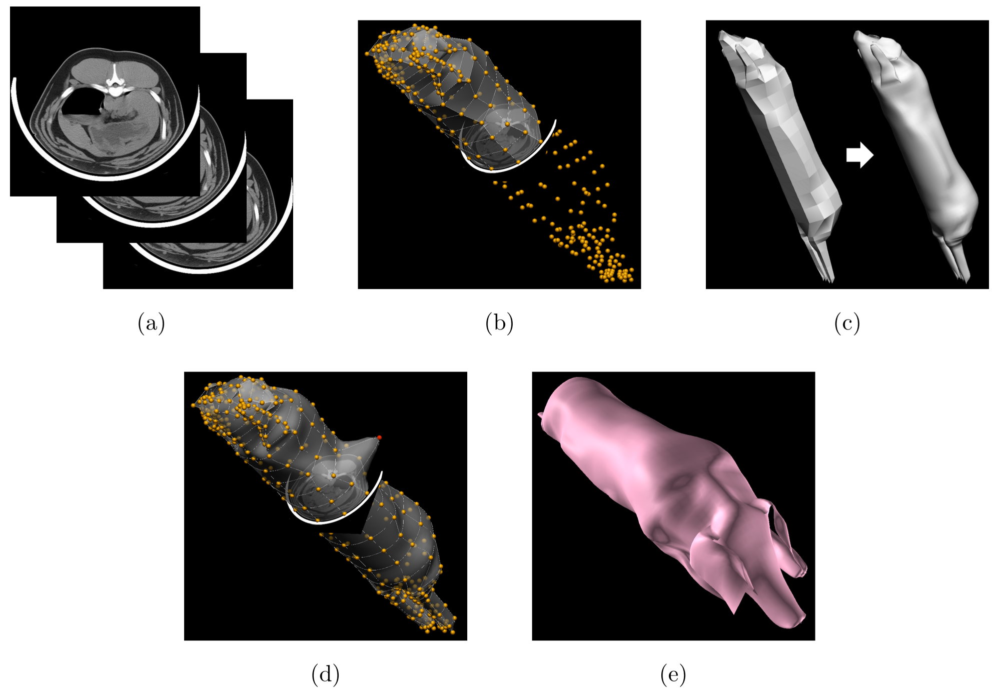


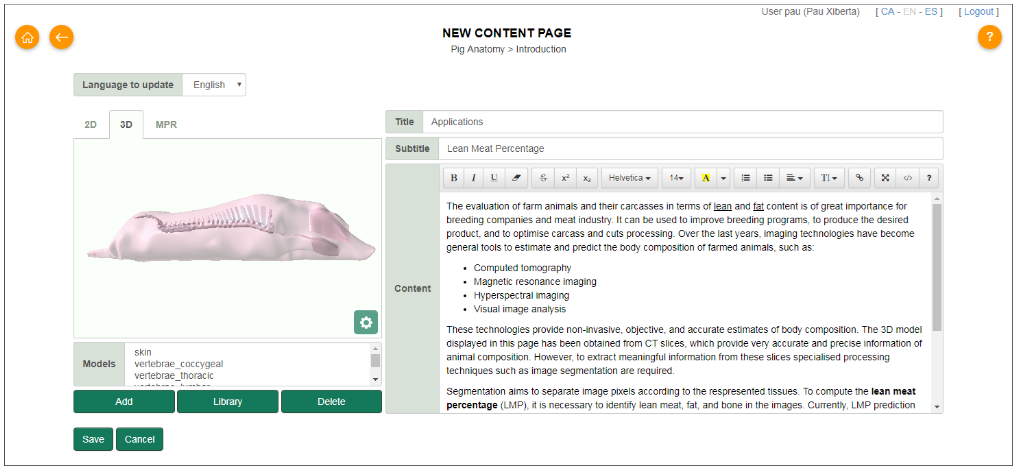
Fig 2. Manual segmentation pipeline. The five steps of the segmentation pipeline used to create a 3D surface model with the CMISS software: (a) input CT scans; (b) selection and connection of nodes to obtain the exterior faces of the model; (c) conversion from the linear model to a cubic model; (d) optional model post-processing; and (e) conversion to the JSON format.

required by interviewing them. The main interest of this first evaluation is to know whether this platform can improve current teaching methodologies in the veterinary science, especially with the incorporation of interactive theory material and exercises which are based on 2D images, 3D models and other medical imaging visualisations. In this sense, their opinion about the content creation process is also required. No questionnaire has been involved in this evaluation, but only some open questions asking the teachers whether the platform is interesting for them, and whether they would use it as part of their teaching methodology.

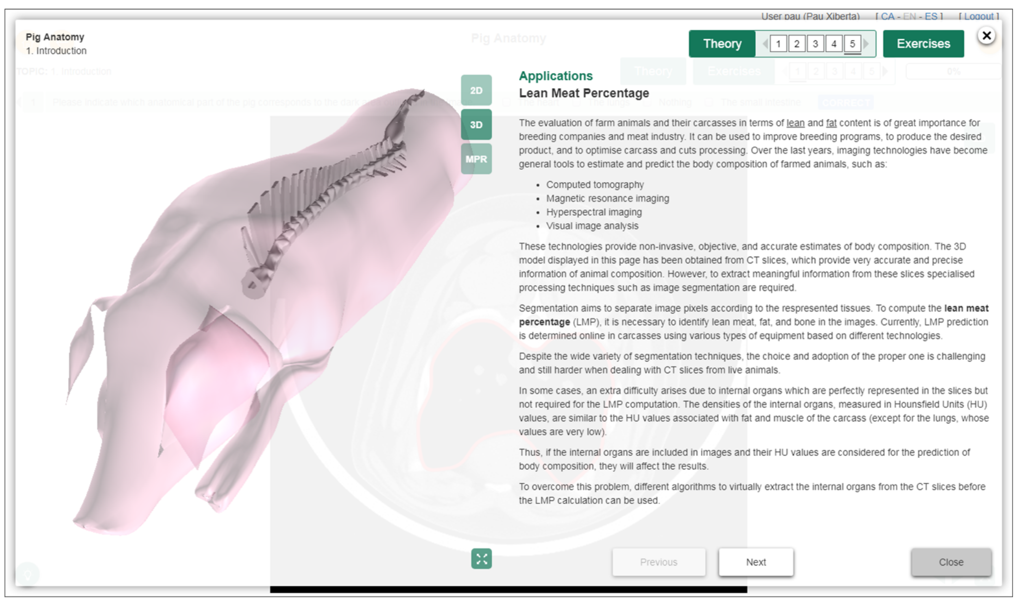
Results

In this section, some of the main platform interfaces and the description of their main functionalities will be presented.

The theory editor is illustrated in Fig 3(a), where the interface for a new content page is shown. A page can be considered similar to a single presentation slide. Under the main title of the interface, the path helps teachers know which topic or subtopic of the course they are editing. Teachers are able to select the language in which they want to write the content, which is divided in three main parts: the title, the subtitle, and the body of the page. The text of the content can be formatted by using features such as bold characters and subscripts. The image editor, which is also used in the exercise editor, is located on the left side of the theory editor. Different viewers can be alternated by using the corresponding tabs, which are placed above the viewer. These tabs, namely 2D, 3D, and MPR, vary depending on the exercise type, since some of them do not allow all the viewers. In the case of the theory editor, all the viewers are allowed, so that all the tabs are visible. The interfaces for each tab will be described below, together with the exercise editor.



(a)



(b)

Fig 3. Theory interfaces of the IVET platform. Interfaces of the IVET platform corresponding to (a) the theory editor used by the teachers to create theoretical content, and (b) the theory viewer used by the students to visualise this content. Both interfaces include functionalities to manipulate and interact with 2D images and 3D models.

The theory viewer is illustrated in Fig 3(b), and it is what students see when accessing the theoretical content. Students can navigate and access through the content pages using the corresponding buttons. The main body of the interface is divided in two parts: the image viewer on the left hand, allowing the students to see the viewer in full screen mode, and to switch between the 2D, 3D and MPR viewers, if they are visible; and the text viewer on the right hand.

The exercise editor presents different interfaces depending on the exercise type. Therefore, the interfaces of three exercise types will be presented, namely the test, the 3D location, and the MPR exercises, each one using different features of the image editor.

The editor for the test exercise is illustrated in Fig 4(a). Similar to the theory editor, and shared with the editors of the other exercise types, teachers can select the language, and enter the name and the description of the exercise, the question and its solution, and a tip to help students solve the exercise. Other common features are the option to assign a difficulty level to it, as well as some keywords and the user types to whom it is addressed, improving by this way the exercise filtering. Taking into account that an exercise can be reused, the last common feature allows to assign it to different topics. As for the specific features of the test exercise, the editor allows the teachers to add as many possible answers as they want. Each answer has its own feedback, so that teachers can customise the response to the students when they fail. Teachers can indicate the correct answers by checking the little box on the left of each answer. Regarding the image editor for the test exercise, it allows all kinds of graphic content. Fig 4(a) shows the interface for the 2D tab, which allows to upload new images, select them from the library, or delete them. The viewer also allows to pan and zoom the images, and their order can be changed using the arrows on the right.

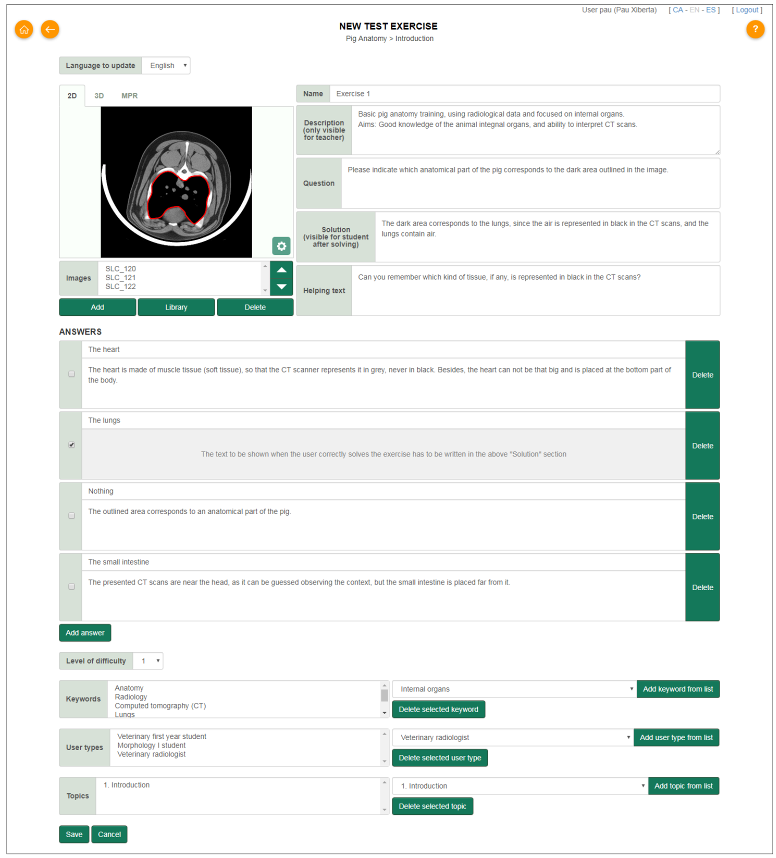
The viewer for the test exercise is illustrated in Fig 4(b), and it also has some shared features with the other exercise viewers, such as the button to access the theory, the indices to navigate between the exercises, and the progress bar to show the percentage of completed exercises. At the bottom of the page, other common features are the tip button on the bottom-left corner, and the full screen button on the bottom-right one. Focusing on the specific features of the test exercise, the possible answers are embedded in the question box, and students can check as many of them as they want. They can also pan and zoom the image displayed in the viewer, and change it by using the bottom-right arrows, if there is more than one.

The editor for the 3D location exercise is illustrated in Fig 5(a), and only the image editor presents some differences with respect to the previous exercise. As it is a 3D location exercise, only the 3D tab is shown. Teachers can upload new 3D models or load them from the library, and they can pan, zoom and rotate the 3D models in the viewer. They can also choose the solution models by selecting them from the list, or by selecting them directly in the 3D viewer.

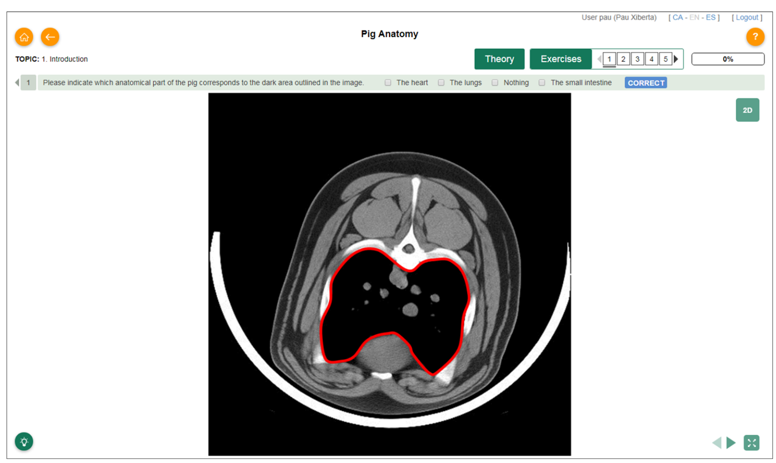
The viewer for the 3D location exercise is illustrated in Fig 5(b), and students only have to select the models asked in the question and send their solution. The viewer also allows the students to pan, zoom and rotate the 3D models to get better viewpoints.

Finally, the editor for the MPR exercise is illustrated in Fig 6(a). Similar to the 3D location exercise, only the MPR tab of the image editor is visible, since only this kind of graphic representation is expected. Taking into account the amount of slices for a single MPR visualisation, and the time required to upload them, teachers can only load models which already exist in the library. They can pan, zoom and rotate the MPR visualisation, as well as move the anatomical planes by dragging them. The planes can also be moved using the corresponding boxes under the viewer (titled ‘axial’, ‘sagittal’ and ‘coronal’), and their intersection point is displayed in the box titled ‘centre’. Since detecting the exact intersection point would be difficult for the students, teachers have the option to assign a 3D error radius represented in the viewer as a green sphere; if the students select an intersection point which lies inside the sphere, the solution will be considered as correct.

The viewer for the MPR exercise is illustrated in Fig 6(b), where the students have

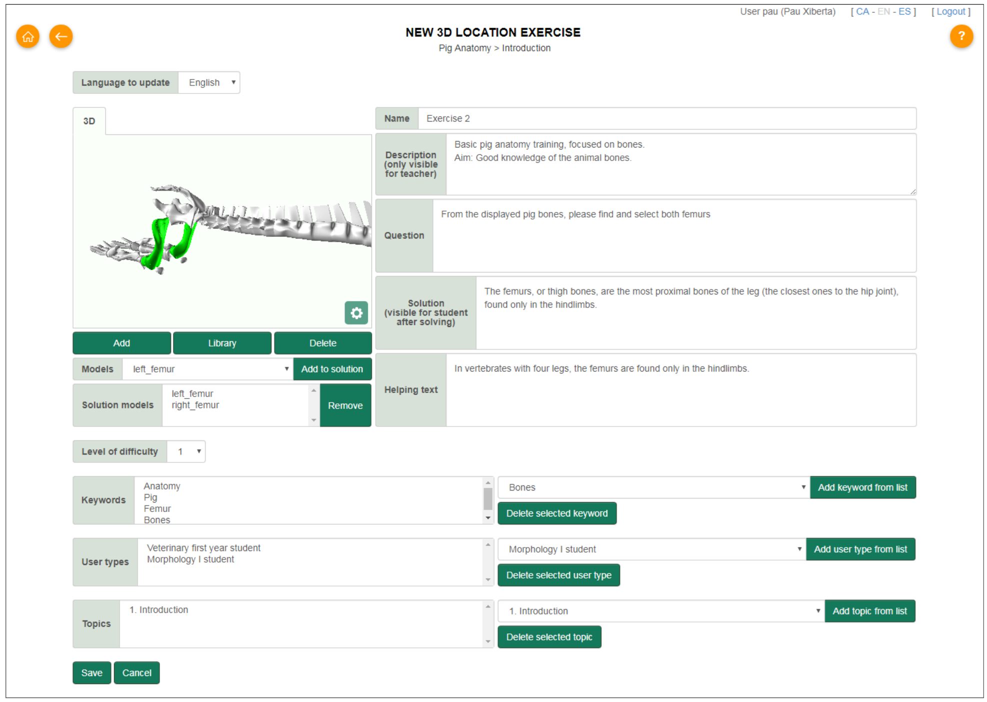


(a)

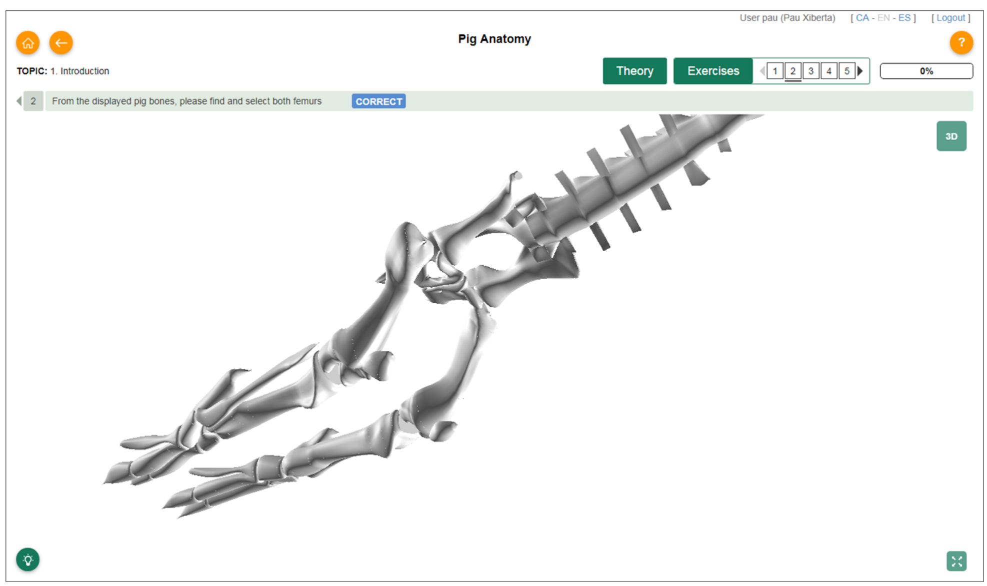


(b)

Fig 4. Test exercise interfaces of the IVET platform. Interfaces of the IVET platform corresponding to (a) the exercise editor used by the teachers to create test exercises, and (b) the exercise viewer used by the students to solve test exercises. Both interfaces include functionalities to manipulate and interact with 2D images and 3D models, which can be relevant to solve the exercise.

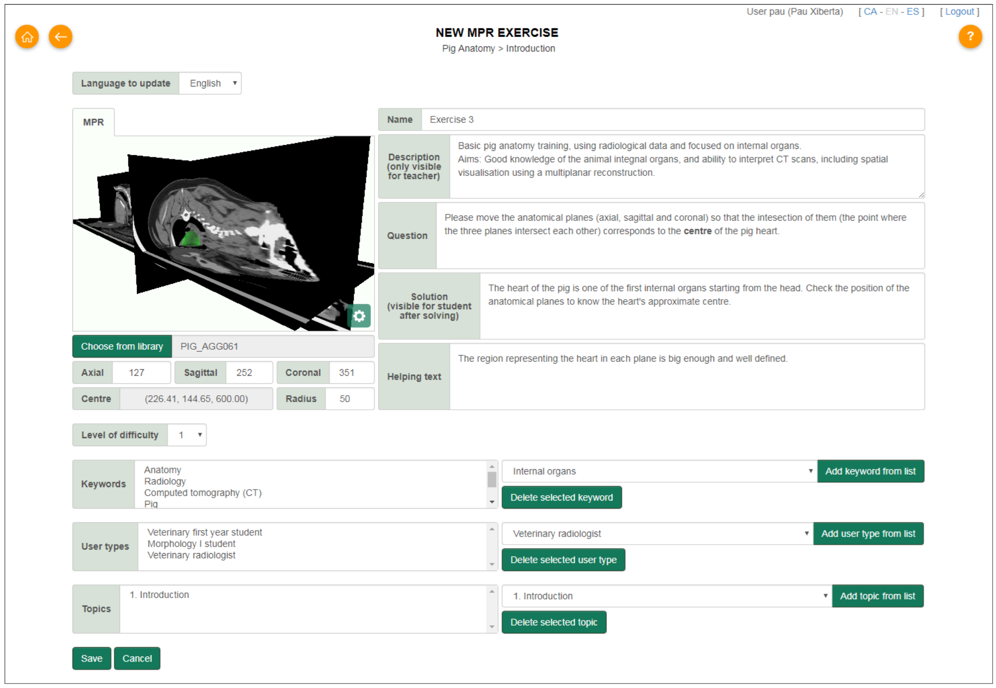


(a)



(b)

Fig 5. 3D location exercise interfaces of the IVET platform. Interfaces of the IVET platform corresponding to (a) the exercise editor used by the teachers to create 3D location exercises, and (b) the exercise viewer used by the students to solve 3D location exercises. Both interfaces include functionalities to manipulate and interact with the 3D models to enter the answer.



(a)

(b)

Fig 6. MPR exercise interfaces of the IVET platform. Interfaces of the IVET platform corresponding to (a) the exercise editor used by the teachers to create exercises which require the use of the multiplanar reconstruction (MPR) visualisation, and (b) the exercise viewer used by the students to solve MPR exercises. Both interfaces include functionalities to manipulate and interact with the anatomical planes.

to move the anatomical planes by dragging them directly in the viewer.

To obtain the first user impressions, a group of teachers have been interviewed. Since there is almost no platform which offers interactive theory and exercises in veterinary science, their opinion has been highly favourable, and no important suggestions have been made to improve it. They have valued the option to easily enter their teaching material to the platform, since the structure of the IVET's theory viewer is slide-based, as well as the intuitive and fast content creation process, which enables them not to start from scratch. They have also appreciated the option to assign interactive exercises to their students, as well as the automatic correction and scoring, as they were not aware of any such platform which allows so. Thus, the overall impression is that IVET is a novel and useful tool which allows a high degree of interactivity between the students and the teaching material. Summarising these open questions, they have found the platform interesting and they would use it as part of their teaching methodology.

Discussion

Once the proposed platform has been described, in this section its functionalities will be compared to the ones from the platforms presented above.

The selected tools have been analysed and compared considering a set of parameters grouped in four major areas (see Table 1). These parameters are represented as P_n and, in the analysis of a parameter over a platform, only 'yes' (+) or 'no' (-) are assigned as possible categories for the answer, so that it is easier to evaluate them. Table 1 shows the analysis and the description of each parameter.

Note that most of the platforms are non-web-based (some of them are delivered in CD-ROM format), or they require the users to install one or more plug-ins to run the application in a web browser. Only two of them [15, 24] seem to work in a web browser without the need of any plug-ins, although this is not specified in the corresponding publications. Besides, none of them describes the possibility to run the application using a mobile device, such as a smartphone or a tablet. The IVET platform can be run in any web browser without the need to install any plug-in, and it can also be run in smartphones and tablets.

Regarding the e-learning parameters, almost all the platforms offer theoretical content, and they usually have this content structured in topics, with the exception of the platforms presented by Tawfiek [14], which is structured following some anatomical parts; Phillips et al. [18], which is case-structured; and Raffan et al. [16], which uses the features of the platform to build customised tutorials, making them more interactive, but complicating the content creation. The proposed platform provides theoretical content structured in topics, with the option for each topic to have as many subtopics as needed, and so on. Moreover, each topic and subtopic is divided in content pages, so that teachers can separate the content for each unit. Some of the platforms also integrate self-evaluation exercises to help the students test their knowledge, but almost all of the exercises are quizzes, i.e. multiple-choice questions. Only Ertmer and Nour [20] offer exercises which require the user to interact with images, as well as quizzes. The IVET platform provides different types of exercises, including quizzes, location problems, and other image-based exercises which require user interaction. Finally, few platforms have the option for the teachers to track the students' work. Ertmer and Nour [20] provide a full tracking of the students' actions, while Pop et al. [21] allow to access the students' results, and Grizzle et al. [24] only offer the option to know the number of quizzes attempted by the students. The proposed platform allows to track the solutions sent by the students, the number of attempts and the errors, and the date and time they submitted the answers. The platform is able to automatically correct all the exercises, and it also computes different final scores based

Table 1. Comparison of state-of-the-art e-learning platforms for veterinary science considering a set of parameters grouped in four areas.

	Installation requirements			Content creation				Statistics	Others	
	Non-WB	WB plug.	WB	Theory	Exercises	Image		Statistics	Community	Sugg.
						2D	3D			
	P_1	P_2	P_3	P_4	P_5	$P_{6.1}$	$P_{6.2}$	P_7	P_8	P_9
The1994 [17]	+	-	-	+	+[2]	+	-	-	-	-
Phi2001 [18]	+[1,6,10,12]	-	-	+[14]	-	+	+[7]	-	+[15]	-
Mal2003 [22]	+[1,10,11,12]	-	-	-	-	+	+[7]	-	-	+
Dal2005 [19][4]	-	+[1,5,6]	-	+	-	+	+[7,8]	-	-	-
Lin2005 [23]	+[10]	-	-	+	-	+	+[7]	-	-	+
Ert2007 [20]	-	+[1,6,9]	-	+	+	+	-	+	+	+
Gri2008 [24]	-	-	+	-	+[2]	+	-	+[16]	-	-
Taw2011 [14]	+[1,6,10,11,12]	-	-	+[13]	+[2]	+	+[7]	-	-	-
Pop2013 [21]	-	+[1]	-	+	+[2]	+	-	+[3]	-	-
ElS2015 [15]	-	-	+	+	-	+	-	-	-	+
Raf2017 [16]	+[17]	-	-	+[18]	+[2]	+	+	-	-	-
IVET	-	-	+	+	+	+	+	+	-	-

P_1: Non-web-based platforms, P_2: Web-based platforms with plug-ins, P_3: Web-based platforms without plug-ins, P_4: Platforms which support theory, P_5: Platforms which support self-evaluation exercises, P_6: platforms which support images, $P_{6.1}$: Use of 2D images, $P_{6.2}$: Use of 3D representations, P_7: Platforms which support statistics, P_8: Platforms with community support, P_9: platforms with a suggestions area.
[1]Requires Adobe Flash Player, [2]Only quizzes, [3]Access to the results obtained by students, [4]Several modules under the same consortium, [5]Requires Authorware Web Player, [6]Requires Shockwave Player, [7]Photos from different angles, [8]Only in some modules, [9]Requires Java (through Java applets), [10]Delivered in CD-ROM, [11]Designed for Windows, [12]Requires QuickTime Player, [13]Structured in anatomical parts, [14]Structured in cases, [15]Provides a chat, [16]Only the number of quizzes attempted, not the scores, [17]Made using Unity 3D, [18]Structured in tutorials.

on the completed exercises, the correct ones, and the number of attempts.

Focusing on the image-based content, all the platforms make use of 2D images to illustrate theory concepts or as a part of some exercises, and some of them try to build 3D representations to improve the students' spatial ability. However, almost all of the platforms which try to build such 3D representations make use of QuickTime Virtual Reality or similar techniques, which gather together a set of photographs of a model from different angles so that the user can rotate it as if it was a 3D model. Only Raffan et al. [16] offer a 3D model reconstructed after segmenting a set of scans and manually smoothing the results. The proposed platform is able to visualise 2D images, giving the option to pan and zoom them, and also 3D surface models and multiplanar reconstructions using a WebGL environment, that is, without the need for any plug-in. The scans for the MPR visualisation are extracted from DICOM files, and the 3D surface models are manually segmented to obtain accurate results.

Finally, the support that each platform offers with respect to the communication between the student and the teacher is evaluated, and also how the platforms collect the users' impressions to perform improvements. Only Ertmer and Nour [20] and Phillips et al. [18] provide a communication channel, the former using a bulletin board where users can post messages and earn points if the participation is relevant, and the latter offering it as a chat. As for the testing, seven platforms have been evaluated by users, from which four have provided a survey to the students to analyse their strengths and weaknesses and carry out improvements. In this case, the IVET platform does not provide a direct communication channel between students and teachers, and it does not offer the option for the users to send suggestions. Both functionalities are planned to be included in the future, as well as the preview of the theoretical content and the exercises when teachers create them, so that they can check what the students will see; the integration of a helping system to guide the students through the solving process; and a tutoring system based on the students' results, suggesting exercises of different difficulty levels depending on their progress. Extending the functionalities based on image interaction, such as adding annotations over the images and models, is also considered. The current version of the platform has been tested by a group of teachers with very well acceptance. This first evaluation has been performed only to find out whether the development of this platform makes sense; now the content of a first course is being developed to carry out a new experiment with students, which will lead to a deeper evaluation of the platform using a specific questionnaire to assess its usability, content, and other related parameters.

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CHAPTER 5

Evaluation of an automatic lean meat percentage quantification method based on a partial volume model from computed tomography scans

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The third main goal of this thesis is to apply medical imaging processing techniques to improve the quality classification process of animals in the meat industry. This chapter proposes and evaluates an automatic, fast and accurate method to classify animal tissues from CT scans, using a partial volume model to make the method robust to data variability.

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Evaluation of an automatic lean meat percentage quantification method based on a partial volume model from computed tomography scans

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Abstract

The quality of a pig carcass is mainly measured by the lean meat percentage (LMP), which can be virtually estimated from computed tomography (CT) scans. Different strategies exist to classify the CT voxels into tissues such as fat, lean and bone, being the thresholding-based methods the most commonly used. However, these methods are usually affected by the partial volume effect, and also by data variability, which is implicit from different CT scanners and protocols, since no standard behaviour has been defined. The aim of this paper is to extend an LMP quantification method which uses a partial volume model by adding a new step to detect the animal skin, and evaluate the new approach. The evaluation is performed by comparing the whole pipeline of the proposed approach with a simple thresholding method and a thresholding method with bone filling and skin detection, which is an intermediate step of the new pipeline. Four experiments have been designed to test how accurate are the results of the method regarding the LMP values computed from the manual dissection, as well as the robustness to data variability. Two different manual dissection methodologies have been tested: the simplified dissection, which estimates the LMP using the lean of the four main cuts of the carcass plus the tenderloin, and the full dissection, which uses the lean of the twelve main cuts. A total of 146 half carcasses have been used for this study (105 using the simplified dissection methodology, and 41 using the full dissection one). To evaluate the experiments, the LMP values virtually obtained from the three methods have been compared mostly with the LMP values from the manual dissection, computing the coefficient of determination R^2 from the correlations, as well as the root mean square error of prediction by means of leave-one-out cross-validation. A statistical analysis is performed to resolve if two correlations are significantly different. The experiments' results confirm the high accuracy of the proposed approach for the LMP estimation, and also its high robustness to data variability. The experiments also disclose that the detection of the animal skin and its classification as a new tissue, instead of classifying it as lean, improve the results. The evaluated method has demonstrated to be as effective as the thresholding method with bone filling and skin detection, and more robust to data variability than the other evaluated methods.

Keywords: Lean meat percentage, Computed tomography, Partial volume effect, Segmentation, Pig carcass quantification

1. Introduction

Lean meat percenatge (LMP) is a key parameter to measure pig carcass quality. To compute the LMP from computed tomography (CT) scans, special methods to classify CT voxels into tissues according to its Hounsfield Units (HU) values are required. Unfortunately, variability between animals and breeds, and also between scanners and protocols, makes the definition of a standard correspondence between HU values and tissues difficult (Olsen et al., 2017), and each country has defined its own model (Romvári et al., 2006; Font-i-Furnols et al., 2009; Daumas and Monziols, 2011). Moreover, partial volume effect further complicates LMP computation, that is, voxels which are usually placed in the border between two tissue regions may have a big uncertainty, and they cannot be classified because they contain more than one tissue. This difficulty has been studied in other fields such as oncology (see Cysouw et al., 2017, for a review), but mainly in the field of neuroimaging (see Tohka, 2014, for a review), evaluating its impact (Dukart and Bertolino, 2014), compiling differ-

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ent methods to enhance the image visualisation (Salminen et al., 2016), and still proposing novel techniques to reduce the effect (Bural et al., 2015; Şener et al., 2016).

Tot tackle the partial volume problem, different strategies have been proposed. Assuming a uniform probability for the non-pure tissues over the image, i.e. each partial volume voxel has the same probability for every non-pure tissue, Santago and Gage (1993) propose a model with six Gaussian distributions, three for the pure tissues and three for the two-class partial volume ones, with a set of parameters which have to be minimised to fit the model to the histogram. With the same assumption, Laidlaw et al. (1998) reconstruct a continuous function incorporating neighbouring voxels information into the classification process to improve its accuracy, and Ruan et al. (2000) first use a mixture model to define a Gaussian distribution for each pure and partial volume tissue, and then reclassify the partial volume classes into the pure ones using a Markov random field and multifractal analysis.

Other studies assume little variation in the probability for the non-pure tissues between neighbouring voxels, which can be modelled using a Markov random field. Choi et al. (1991) use a maximum *a posteriori* estimation of partial volume voxels in multichannel images, and a method to iteratively reestimate the mean intensities of each tissue class in each slice, while Pham and Prince (2000) propose a similar method for single-channel images using a Bayesian approach which places a prior probability model on the parameters. Finally, Nocera and Gee (1997) describe a segmentation algorithm which also uses a maximum *a posteriori* estimation with an adaptive Bayesian approach, and takes into account both the partial volume and the shading effect.

Focusing in the LMP computation, some strategies exist to avoid dealing with the partial volume effect. In Dobrowolski et al. (2004), Judas et al. (2006) and Font-i-Furnols et al. (2009) data from CT images is analysed using partial least squared regression, which does not require the classification of voxels in lean or fat. In this case, volume associated to each HU value is obtained from CT images and used as predictors in the regression. In Vester-Christensen et al. (2009) the partial volume effect has been minimised applying a Bayesian 2D contextual classification scheme to classify voxels into fat, lean and bone. Differently, in Bardera et al. (2014) a five-step process which automatically quantifies fat, lean, and bone tissues from CT scans using a partial volume model based on the one presented by Van Leemput et al. (2003) is described. A first validation of this method considering 10 carcasses was carried out.

The aim of this paper is to present an improvement of the method presented in Bardera et al. (2014) by introducing a new step which identifies and classifies the animal skin tissue, and also to evaluate the method considering 146 half carcasses which have been manually dissected after scanning (105 using a simplified dissection, and 41 using a full dissection). The obtained results have been compared in terms of LMP accuracy and robustness to data variability.

2. Material and methods

2.1. Carcasses, computed tomography scanning and manual dissection

A total of 146 left half carcasses have been used for this study. From these, 133 carcasses come from two commercial abattoirs and have been selected to mimic the Spanish pig carcass population in terms of fat thickness, being all the three sexes represented. Additionally, 13 carcasses from gilts, slaughtered at the pilot abattoir placed at IRTA-Monells, have also been used in this study. These carcasses are from 3 different genotypes as described in Carabús et al. (2014) and Font-i-Furnols et al. (2015). In total, carcasses included in this study have a carcass weight of 86.7 ± 8.7 kg, a fat thickness of 15.7 ± 3.8 mm measured at 6 cm of the midline between the 3rd and the 4th last ribs, and they are from three sexes (47% females, 41% entire males and 12% castrated males).

At 24-48 h post mortem carcasses were CT scanned with a General Electric HiSpeed Zx/I device placed at IRTA-Monells. Acquisition parameters were 140 kV, 145 mA, Display Field of View (DFOV) between 460 and 500 mm, and matrix size 512×512 pixels. Images were acquired helically every 10 mm with pitch 1. Thus, there was not overlapping between images and all the carcasses were scanned completely.

After scanning, carcasses were cut following the Walstra and Merkus method (Walstra and Merkus, 1996) and dissected by trained butchers. A total of 105 carcasses were dissected using the simplified dissection methodology, i.e. the lean from the four main cuts (ham, shoulder, belly and loin) was manually separated with a knife and weighed. The LMP values were obtained dividing the weight of the lean of the four main cuts plus the tenderloin by the total weight of the four main cuts plus the tenderloin. A correction factor of 0.89 was applied to obtain the LMP values of the carcasses from these cuts, according to the European Regulation definition (The Commission of the European Communities, 2008). The other 41 carcasses were fully dissected, i.e. the lean of all the 12 cuts was manually obtained and weighed, and this weight was divided by the weight of the carcass to obtain the LMP (The Commission of the European Communities, 2008).

2.2. Automatic LMP quantification method based on a partial volume model

The proposed approach to quantify fat, lean and bone from CT carcasses is an improvement of the method presented in Bardera et al. (2014). We propose to extend this automatic five-step method with a new step which detects the animal skin. The six steps are illustrated in Fig. 1 and described below. For more details see Bardera et al. (2014).

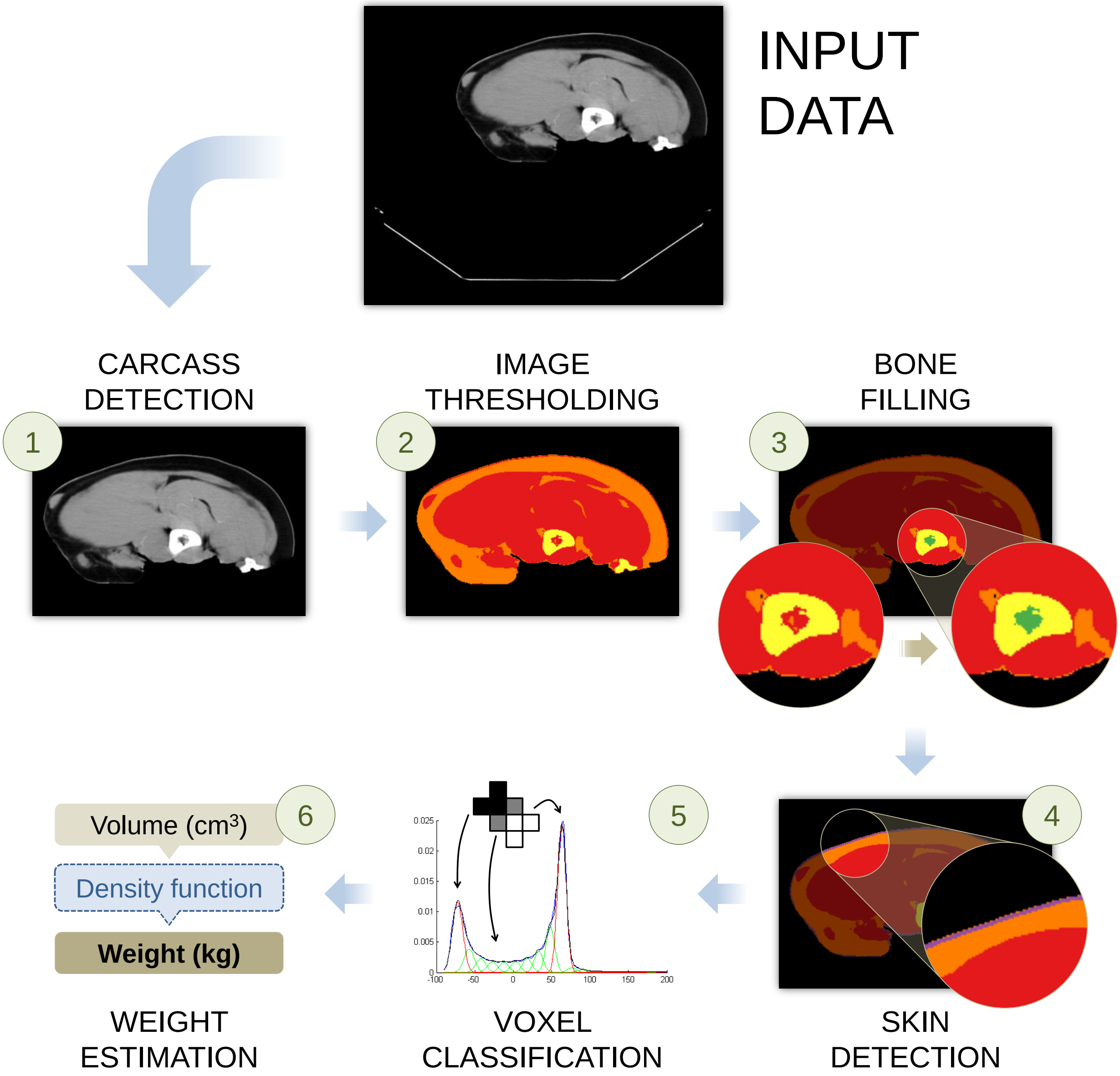


Fig. 1. The six main steps of the proposed approach to compute the LMP values from pig carcasses CT images.

1. **Carcass detection.** The pig carcass is detected from the input CT scans, and other structures of the image such as the scanning table and the air are removed.
2. **Image thresholding.** A thresholding technique based on the HU values is applied in order to identify fat, lean and bone tissues. By default, a value of -100 HU has been defined as a threshold between air/background and fat, 0 HU between fat and lean, and 120 HU between lean and bone (Font-i-Furnols et al., 2009).
3. **Bone filling.** Since the marrow tissue is often confused with fat in the thresholding step, the marrow surrounded by bone tissue is also considered as bone.
4. **Skin detection.** Although it represents a little part of the whole carcass, the skin tissue should not be confused with the lean tissue, as both tissues have similar HU values. Knowing that the skin is the outermost tissue, and that the subcutaneous fat separates it from the lean tissue, a measure to detect the skin voxels is proposed, avoiding by this way to take them into account when computing the LMP values. All the voxels with values lying in the HU range of lean tissue are filtered so that the ones at 3 mm from the background are considered as skin. This is the new step introduced in the method.
5. **Pure class identification and partial volume model.** The pure and partial volume voxels are classified using the partial volume model without spatial correlation proposed by Van Leemput et al. (2003), which includes an iterative expectation-maximisation algorithm. In this case, the input of the method is

just the histogram, leading to a very fast process.

6. **Weight estimation.** The weight of the carcass is computed estimating the weight of each tissue. The model proposed by Vester-Christensen et al. (2009) has been followed, considering a density of 0.994 gr/cm^3 for fat, 1.114 gr/cm^3 for lean, and 1.516 gr/cm^3 for bone.

2.3. Software implementation

The proposed approach has been implemented using C++, Qt, ITK and VTK libraries as a new module of the VisualPork software (Bardera et al., 2012). This software supports DICOM standard and IHE profiles, and provides 2D and 3D visualisation functionalities.

2.4. Evaluation metrics

The goal of the proposed approach is to find a method which is able to compute the LMP values from a pig carcass, with the purpose of getting a value as close as possible to the manually computed LMP. Thus, the first measure to be taken into account when analysing the CT images from the carcasses is the LMP, which is the ratio of the lean meat voxels to the total.

To compare the virtually obtained LMP values with the manually obtained ones, a correlation between these values is needed. Indeed, this correlation is needed to compare between two different methods, and also to compare between different ways of using the same method. The coefficient of determination R^2 (i.e. the square of the correlation coefficient R) will be used to analyse the correlations.

Considering the LMP values obtained from the manual dissection as the true value, the root mean square error of prediction (RMSEP) can also be computed by means of leave-one-out cross-validation as another measure of accuracy.

Finally, to determine whether the differences between the correlations of two different methods are significant, several statistical tests can be applied, being one of the most representative the one proposed by Steiger (1980). To apply these tests, the tool implemented by Diedenhofen and Musch (2015) will be used with a significance level of 0.05.

2.5. Experiments' description

To evaluate the proposed approach and other related methods, different experiments have been carried out to determine whether the proposed approach can be selected as a method of reference to compute the LMP values of pig carcasses. As previously mentioned, two different methodologies have been used to perform the manual dissection: the simplified dissection, and the full dissection. All the experiments have been executed separately, using a different set of carcasses for each situation.

Experiment 1. In the first experiment, three methods to compute the LMP values have been compared to the manual dissection, which is considered as the reference model. These methods include a simple thresholding segmentation (Gonzalez and Woods, 2002), a thresholding with bone filling and skin detection, and the proposed approach. The first one can be considered as the base method, since only a simple thresholding segmentation is performed (first to second step of the pipeline represented in Fig. 1). The second one is an extension of the base method, applying also a bone filling operation and the new skin detection step described in Section 2.2 (first to fourth step of the pipeline). Finally, the last method corresponds to the whole proposed approach, including the application of a partial volume model. The correlations of the different strategies have been computed to know which method better approximates the LMP values.

Experiment 2. While the CT scans of pig carcasses provide a good means to obtain the volume of each tissue by counting the number of voxels, the LMP values of the manual dissection are based on weights. To simulate this procedure, a density estimation is needed to compute the weight of the segmented tissues once the number of voxels of each one is known. Actually, several studies have analysed the density estimation which best fits their results (Campbell et al., 2003; Christensen et al., 2006; Vester-Christensen et al., 2009; Picouet et al., 2010). However, the second experiment aims to show the results when there is no density estimation, and all the voxels are assigned the same weight, i.e. the results take into account the volume, not the weight. The correlation between the volume-based results and the manual dissection has been computed, so that it can be compared with the results of the previous experiment.

Experiment 3. When using thresholds to segment the tissues from a carcass, the segmentation of the skin is troublesome, since the skin voxels have values very similar to the lean voxels' values. To solve this problem, all the voxels considered as lean which are at a distance of 3 mm from the background are considered as skin (see the fourth step of Fig. 1). Thus, these voxels are not computed as lean when obtaining the LMP values, i.e. the skin tissue is not taken into account in the numerator of the LMP computation. The third experiment compares the results considering the skin as lean with the results considering the skin as a new tissue. The correlation between the results considering the skin as lean and the manual dissection has been computed, so that it can be compared with the results of the previous experiment, which considers the skin as a new tissue.

Experiment 4. Measurements of the same carcass using CT scanners from different vendors may show variation because of several factors, including the convolution kernel, reconstruction artefacts, beam hardening, spectral energy, and scatter, as well as variations in carcass size, shape, and position in scanner (Lamba et al., 2014; Mackin et al., 2015). Moreover, although the difference is not so significant, measurements using the same scanner can also show variation (Jacobsen et al., 2016; Symons et al., 2016). For this reason, the last experiment modifies the original CT images to simulate this image variability. Similarly to Bardera et al. (2014), a distortion function given by $\mathrm{HU_{scale}} \times value + \mathrm{HU_{shift}}$ has been applied to the values of all CT scan voxels, where $\mathrm{HU_{scale}}$ takes a value randomly generated between 0.97 and 1.03, and $\mathrm{HU_{shift}}$ takes a value between -20 and 20. Note that this distortion is different for each carcass, but the same for all voxels of the same carcass, so that noise is not added to the image, but only a global transform that will modify the histogram with a scaling factor and a shift. To find out which method best tolerates data variation, the correlation between each method with distortion and the manual dissection has been computed, as well as the correlation between the distorted results and the ones without distortion.

Table 1
P-values of the comparison between the methods' correlations for the simplified and the full dissection methodologies, showing the minimum and the maximum p-value from all the tests applied, and also the p-value of the Steiger's test (PA = Proposed approach, Th = Thresholding, ThBS = Thresholding with bone filling and skin detection).

Dissection methodology	Compared correlations	min	max	Steiger
Simplified	PA vs. Th	0.0030	0.0079	0.0032
	PA vs. ThBS	0.5346	0.5390	0.5381
Full	PA vs. Th	0.2854	0.2915	0.2860
	PA vs. ThBS	0.1338	0.1574	0.1351

Table 2
P-values of the comparison between the weight-based or volume-based correlations of the proposed approach for the simplified and the full dissection methodologies, showing the minimum and the maximum p-value from all the tests applied, and also the p-value of the Steiger's test (PAW = Proposed approach based on weight, PAV = Proposed approach based on volume).

Dissection methodology	Compared correlations	min	max	Steiger
Simplified	PAW vs. PAV	0.0526	0.0652	0.0564
Full	PAW vs. PAV	0.4693	0.4792	0.4776

3. Results and discussion

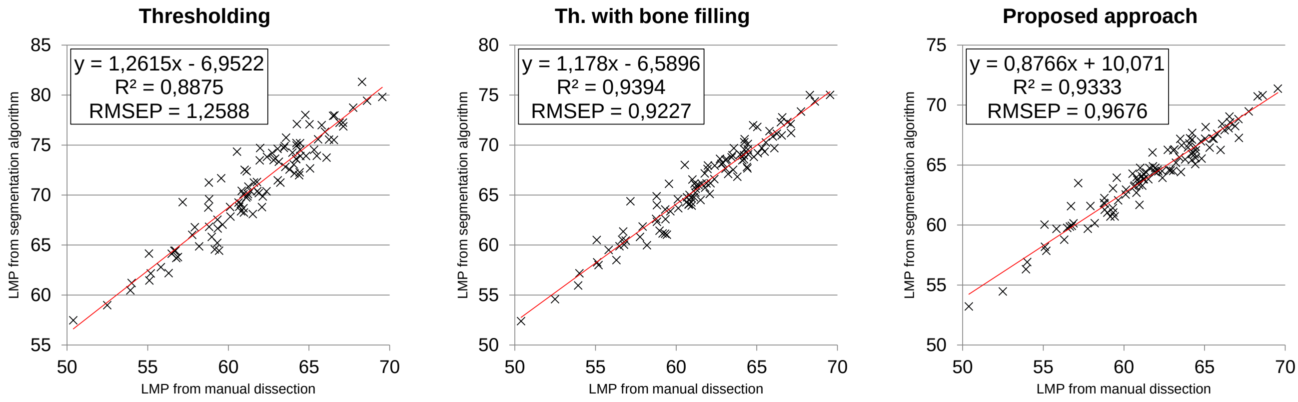
In this section, the results of the experiments described in Section 2.5 are presented and discussed, always discerning between the simplified dissection and the full dissection methodologies. The experiments aim to show how the proposed approach improves the LMP computation.

The results of the first experiment for the simplified dissection methodology are shown in Fig. 2, where the scatter plot between each method and the manual dissection is represented, and the R^2 and RMSEP values are given. The proposed approach and the thresholding with bone filling and skin detection, which is an intermediate step of the proposed pipeline, clearly get the best results, with no significant differences between them (see Table 1 for the p-values). Similarly, the results for the full dissection methodology are shown in Fig. 3, where there are no significant differences between the proposed approach and the thresholding with bone filling and skin detection either. However, although it is the lowest one, in this case the simple thresholding method also achieves a high correlation, with no significant differences with respect to the proposed approach.

Regarding the second experiment, Fig. 4 shows, for the simplified dissection methodology and for each method, the scatter plot between the volume-based results (i.e. without density estimation) and the manual dissection, and also the R^2 and RMSEP values. Similarly, Fig. 5 shows it for the full dissection methodology. For the thresholding-based methods, and interpreting the results for both dissection methodologies, the best option is to estimate the density, while for the proposed approach the best option is to take into account only the volume, not the weight. Although the differences are not significant for the proposed approach (see Table 2 for the p-values), the volume-based results will be used in the next experiments.

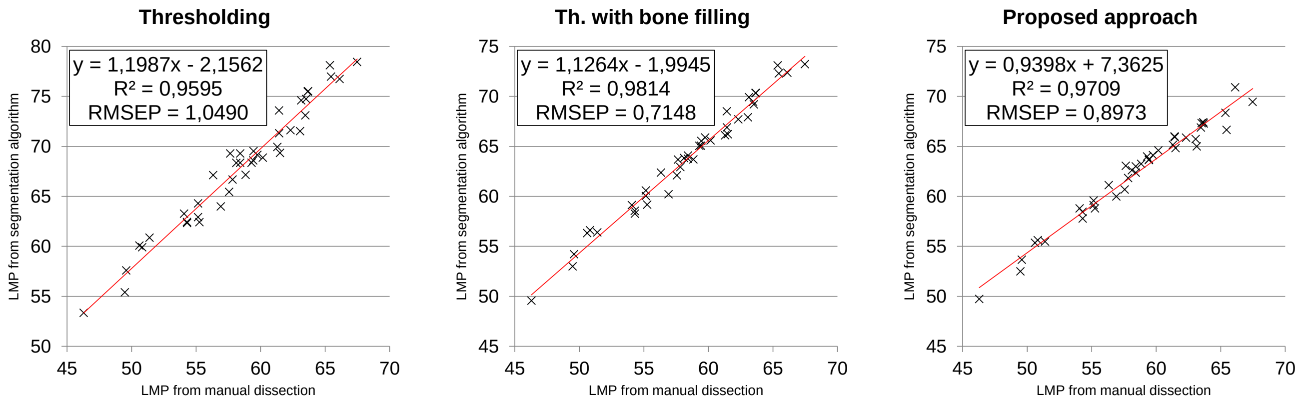
The third experiment analyses the importance of classifying the skin as a new tissue in the fourth step of the proposed pipeline. For both dissection methodologies, Fig. 6 shows the scatter plot between the results considering the skin as lean, i.e. ignoring the fourth step of the pipeline, and the manual dissection for the proposed approach, and also the R^2 and RMSEP values. The results considering the skin as a new tissue, and hence not considering it as lean when computing the LMP values, i.e. considering all the steps of the pipeline, are represented in Fig. 4c and Fig. 5c for the simplified and the full dissection methodologies, respectively. Clearly, the latter are much better and have significant differences with respect to the former (see Table 3 for the p-values). Two reasons can explain this outcome. Firstly, the manual dissection takes into account the skin, so that it makes sense that detecting the skin in the segmentation step helps to improve the results. Secondly, some voxels which are close to the background may have a big uncertainty since it is difficult to know the tissue where they belong; when assigning some of these voxels to the skin tissue, the chances of assigning them to a wrong tissue disappear.

Taking into account the results from the first experiment, the proposed approach achieves results similar to the ones obtained using an intermediate step, i.e. the thresholding segmentation with bone filling and skin detection. However, one of the main goals of the proposed approach, which is analysed in the last experiment, is to be robust on data variability. Fig. 7 shows the results for the



(a) (b) (c)

Fig. 2. Correlation and error between each method and the manual dissection (simplified dissection methodology).



(a) (b) (c)

Fig. 3. Correlation and error between each method and the manual dissection (full dissection methodology).

Table 3
P-values of the comparison between the proposed approach correlations considering the skin as lean (ignoring the skin detection step) or as a new tissue (considering all the steps) for the simplified and the full dissection methodologies, showing the minimum and the maximum p-value from all the tests applied, and also the p-value of the Steiger's test (PASL = Proposed approach considering the skin as lean, PASNT = Proposed approach considering the skin as a new tissue).

Dissection methodology	Compared correlations	min	max	Steiger
Simplified	PASL vs. PASNT	< 0.0001	0.0009	0.0001
Full	PASL vs. PASNT	0.0004	0.0141	0.0013

simplified dissection methodology, where the scatter plot between each method with distortion and the manual dissection is represented, and the R^2 and RMSEP values are given. Likewise, Fig. 8 shows the results for the full dissection methodology. Furthermore, Fig. 9 shows, for each method, the scatter plot between between the distorted results and the ones without distortion, giving also the R^2 and RMSEP values. In this case, all the carcasses are taken into account, since the values compared in the correlations are all obtained from the virtual methods, and no differentiation between manual dissection methodologies is needed. The results show that the proposed approach (the whole proposed pipeline) is the most robust method to image variability, obtaining correlation rations significantly higher than the thresholding-based methods (see Table 4 for the p-values).

Correlation is higher, and RMSEP is lower, when full dissection is considered instead of simplified dissection. This is comprehensible since the carcasses were fully scanned, and this procedure is more similar to the full dissection than the simplified dissection. In full dissection the lean of all the cuts of a carcass are separated manually and weighed; hence, the weight corresponds to the lean of the whole carcass (the same which has been scanned). In simplified dissection, the lean separated with a knife come from the 4 main cuts and the tenderloin, and the

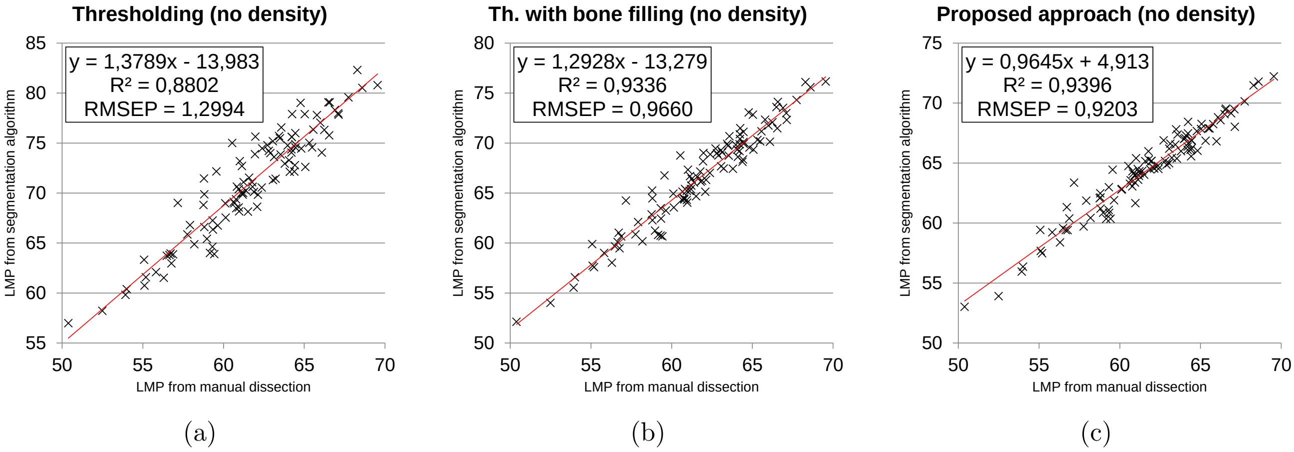


Fig. 4. Correlation and error between each volume-based method and the manual dissection (simplified dissection methodology).

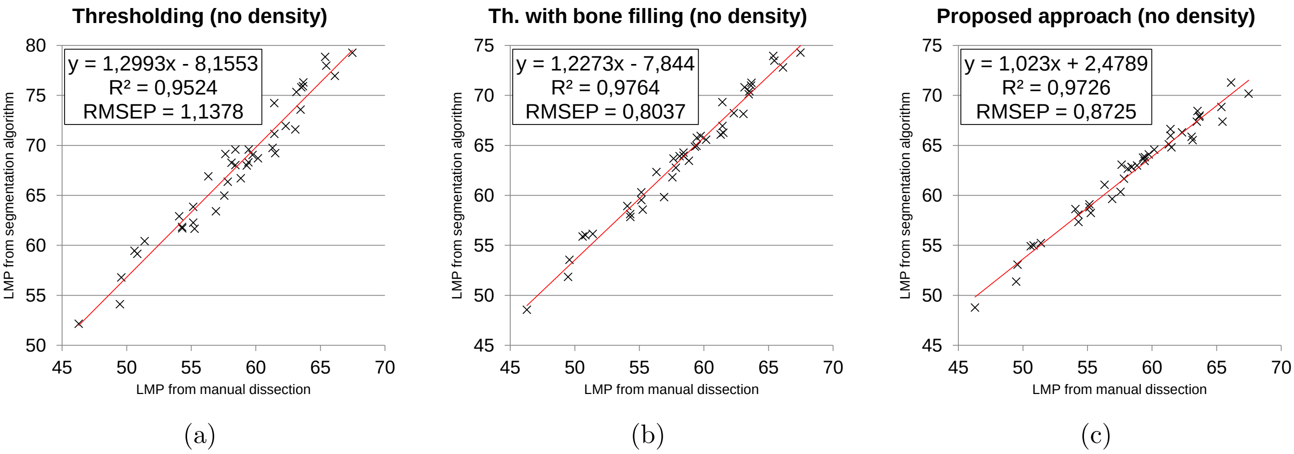
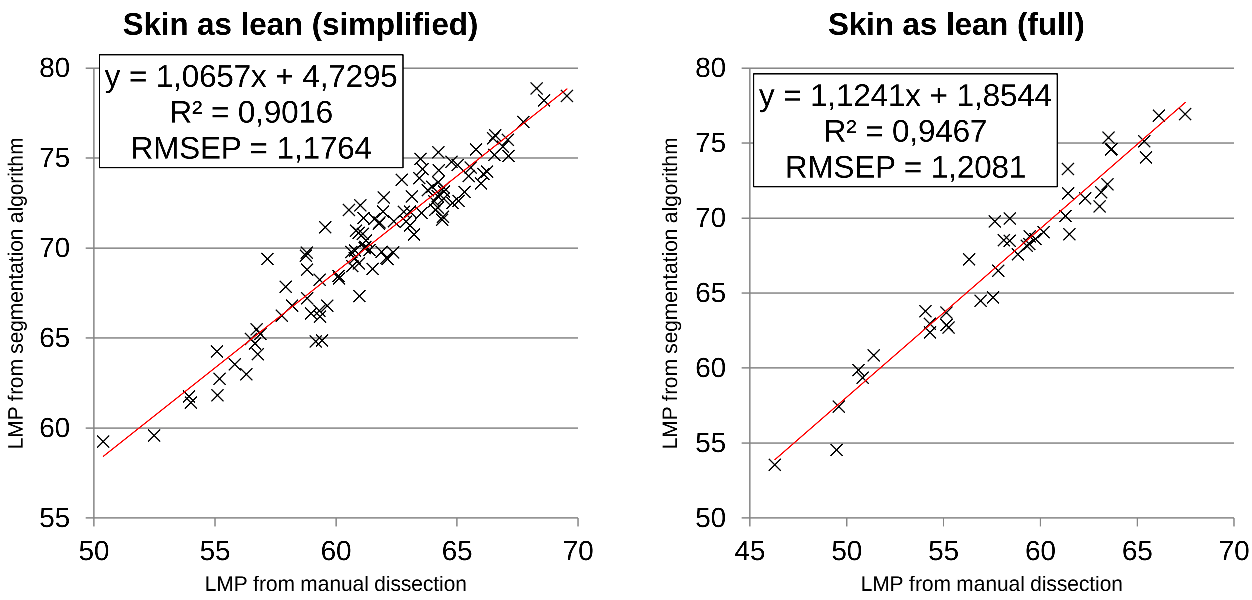


Fig. 5. Correlation and error between each volume-based method and the manual dissection (full dissection methodology).

LMP value of the whole carcass is computed from the lean of these cuts after correcting the result with a coefficient (0.89), which was agreed to be the same for all EU countries although there were some differences between them. Thus, the use of the coefficient is a correction, and the LMP value of the whole carcass is estimated from the lean of the 4 main cuts plus the tenderloin. Furthermore, because of the way to compute the LMP values from 4 cuts, the cutting has an important effect on the obtained lean, and it is known that there are errors due to the cutting, es-

Table 4
P-values of the comparison between the methods' correlations with distortion for the simplified and the full dissection methodologies, and also between the methods' correlations with or without distortion, showing the minimum and the maximum p-value from all the tests applied, and also the p-value of the Steiger's test (PAD = Proposed approach with distortion, ThD = Thresholding with distortion, ThBSD = Thresholding with bone filling and skin detection with distortion).

Dissection methodology	Compared correlations	min	max	Steiger
Simplified	PAD vs. ThD	< 0.0001	< 0.0001	< 0.0001
	PAD vs. ThBSD	0.0003	0.0022	0.0004
Full	PAD vs. ThD	< 0.0001	0.0055	< 0.0001
	PAD vs. ThBSD	0.0029	0.0237	0.0045
None (dist. vs. non-dist.)	PAD vs. ThD	< 0.0001	< 0.0001	< 0.0001
	PAD vs. ThBSD	< 0.0001	< 0.0001	< 0.0001



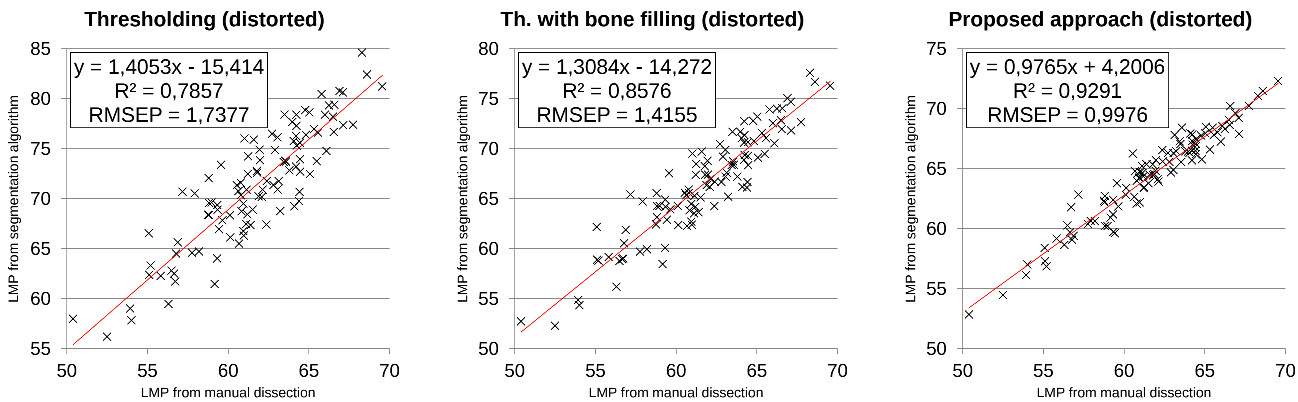
(a) (b)

Fig. 6. Correlation and error between the results of the proposed approach considering the skin as lean and the manual dissection (simplified and full dissection methodologies).

pecially in some cuts (Nissen et al., 2006), that may affect the accuracy of the LMP prediction. The cutting errors are not so important in full dissection because all the cuts are dissected and the total lean is obtained by knife.

4. Conclusion

The LMP is the main measure to determine the quality of a pig carcass and it can be virtually computed using segmentation methods applied to CT images obtained from the carcasses. However, some problems arise when classifying the CT voxels into fat, lean and bone tissues, such as the partial volume effect and the variability between scanners. In this paper, the pipeline proposed by Bardera et al. (2014), which is based on the partial volume model described in Van Leemput et al. (2003), has been extended adding a new step to detect the animal skin in the thresholding stage, so that the skin is not considered as lean, but as a new tissue. The method has also been tested with 146 half carcasses, and compared with a simple thresholding method and a thresholding method with bone filling and skin detection, which corresponds to an intermediate step of the proposed pipeline (from the first to the fourth step of Fig. 1). To measure the performance of the different methods, the correlation between the obtained results and the manual dissection has been computed (R^2 values), as well as the root mean square error of prediction by means of leave-one-out cross-validation, always discerning between



(a) (b) (c)

Fig. 7. Correlation between each method with distortion and the manual dissection (simplified dissection methodology).

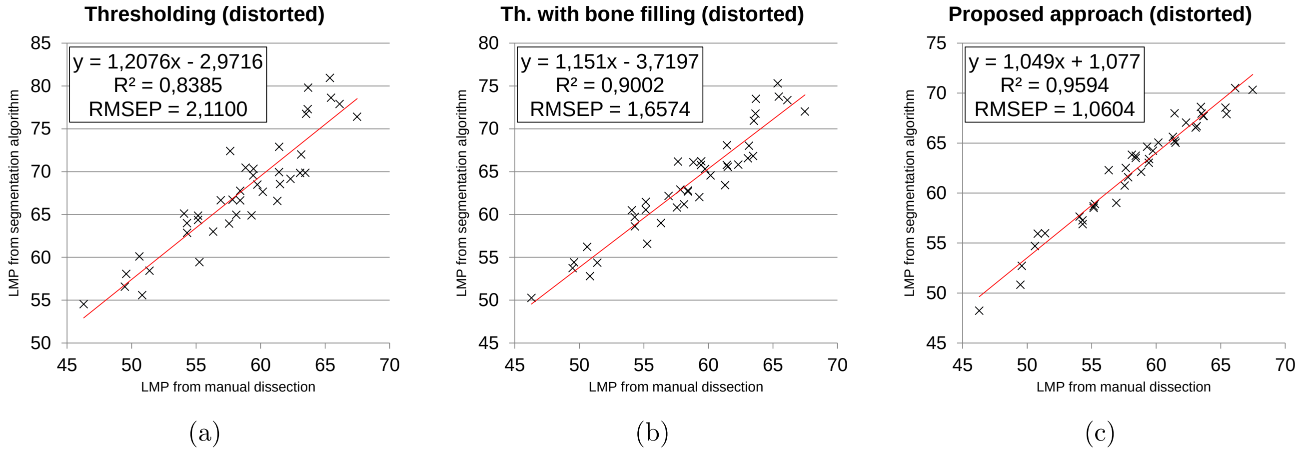


Fig. 8. Correlation between each method with distortion and the manual dissection (full dissection methodology).

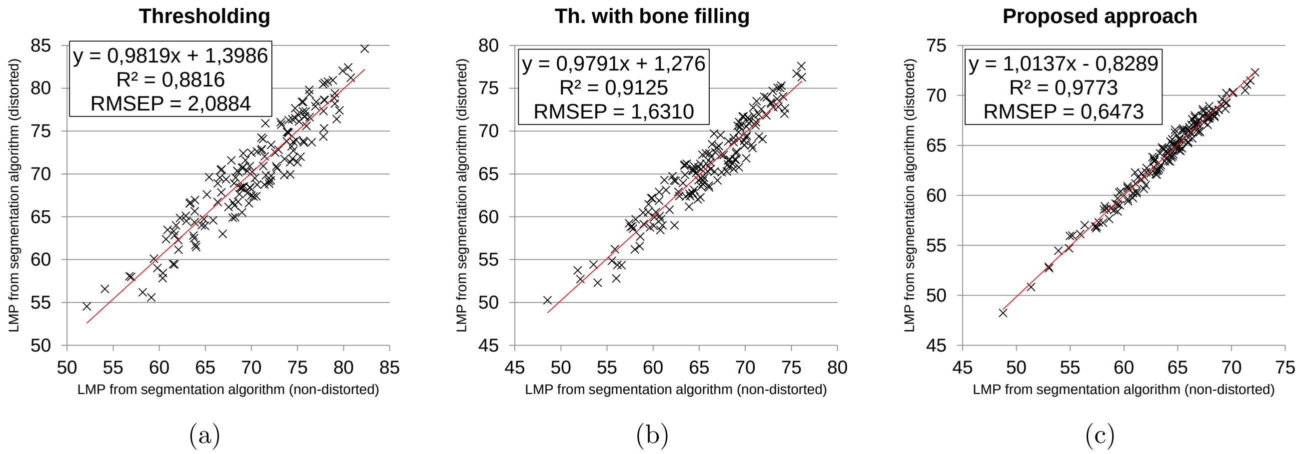


Fig. 9. Correlation between the distorted results and the ones without distortion for each method.

the carcasses dissected using the simplified methodology and the fully dissected ones.

Four experiments have been designed which lead to the four main conclusions. The first experiment has shown that the results from the whole proposed approach are as acceptable as the ones obtained from a part of the same pipeline, i.e. the thresholding method with bone filling and skin detection, so they can both be used indistinctly. From the second experiment, the need of estimating the tissues' density could not be demonstrated, so that only the volume has been taken into account for the next experiments. The convenience to detect the animal skin has been evaluated in the third experiment, which has determined that the accuracy of the LMP computation is higher when considering the skin as a new tissue. Finally, the fourth experiment has tested the different methods with distorted images, and the results prove that the proposed approach is much more robust to data variability than the other thresholding-based methods. Hence, the proposed approach is an accurate method to compute the LMP values of pig carcasses from CT scans, since the correlation with the manual dissection is high both for the simplified and the full dissection methodologies, and it is not as affected by data variability as the other evaluated methods are.

In the future, we intend to improve the bone tissue model from Bardera et al. (2014), and apply the proposed approach to live pig CT scans. As for the latter, some efforts have been made to remove the internal organs which are present in the live pig CT images, but not required for the LMP computation (Xiberta et al., 2017). Finally, the same automatic pipeline may be used to compute the LMP values of other species which may be of interest to the breeding companies and the meat industry.

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Xiberta, P., Boada, I., Bardera, A., Font-i-Furnols, M., 2017. A semi-automatic and an automatic segmentation algorithm to remove the internal organs from live pig CT images. *Computers and Electronics in Agriculture* 140, 290–302. doi:10.1016/j.compag.2017.06.003.

CHAPTER 6

A semi-automatic and an automatic segmentation algorithm to remove the internal organs from live pig CT images

One of the purposes of the third main goal of this thesis is to improve the quality classification process of live animals to avoid invasive methods. This chapter describes two segmentation algorithms which allow the removal of the internal organs from animal CT scans, so that medical imaging processing techniques can be used to determine the animal quality in a non-invasive approach.

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Original papers

A semi-automatic and an automatic segmentation algorithm to remove the internal organs from live pig CT images

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ABSTRACT

Removal of internal organs such as lungs, liver, and kidneys is a key step required to compute the lean meat percentage from Computed Tomography (CT) scans of live animals. In this paper, we propose two segmentation techniques to remove these organs focusing on pigs. The first method is semi-automatic, and it starts with the first CT slice and a manually defined mask with internal organs. Then, it applies a four-step iterative process that computes the masks of the next CT slices by using the information of the previous one. To find the best boundary it uses a Dynamic Programming-based approach. At each iteration the user can check the correctness of the new computed mask. The second method is fully automatic, and segments each slice individually by using distance maps and morphological operators, such as dilation. It is composed of three main steps which detect the pig's torso, pre-classify the voxels in different tissues, and segment the internal organs using the information of such classification. Although it has some parameters, user interaction is not required to obtain the results. The proposed approaches have been tested on CT data sets from 9 pigs, and compared with a manual segmentation. To evaluate the results, the precision, recall, and F-score measures have been used. From our test, we can observe that the performance of both methods is very high according to their average F-score. We also analyse how the accuracy of the results in the semi-automatic approach increases when more user interaction is applied. For the automatic approach, we evaluate the dependence of the results on the algorithm's parameters. If robustness is enough, and high accuracy is not required, the automatic algorithm can be used to segment a whole pig in less than 50 s. However, if the user wants to control the level of accuracy, the semi-automatic algorithm is preferred. Both methods are useful to reduce the time needed to segment the internal organs of a pig from hours (manual segmentation) to minutes or seconds.

1. Introduction

The evaluation of farm animals and their carcasses in terms of lean and fat content is of great importance for breeding companies and meat industry. It can be used to improve breeding programs, to produce the desired product, and to optimise carcass and cuts processing. Over the last years, imaging technologies have become general tools to estimate and predict the body composition of farmed animals, such as computed tomography (Lambe et al., 2013; Carabús et al., 2015), magnetic resonance imaging (Mitchell et al., 2001; Kusec et al., 2007; Kremer et al., 2013), hyperspectral imaging (Akbari et al., 2008), and visual image analysis (Doeschl-Wilson et al., 2005). For a review see Scholz et al. (2015). These technologies provide non-invasive, objective, and accurate estimates of body composition. In this paper, we focus our interest on computed tomography (CT) slices which provide very accurate and precise information of animal composition, either to analyse sheep (Glasbey and Robinson, 1999), pig carcasses (Font-i-Furnols et al., 2009; Vester-Christensen et al., 2009; Picouet et al., 2010; Bardera et al., 2014), live pigs (Luiting et al., 1995; Kolstad, 2001), or the comparison between live pigs and their carcasses (Lambe et al., 2013; Carabús et al., 2015). However, to extract meaningful information from these slices specialised processing techniques such as image segmentation are required.

Segmentation aims to separate image pixels according to the represented tissues (Banik et al., 2009; Gonzalez and Woods, 2002). To compute the lean meat percentage (LMP), it is necessary to identify lean meat, fat, and bone in the images. Currently, LMP prediction is determined online in carcasses using various types

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of equipment based on different technologies (Pomar et al., 2009). Despite the wide variety of segmentation techniques, the choice and adoption of the proper one is challenging and still harder when dealing with CT slices from live animals. In this case, an extra difficulty arises due to internal organs which are perfectly represented in the slices but not required for the LMP computation. The densities of the internal organs, measured in Hounsfield Unit (HU) values, are similar to the HU values associated with fat and muscle of the carcass (except for the lungs, whose values are very low). Thus, if the internal organs are included in images and their HU values are considered for the prediction of body composition, they will affect the results (Font-i-Furnols et al., 2015a). To overcome this problem, we propose two different algorithms to virtually extract the internal organs from the CT slices before the LMP calculation.

The first algorithm (based on Glasbey and Young, 2002; Glasbey, 2013) is semi-automatic. First, it takes two consecutive CT slices and the mask of the internal organs represented in the first slice. Then, it applies a four-step iterative process that computes the masks with the internal organs of the next slices. At each iteration, the user can interact to check the correctness of the computed mask. To create these masks, a Dynamic Programming-based approach is used (Bellman, 1957). Dynamic Programming methods are able to solve a complex problem (usually an optimisation problem) by breaking it down into simpler subproblems. The solutions of these subproblems are computed only once and stored for later reuse, thus saving computation time (Brown, 1979). The proposed method has some parameters related to the resolution and the smoothness of the masks. To support the processing of different animals, the proposed algorithm also integrates an optimisation process which automatically fits these parameters to the animal species.

The second algorithm (an improved version of Bardera et al. (2013)) is fully automatic and specifically designed for pig CT slices. To process a single CT slice, it detects the pig's torso, preclassifies it in several tissues, and segments the internal organs by using the knowledge of these tissues and performing different morphological operations. To obtain the whole segmentation this method is applied to each slice individually.

The aim of this paper is to present these algorithms and the experiments that have been carried out to evaluate their performance. Both approaches have been tested on pig CT slices and compared to a manual segmentation carried out by trained personnel.

2. Materials and methods

2.1. Animals and the CT scan

The set of pigs is composed of 9 female live pigs about 120 kg, and from 3 different genotypes (3 pigs of each one); namely, Duroc × (Landrace × LargeWhite), Pietrain × (Landrace × LargeWhite), and Landrace × LargeWhite. These animals have been CT scanned for previous studies (Font-i-Furnols et al., 2015b; Carabús et al., 2014), where additional information such as breeding, feeding, the CT scanning device and the instrumental settings can be found.

2.2. The semi-automatic algorithm

A key step of the semi-automatic algorithm is the contour detection of the internal organs represented in multiple CT slices, i.e. a 3D image. To carry out this process, we were inspired by the method presented by Glasbey and Young (2002), where an appropriate optimisation problem for 2D images is defined. To solve such problems, a cost function is needed to measure the quality of a solution, and an algorithm has to be used to optimise this function. The cost function can either measure the goodness or badness of a solution; when it measures the badness, it is often called *energy function*, and the optimisation algorithm is used to minimise it (Felzenszwalb and Zabih, 2011). In this approach, an energy function is used, and the optimisation algorithm is based on Dynamic Programming. Below, we describe how Dynamic Programming is applied to segment regions in an image, including the definition of the energy function equations, and we analyse the four steps of the semi-automatic algorithm.

2.2.1. Dynamic programming to segment image regions

Dynamic Programming is a powerful general technique for developing efficient discrete optimisation problems, such as finding the shortest path in a graph. In computer vision, it has been extensively used (Glasbey, 2009; Geiger et al., 1995; Ohta and Kanade, 1985; Amit and Kong, 1996). In our case, we are going to consider the image as a graph where pixels are nodes and the connections between pixels from adjacent columns are edges. The weight of each edge is given by an energy function, and the aim of the algorithm is to find the path that minimises it, which will correspond to the internal organs boundary. The first step, hence, is to define the energy function.

Assuming we have a template of the boundary, i.e. the average of some validated boundaries from other sets of slices, we can compare this template with each possible boundary in the slice to be segmented. For each column, as shown in Fig. 1, a range of consecutive pixels (rows) is selected and compared with the template by computing the root-mean-square difference (RMSD). By moving this range of pixels up and down we obtain a new possible location for that boundary point, and the best fit is considered to be the one with the lowest differences. If y is the slice to be segmented, and μ is the boundary template, and assuming that K is the number of pixels of the range, I is the number of columns, $y_{k,i}$ is the kth pixel of the ith column (the same for $\mu_{k,i}$), the boundary shifts range from $-B$ to B, β is the set of selected boundaries (rows) for all the columns, and row β_i is the selected boundary (shift of the range) for the ith column, we can define the energy function of the boundary as

$$E_B(y,\beta) = \sum_{i=1}^{I} f_i(y,\beta_i), \tag{1}$$

where

$$f_i(y,\beta_i) = \sum_{k=1}^{K}\left(y_{k+\beta_i,i} - \mu_{k,i}\right)^2, \quad \beta_i \in \mathcal{B} = \{-B,\ldots,0,\ldots,B\}. \tag{2}$$

Nevertheless, this formula does not take into account the roughness of the boundary, i.e. two consecutive points of the boundary can be very distant. To get a smooth boundary an extra energy term must be added to the function in order to penalise the gap between rows in consecutive columns. We can define this extra energy term (roughness penalty), E_{RP}, as

$$E_{RP}(\beta) = \sum_{i=1}^{I-1}(\beta_i - \beta_{i+1})^2. \tag{3}$$

If λ is the roughness penalty coefficient ranging from a value of 0 up to ∞, then we just need to apply Dynamic Programming to find the boundary with the minimum energy:

$$\begin{aligned}\hat{\beta} &= \arg\min_{\beta\in\mathcal{B}^I}\{E_B(y,\beta) + \lambda E_{RP}(\beta)\} \\ &= \arg\min_{\beta\in\mathcal{B}^I}\left\{\sum_{i=1}^{I} f_i(y,\beta_i) + \lambda\sum_{i=1}^{I-1}(\beta_i-\beta_{i+1})^2\right\}.\end{aligned} \tag{4}$$

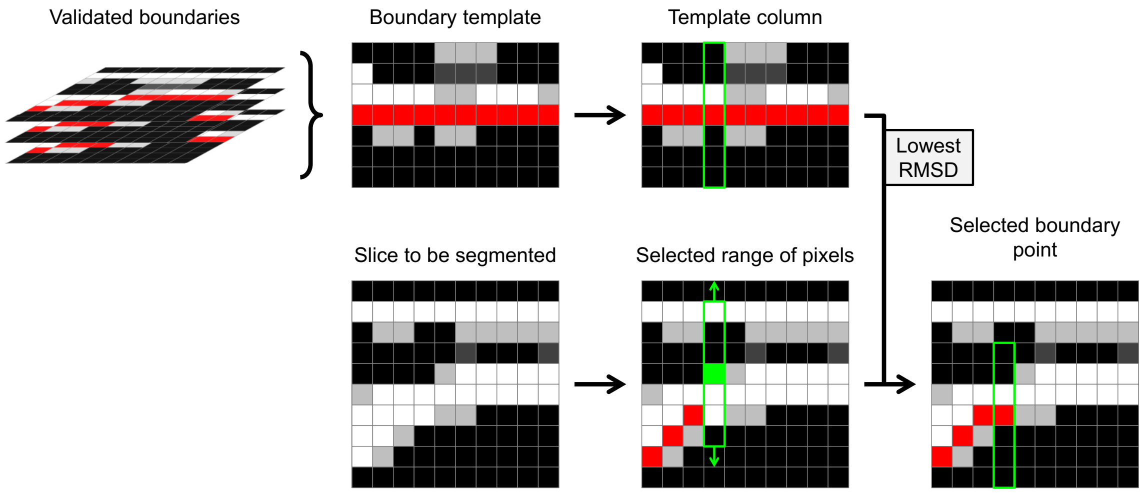


Fig. 1. Obtaining the best boundary by comparing each slice with a boundary template. The boundary template corresponds to the average of some validated boundaries from other sets of slices, and the root-mean-square difference (RMSD) is used to select the best fit, i.e. the selected boundary point. Note that this image does not reflect the current behaviour of the algorithm, but only the idea of Glasbey and Young (2002) by which we were inspired.

In our case, however, the boundary to be segmented can be any region of the slice; therefore, it can intersect the same column of the image more than once. To solve this problem, we can consider that the columns to be compared do not match exactly the columns of the image, but any set of consecutive pixels instead (any set of pre-specified lines or simple curves). In that case, a column is composed of K consecutive pixels which follow any direction. If we trace several perpendicular profiles to the boundary of the template (see Fig. 3), we can consider these profiles to be the actual columns. Then, we can obtain the new boundary by joining the pixels from one profile to another.

As stated by Glasbey and Young (2002), this technique can be used to segment a two-dimensional image, but not a three-dimensional one. To do so, we can divide the image in two-dimensional slices and we can perform the segmentation individually in each one of them. Then, instead of using boundary

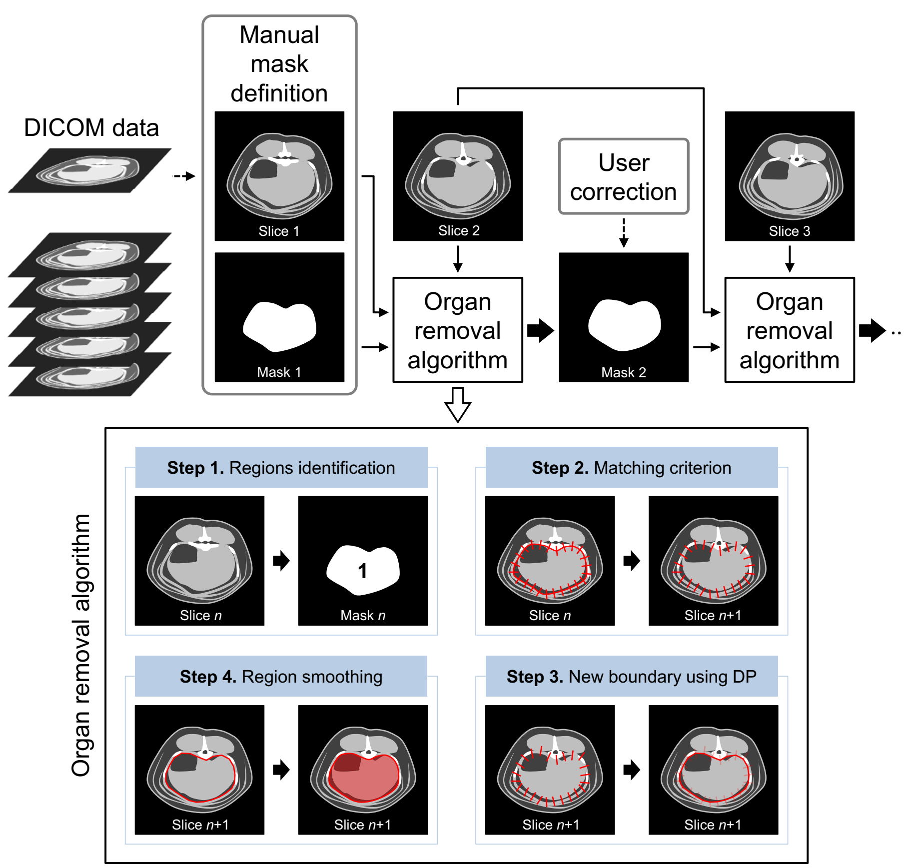
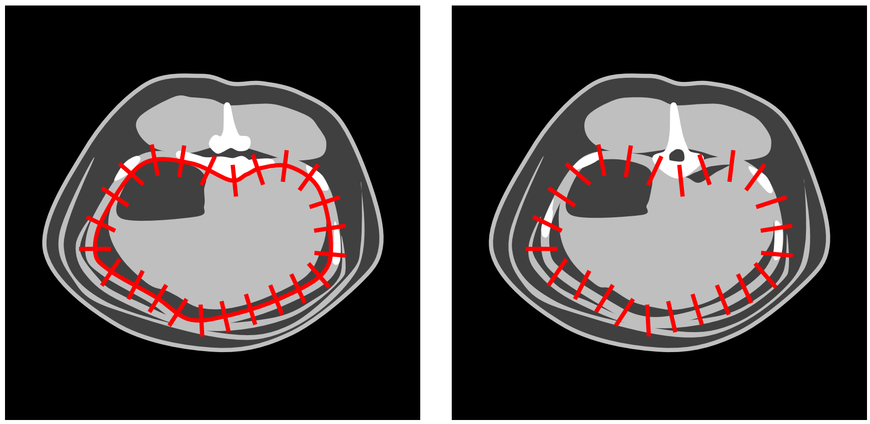


Fig. 2. Main steps of the semi-automatic algorithm. The first slice from the CT DICOM file (*Slice 1*) and the manually defined mask containing the internal organs of this slice (*Mask 1*) are taken as input. Then, the four steps of the algorithm are applied using the next slice (*Slice 2*) and its mask is returned (*Mask 2*). The user can correct the mask before repeating the process, which finishes when all slices have been processed.

templates, we can use the segmentation performed on the previous slice (Glasbey, 2013).

If we denote y as the current slice and y' as the previous one, and we assume that I is the number of perpendicular profiles, K is the number of pixels for each profile, and $p_{i,k}$ is the kth pixel of the ith profile, we can rewrite Eq. (2) to obtain

$$f_i(y, \beta_i) = \sum_{k=1}^{K} \left(y_{p_{i,k+\beta_i}} - y'_{p_{i,k}} \right)^2 \quad \beta_i \in \mathcal{B}. \tag{5}$$



(a) (b)

Fig. 3. Perpendicular profiles traced over the (a) old boundary and translated to the (b) current slice.

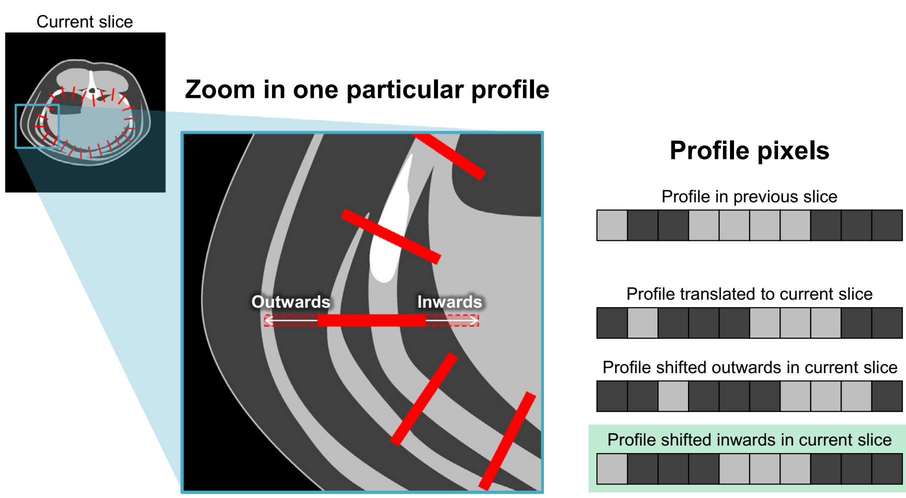
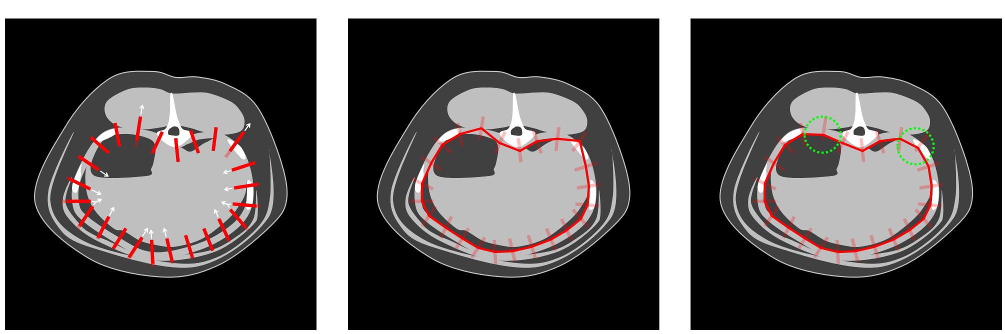


Fig. 4. Comparison of different shifts for a particular profile (the shift with green background is the one with less root-mean-square difference). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) (b) (c)

Fig. 5. Use of Dynamic Programming (with a roughness penalty) to find minimum energy boundary. In (a) the best shift for each profile is found, in (b) the minimum score boundary is obtained, and in (c) the roughness penalty is applied (green circles indicate major changes). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Finally, to find the new boundary we can rewrite Eq. (4) and solve the optimisation problem by using Dynamic Programming, considering that β_{I+1} is the same as β_1:

$$\hat{\beta} = \arg\min_{\beta \in \mathcal{B}^I} \left\{ \sum_{i=1}^{I} f_i(y, \beta_i) \quad + \quad \lambda \sum_{i=1}^{I} (\beta_i - \beta_{i+1})^2 \right\}. \qquad (6)$$

The optimisation problem is applied in the third step of the semi-automatic algorithm, described in Section 2.2.2.

2.2.2. Algorithm description

The proposed semi-automatic algorithm takes as input the first slice from a CT DICOM file (*Slice 1*) and the manually defined mask

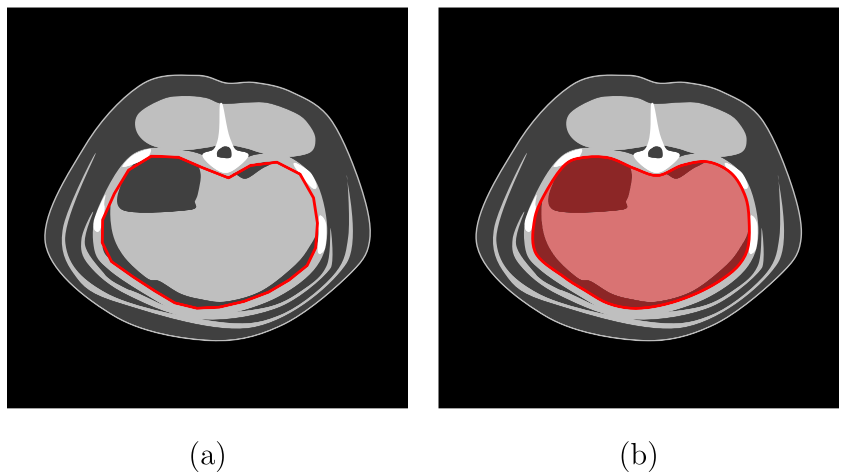


Fig. 6. (a) Before and (b) after applying the moving average filter to smooth the boundary.

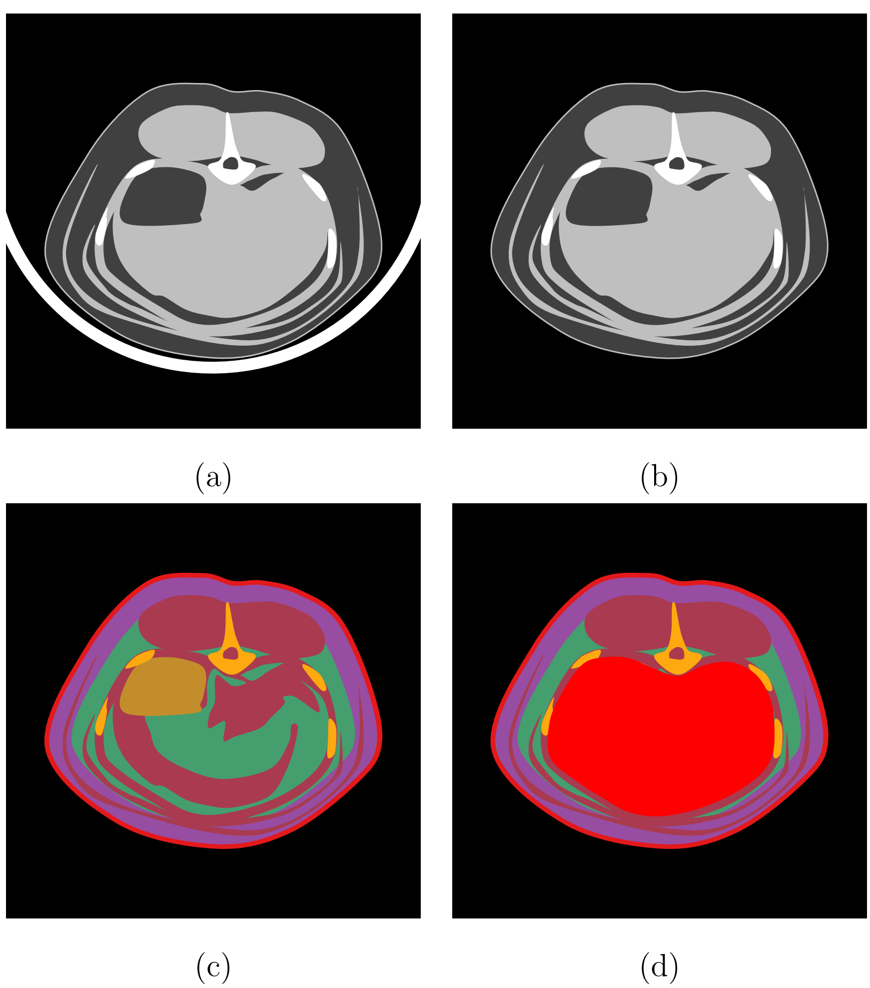


Fig. 7. Results obtained at each step of the automatic algorithm. From (a) to (b) torso segmentation is performed by removing the supporting structure; from (b) to (c) body composition is established by classifying each tissue; from (c) to (d) internal organs are detected (red area). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

containing the internal organs of this slice (*Mask 1*). Then, it takes the next slice (*Slice 2*) and computes its mask (*Mask 2*) using the previous information. The new mask can be corrected by the user. This iterative process is repeated until all the slices have been processed. The four steps of this process are illustrated in Fig. 2 and described below. Note that the slices represented in the figure are not extracted from a real CT DICOM file, but manually created from such file in order to emphasise the concept which is being discussed. All the figures in Section 2 use this technique.

1. **Regions identification.** The first step identifies and labels each region of the well-defined black and white mask from the previous slice (*Mask n*). To carry out the labelling, the algorithm considers two types of regions: (i) exterior regions, which contain the regions of interest of the slice to be taken into account; and (ii) internal regions or holes, which lie inside an exterior region and contain those regions of interest of the external region which are not needed. Depending on the type of data, only exterior regions have to be dealt with. In the example of Fig. 2, as the internal organs area has no holes, no internal regions are defined. This step returns a list of labelled regions.
2. **Matching criterion.** The second step establishes the basis for finding the new boundaries of the labelled regions in the next slice. As input, it needs the list of labelled regions from the previous step, and both the *Slice n* and *Slice n + 1*. For each labelled region, the algorithm compares the same region in both slices. Assuming that little differences exist from one slice to another since consecutive slices are very similar, the method focuses on searching the new boundary near the old one. To determine how this boundary evolves, a set of points are chosen from the contour which are equally distributed along the boundary, being the distance between them a customisable parameter. For each point, a profile perpendicular to the contour is traced, thus obtaining a set of profiles for the region (see Fig. 3).
The profiles are needed to know how this particular point evolves in the new slice (*Slice n + 1*). For each profile, several shifts are tested in *Slice n + 1* to compare how similar are the profile pixels. Each shift is done in the direction of the profile, inwards or outwards. To compare the similarity between the original profile in *Slice n* and the shifted one in *Slice n + 1*, the RMSD is computed using the pixels in both profiles. The lower the difference, the more similar the profiles (see Fig. 4). As output, this step returns the RMSD value for each shift of each region profile.
3. **Finding new boundary using Dynamic Programming.** From the results obtained in the second step, the third step finds the best new boundary by using Dynamic Programming (see Eq. (6), in Section 2.2.1). The optimal path between profile shifts is considered to be the one with the lowest overall RMSD. However, if the profile shift is too distant from the shift selected for the previous profile, then a roughness penalty is applied in order to obtain a smoother region (see Fig. 5). This penalty can also be customised as a parameter. The output of this step is the new boundary for each region in *Slice n + 1*, but only linearly connecting the best shifts, that is, with some sharp vertices.
4. **Region smoothing.** Finally, once the new boundaries of the regions have been filled and added to the output mask (*Mask n + 1*) and the holes have been subtracted, a fourth step is needed to smooth the mask (see Fig. 6). The input is the rough new boundary of each region, which comprises a set of points corresponding to the best shifts of each profile. The moving average filter is then used to remove the rough parts of the contour, and it is applied to the whole mask as many times as indicated by the corresponding parameter, or until no improvement is achieved. This last step returns the mask of *Slice n + 1*, which will be used as *Mask n* in the new iteration of the algorithm. Before this new iteration starts, the user can perform manual corrections over the mask if needed.

In this paper, we have applied this semi-automatic segmentation approach to remove the internal organs of pigs. Note that this algorithm can also be used to tackle other problems due to its generic definition. For this reason, some parameters of the method,

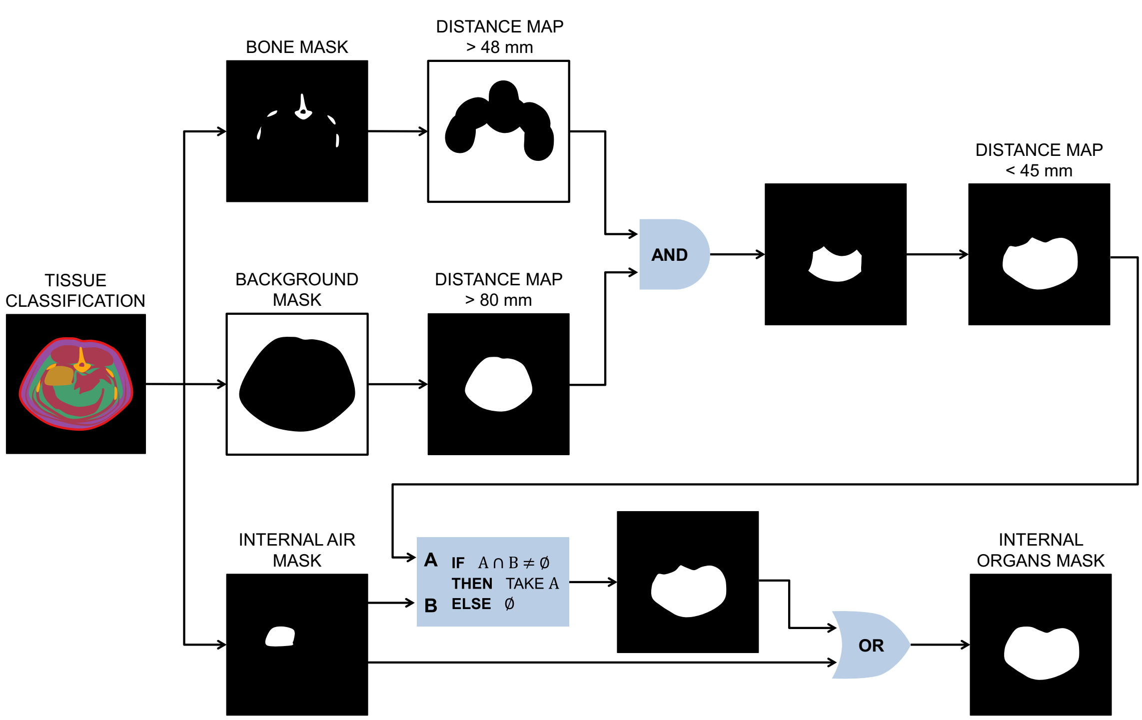


Fig. 8. Diagram of the process to obtain the internal organs mask of a slice from the tissue classification.

such as the number of pixels of each profile, the distance between profiles and the number of shifts, amongst others, can be tuned to improve the results for a particular problem. In our case, we have chosen these parameters by using an optimisation algorithm. After analysing some of them, we have considered the simulated annealing algorithm (Mehlhorn and Sanders, 2008) to be the more appropriate, since it avoids falling in local optima, it has the possibility to create new random parameters at each step, and it facilitates the change of some parameters in order to vary the time it takes to get the results (the more time it takes, the better the results are). A greedy algorithm (Mehlhorn and Sanders, 2008) has also been used to improve the results.

2.3. The automatic algorithm

The second proposed algorithm is fully automatic and it has been specifically designed to remove the internal organs from pig CT slices. The algorithm is based on Bardera et al. (2013), and it processes each slice individually in order to perform the whole segmentation. It is composed of three main steps illustrated in Fig. 7 and described below.

1. **Torso segmentation.** The first step obtains the area of the slice corresponding to the pig data. Due to the high weight of pigs, a big structure is placed underneath to hold them in the scanning tube, and this structure is obviously detected in the final CT scan producing high intensity values in the same range as the bone structure. Therefore, a segmentation process is needed to remove it from the CT scan in order to keep only the region corresponding to the pig. This segmentation process starts removing the background (mainly air) by using a threshold value of −200 Hounsfield Units (HU), which has been obtained from Bardera et al. (2013). As some internal areas of the pig also contain air, such as the lungs or the intestines, a mask filling operation is needed in order to keep them. Finally, an opening operation is performed only with the objects of the mask greater than a given size, which is 15 cm^2 by default since we have empirically observed that this value correctly removes the supporting structure without affecting the area corresponding to the pig. Not all of the slices represent the pig's torso. We have observed that the first 12% of them correspond to the head and neck of the pig. Hence, for our purpose, these slices have been ignored.
2. **Body composition.** The second step classifies the voxels of the pig's torso represented in the slice as bone, air, subcutaneous fat, other fat, lean meat, or skin. This procedure is mainly done by thresholding. The bone structure is considered to be composed of voxels with an intensity above 200 HU. However, since the voxels from the marrow have lower values and they are very similar to the voxels from the fat, a mask filling operation is performed. On the other hand, the internal air (mainly from the lungs and the intestines) is considered to be composed of voxels with an intensity below −200 HU, just like the threshold value we have used to segment the background. As the lungs may contain a small amount of voxels inside corresponding to the pulmonary system, a mask filling operation is also performed. Regarding the other tissues, the voxels from the fat are considered to range from −200 to 0 HU, and the voxels from the lean meat and the skin are considered to range from 0 to 200 HU. To differentiate the subcutaneous fat from the other fat the distance to the background is used. The voxels from the fat which are 30 mm or less from the background are classified as subcutaneous fat. Similarly, the skin is distinguished from the lean meat by classifying as skin the voxels which are 20 mm or less from the background. As in the previous step, all these thresholds and values are obtained from Bardera et al. (2013).
3. **Internal organs segmentation.** The last step, which detects the internal organs of the slice, is ready to start when each part of the pig's torso has been labelled in one of the tissues described above. In this case, threshold or gradient-based strategies are not appropriate due to the high diversity of structures in the area to be segmented. In this context, this step considers the following two assumptions: (i) the internal organs (the lungs and the intestines) have air inside them, and (ii) the internal organs are distant from the bones and from the background. Taking into account these assumptions, the method uses 3D

Table 1
Results obtained performing the semi-automatic segmentation method considering from 1 to 10 consecutive slices with no user interaction.

Consecutive slices without manual corrections	F-score mean
1	0.9819
2	0.9770
3	0.9737
4	0.9678
5	0.9643
6	0.9603
7	0.9553
8	0.9481
9	0.9449
10	0.9408

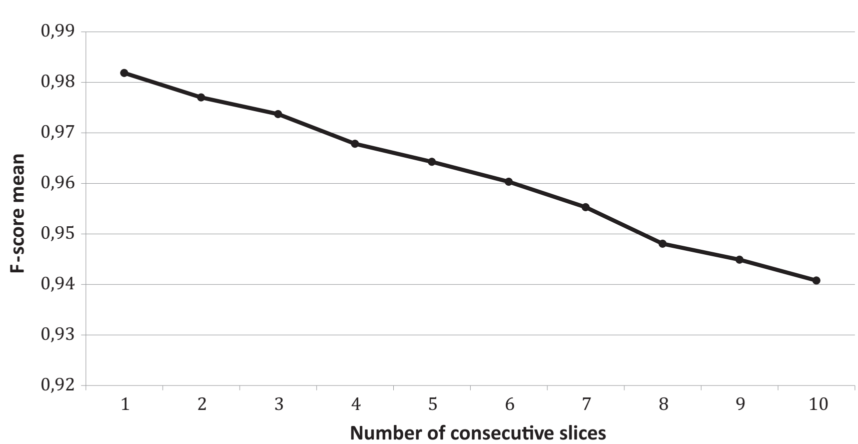


Fig. 9. F-score mean evolution of the semi-automatic segmentation method as the number of consecutive slices without performing manual corrections increases.

distance maps and morphological operators, such as dilation (using a spherical structuring element with a unit radius of 1 voxel), to detect the internal organs. This process is represented in Fig. 8. First, a mask is created with the voxels that are located at a distance from the bones greater than 48 mm, and at a distance from the background greater than 80 mm. Next, this mask is dilated 45 mm in order to approach the bones. All these values have been experimentally obtained (see Section 3). Then, a second mask is created with the internal air structures segmented in the previous step. For each slice, the algorithm only keeps those regions of the first mask which have at least one pixel matching the mask corresponding to the internal air structures, removing by this way the regions which are not over the internal organs. Finally, the resulting regions are merged with the internal air mask to obtain the main parts of the internal organs. Despite the high robustness of the method, the border accuracy is not very high.

Although this algorithm has been specifically designed for pig CT slices, it could be adapted to segment the internal organs of other animal species by appropriately modifying some of its parameters. However, the current values for these parameters are linked to the data set used in this study, so one of the limitations of the algorithm concerns the adaptation of these parameters for different data sets (e.g. distance maps thresholds for lighter pigs would be different).

2.4. Manual segmentation

In order to have a reference when comparing the results, a manual segmentation has been performed over the pig CT scans. This segmentation has been carried out by two experts, one from our laboratory and another from IRTA-Monells. The first expert analysed all the slices from the CT scans and one by one delineated the internal organs of each slice. Afterwards, the second expert from IRTA-Monells validated the results as the ground truth.

To manually segment each slice, the edition tools of the VisualPork platform (Bardera et al., 2012) have been used. VisualPork is an internal lab software platform that integrates image processing and 2D and 3D visualisation techniques. It has been developed at the Graphics and Imaging Laboratory (GILAB) from the University of Girona in collaboration with experts from IRTA-Monells. VisualPork has been implemented in C++, using Qt, the Insight Toolkit (ITK), and the Visualisation Toolkit (VTK) libraries. It has a modular design that allows the integration of new functionalities according to demands. It supports DICOM standard and IHE profiles. The proposed semi-automatic and automatic approaches have been implemented and integrated as two new modules of the platform.

Regarding the edition tools, a new module has also been added to the VisualPork platform which allows the user to define a manual segmentation. It is based upon the edition tools that have also been developed for the manual corrections of the semi-automatic algorithm. These edition tools include the creation of as many regions of interest as needed by defining their borders, and the correction of these regions by widening, reducing or removing them.

2.5. Evaluation metrics

To compare the results obtained from the proposed segmentation methods with the ground truth, an evaluation strategy has been defined. Considering the pixels inside and outside the segmented regions, we have classified them in four groups: false positives (FP), true positives (TP), false negatives (FN) and true negatives (TN). From the number of pixels of each group, two inter-

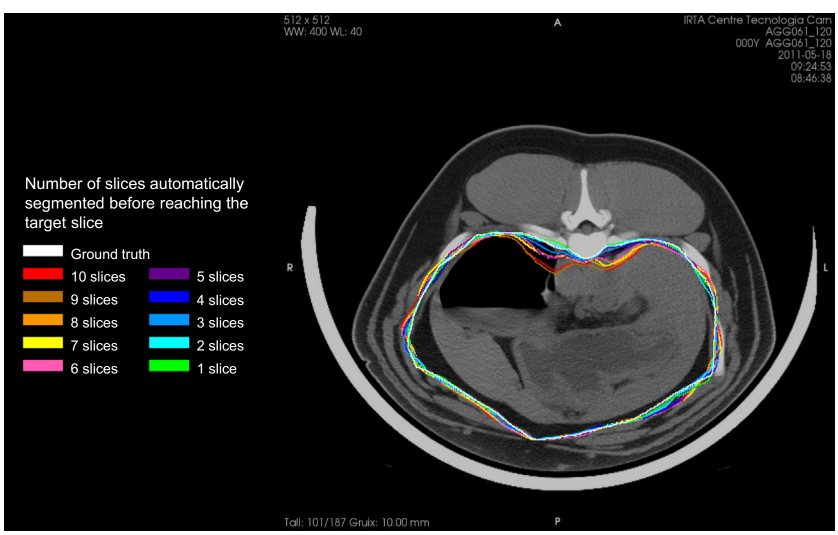


Fig. 10. Segmentation of a certain slice taking into account the number of previous slices that have been segmented since the last time a manual correction was done.

Table 2
Results obtained performing the semi-automatic segmentation method until the F-score measure is lower than a certain threshold. LMP = Lean Meat Percentage.

	Manually corrected slices			
F-score threshold	Mean number	Mean (%)	F-score mean	LMP mean (%)
0.99	76.67	92.68	0.9815	54.77
0.95	20.22	24.46	0.9641	54.83
0.90	12	14.52	0.9431	54.87
0.85	8.67	10.47	0.9267	55.07
0.80	7.22	8.73	0.9018	55.20

esting measures can be computed: precision (P) and recall (R). Precision is given by the proportion of the segmented pixels that are correctly classified as internal organs, that is,

$$P = \frac{TP}{TP + FP}.$$

Recall indicates the proportion of the internal organs that has been segmented, that is,

$$R = \frac{TP}{TP + FN}.$$

Since both measures are complementary (typically when one grows, the other decreases), the harmonic mean of both, usually known as F-score, can also be used to evaluate the results, since it is a combination of both (van Rijsbergen, 1974, 1979). F-score is given by

$$\text{F-score} = 2 \cdot \frac{P \cdot R}{P + R}.$$

Another measure that can be computed is the LMP. It is obtained by using the histograms of the slices without the internal organs segmented by the algorithm. The voxels with values between 0 and 200 HU are considered to be part of the lean meat and the skin, and the ratio of these voxels to the total (excluding the internal organs area, the air, and the supporting structure) is considered to be the lean meat percentage.

The root mean square error of prediction (RMSEP) can also be computed by means of leave-one-out cross-validation as a measure of accuracy, considering the LMP obtained from the manual segmentation as the true value.

2.6. Experiments' description

To evaluate the proposed segmentation algorithms, different experiments have been carried out.

The experiments have been designed according to the features of the proposed methods. Regarding the semi-automatic approach, the experiments aim to evaluate the effect of user interaction on the results. As for the automatic approach, the experiments aim to set the algorithm's parameters in order to obtain the best results. In every experiment, the results are obtained by computing the mean of the results for each pig. In the case of the F-score measure, the result for each pig is obtained by computing the sum of false positives, true positives, false negatives and true negatives of all its slices, and then computing the precision and recall measures, which at the same time are needed to compute the final F-score.

As the algorithms are applied on 9 different individuals, an analysis is also performed to test the robustness of the algorithms by showing the results for each pig and some statistical parameters such as the minimum and maximum values, the mean, the standard deviation, and the coefficient of variation.

2.6.1. Semi-automatic algorithm: effect of user interaction

Our semi-automatic segmentation approach lies between two ends: a completely automatic method, which does not need any interaction, and a completely manual method, which needs a manual mask definition for each slice. For this reason, we have compared this approach and the automatic segmentation method to the manual segmentation carried out by trained personnel, which we consider as the ground truth. To compare them, the F-score measure is used; the higher the score, the better the result is. To carry out our test we have designed two experiments. Note that in both experiments we do not consider the variability in the results of different users, or even of the same user at different moments, when performing manual segmentations; the masks we use for the manual segmentations are the same as the masks of the ground truth.

Experiment 1 measures the quality of the results according to the degree of interaction. It analyses the differences when using the semi-automatic method for a certain number of consecutive times without any interaction. The values which have been tested for this number of consecutive times range from 1 to 10. For example, if this number is 5, the algorithm starts with a mask from the ground truth set (the first slice with internal organs), then performs the segmentation method for the next 5 slices without any interaction, and then it starts again the same steps after taking the mask for the 6th slice from the ground truth set. From Fig. 2,

Table 3
Results obtained performing the automatic segmentation method changing the distance between the internal organs and the background (distance to the bone structures fixed to 48 mm, and then dilated 45 mm). LMP = Lean Meat Percentage.

Distance to the background (mm)	F-score mean	LMP mean (%)
60	0.8319	54.32
65	0.8594	54.24
70	0.8821	54.23
75	0.8982	54.24
80	0.9040	54.20
85	0.8995	54.08
90	0.8866	53.98
95	0.8677	53.94
100	0.8445	53.98

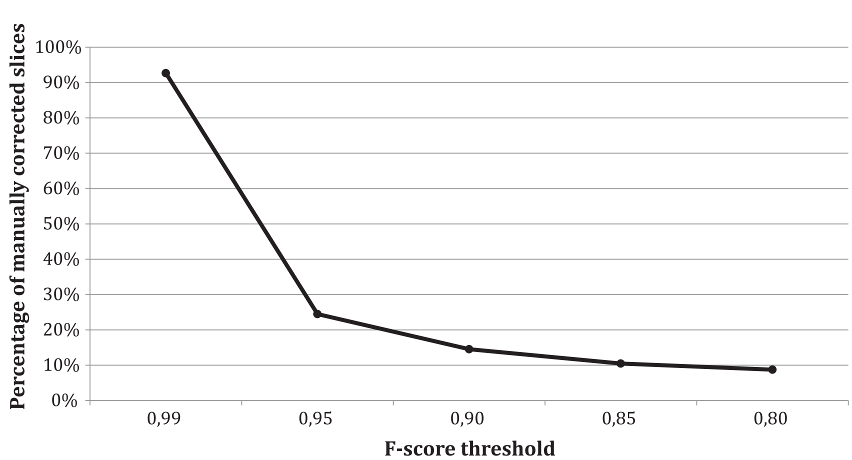


Fig. 11. Evolution of the percentage of manually corrected slices needed in the semi-automatic segmentation method as the F-score threshold decreases.

we can see that in our method users can interact with the output mask (*Mask n + 1*) to perform manual corrections if these are required, so we can imagine that a mask taken from the ground truth set is similar to the mask generated by a manual segmentation. This kind of experiment allows us to know how much the quality decreases when the gap between manual corrections gets bigger.

Experiment 2 computes the number of times (in percentage) that the manual correction is needed taking into account a predefined threshold for the F-score measure. The semi-automatic method is performed without manual corrections until the F-score of the output mask (*Mask n + 1*) is lower than a certain threshold. The thresholds that have been tested are 0.80, 0.85, 0.90, 0.95, and 0.99. This kind of experiment allows us to simulate the behaviour of the user by comparing the thresholds to the user perception, being each threshold the lower limit under which the segmentation is considered to be not good enough, thus needing some manual corrections.

2.6.2. Automatic algorithm: parameters setting

Both segmentation algorithms have some parameters which can be modified in order to obtain different results. Regarding the automatic approach, we observed that the two most influential parameters on the results are the distance between the internal organs and the background, and the distance between the internal organs and the bone structures. Therefore, our next experiments have been designed to test different values for both parameters to find the combination which gives us the best result.

Experiment 3 evaluates the first parameter, which refers to the distance used to separate the internal organs from the background; the lower the distance, the closer the internal organs are to the background, i.e. the contour of the torso. The values that have been tested range from 60 mm to 100 mm by fives. Note that this is not the final distance which separates the internal organs from the background, since a dilation operation has yet to be performed.

Experiment 4 evaluates the second parameter, used to separate the internal organs from the bone structures. Taking into account the steps of the algorithm described in Section 2, we first take a region distant from the bone structures and the background, and then we dilate this region in order to approach the bones, avoiding by this way upper regions near the bone structures which do not correspond to the internal organs area. The second parameter, then, refers to the distance used to separate the internal organs from the bone structures in the first step. The dilation thickness, therefore, is modified according to this distance, being always 3 mm less. In this case, the values that have been tested range from 38 mm (dilation thickness of 35 mm) to 58 mm (dilation thickness of 55 mm) by twos or threes.

3. Results and discussion

In this section we present and discuss the results obtained from the different experiments described in Section 2, which have been designed to evaluate the proposed segmentation algorithms.

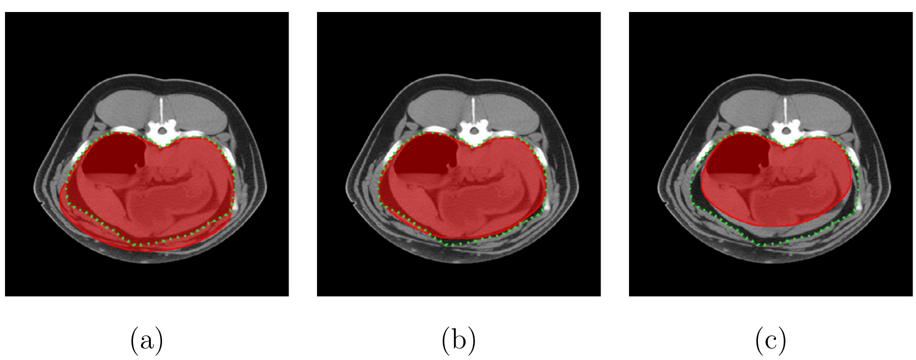


Fig. 12. Internal organs segmentation varying the distance between the background and the internal organs. The ground truth is represented as a green dashed line. In (a) a short distance is represented (60 mm) with high precision, but low recall; in (b) a medium distance is represented (80 mm) with high precision and high recall; and in (c) a large distance is represented (100 mm) with high recall, but low precision. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

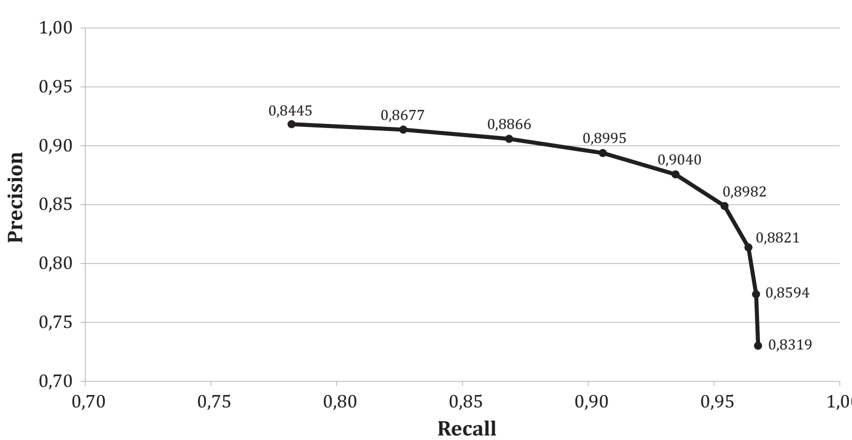


Fig. 13. Evolution of the F-score values as the distance between the internal organs and the background changes from 60 mm (lower right value) to 100 mm (upper left value) by fives (distance to the bone structures fixed to 48 mm, and then dilated 45 mm).

3.1. Results of the semi-automatic algorithm's experiments

Two experiments have been designed to evaluate the effect of user interaction in the semi-automatic algorithm.

In Table 1, the results of the first experiment are shown. As the number of consecutive slices that are not manually corrected grows, the F-score measure decreases linearly (see Fig. 9). This behaviour is due to the fact that the method accumulates the error from slice to slice, and it only disappears when a manual correction is done. In Fig. 10, we can observe how a certain slice is segmented taking into account the number of previous slices that have been segmented since the last time a manual correction was done. Note that if the algorithm performs the segmentation without manual corrections too many consecutive slices, the quality decreases in favour of the time needed to complete all the slices; on the other hand, if a manual correction is done too often, then the quality is better but more time is required. Therefore, there is a trade-off between quality and user effort.

The results of the second experiment are shown in Table 2. We can see that the number of manually corrected slices quickly decreases when the F-score threshold is also reduced (see Fig. 11). These results can be explained because of the comparison between the F-score threshold and the user perception; a lower threshold means a more tolerant user perception, so that the user is liable to accept more outputs and perform less corrections. Note also that the differences between thresholds are bigger at the beginning, reducing much more slices from a threshold of 0.99 to 0.95, than from 0.85 to 0.80. Therefore, if the tolerance of the user is not very restrictive, good results can be achieved by manually segmenting only few slices.

In order to know the effect of the user interaction on the lean meat percentage, this value has also been computed using the histograms without the internal organs segmented by the algorithm, and the results are shown in Table 2. In this case, being the LMP mean of the manual segmentation very similar to the LMP obtained by the manual dissection (Font-i-Furnols et al., 2015b), the RMSEP values range from 0.0003 to 0.0011. The results, then, show little variation between the different evaluated thresholds. The fact that the internal organs have similar values to the lean meat causes the LMP to have little differences. We can consider the LMP as a measure of the content of the segmentation, and the F-score as a measure of its shape; hence, the F-score is more reliable when evaluating the performance of the algorithm.

Regarding the time needed to segment all the slices, it varies depending on the user's expectations. The revision of each mask proposal, the number of masks to be corrected, and the correction of these masks are factors that affect time and are linked to the user's tolerance. Provided that our algorithm has not yet been totally optimised to minimise the response time, in this paper we do not present an extensive analysis concerning this issue. However, as stated by several studies (Miller, 1968; Dabrowski and Munson, 2011), the algorithm still provides an acceptable response time, since it takes between 0.5 and 2 s to create the mask at each iteration. Thus, the time needed to perform the segmentation for a whole pig is reduced from hours (manual segmentation) to minutes.

Table 4
Results obtained performing the automatic segmentation method changing the distance between the internal organs and the bone structures needed to carry out the subsequent dilation operation (distance to the background fixed to 80 mm, and then dilated 45 mm). LMP = Lean Meat Percentage.

Distance to the bone structures (mm)	F-score mean	LMP mean (%)
38	0.7978	54.14
40	0.8922	53.95
42	0.8971	54.02
45	0.9018	54.12
48	0.9040	54.20
50	0.9039	54.23
52	0.9029	54.27
55	0.8986	54.29
58	0.8922	54.32

3.2. Results of the automatic algorithm's experiments

Two experiments have also been designed to evaluate the parameters setting in the automatic algorithm.

Results of the third experiment are shown in Table 3. As illustrated in Fig. 12, a short distance to the background implies that the final computed area takes regions which are not considered to be part of the internal organs area (high precision, but low recall), while a large distance implies that some of the regions of the internal organs area are not included in the final segmentation (high recall, but low precision). Therefore, the best result is obtained when taking a medium distance, which in this case corresponds to 80 mm. Fig. 13 shows how these measures evolve. As we did in the previous experiment of the semi-automatic algorithm, the LMP mean is also shown in Table 3, and the RMSEP values range from 0.0007 to 0.0027. In this case, and for the same reason

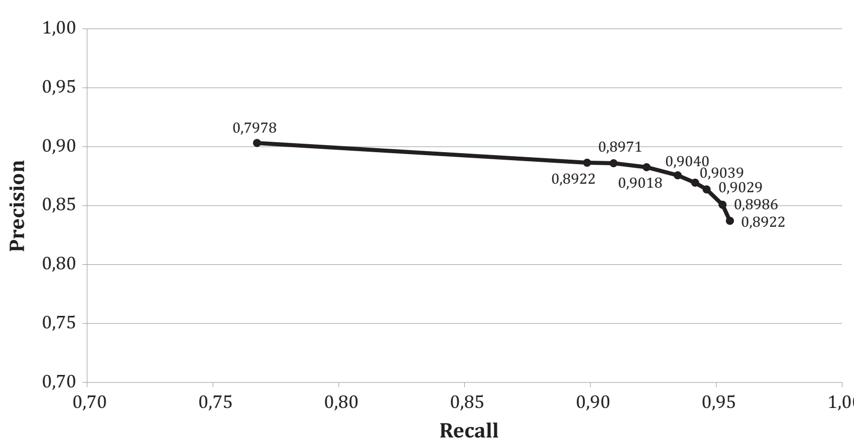


Fig. 14. Evolution of the F-score values as the distance between the internal organs and the bone structures changes from 38 mm (upper left value) to 58 mm (lower right value) by twos or threes (distance to the background fixed to 80 mm, and then dilated 45 mm).

Table 5
F-score values for each pig, minimum and maximum values, mean, standard deviation, and coefficient of variation for both proposed algorithms, using an F-score threshold of 0.90 for the semi-automatic algorithm, and distances to the background and to the bone structures of 80 and 48 mm, respectively, for the automatic algorithm.

Individual	F-score semi-automatic	F-score automatic
1	0.9485	0.9110
2	0.9428	0.8862
3	0.9460	0.9116
4	0.9393	0.9010
5	0.9411	0.9082
6	0.9383	0.8983
7	0.9456	0.9134
8	0.9446	0.9042
9	0.9417	0.9021
Minimum value	0.9383	0.8862
Maximum value	0.9485	0.9134
Mean	0.9431	0.9040
Standard deviation	0.0032	0.0080
Coefficient of variation	0.0034	0.0089

stated before, the variation between the evaluated distances is also small.

Table 4 shows the results of the fourth experiment. Similar to the previous experiment, when the distance to the bone structures is too short or too large, the results are worse because of the low precision or low recall. The best result is obtained when taking a distance of 48 mm, which then is dilated 45 mm. Fig. 14 shows the evolution of these measures. Following the same procedure as in the previous experiments, the LMP mean is shown in Table 4, and the RMSEP values range from 0.0008 to 0.0065. Again, the differences are narrow, and the same analysis can be applied.

Although the automatic algorithm is also not yet optimised to minimise response time, it takes between 40 and 50 s to perform the segmentation for a whole pig, taking less than 40 s in average to detect the internal organs (third step of the algorithm).

3.3. Robustness analysis

To test the robustness of the algorithms, an analysis has been done to compare the results obtained for each individual of the data set.

Table 5 presents, for both proposed algorithms, the F-score values for each pig, as well as the minimum and maximum values, the mean, the standard deviation, and the coefficient of variation. An F-score threshold of 0.90 has been used for the semi-automatic algorithm (acceptable value extracted from the results of the second experiment), and distances to the background and to the bone structures of 80 and 48 mm, respectively, have been used for the automatic algorithm (best configuration extracted from the results of the third and fourth experiments).

From the results, we can clearly state that both algorithms are robust and that they do not present high variation when they are applied to the current data set. As a matter of fact, the coefficient of variation (ratio of the standard deviation to the mean) for both algorithms is particularly low, not even reaching 1%, which indicates that the F-score values for each algorithm are similar amongst all the pigs.

3.4. Final remarks

As expected, the semi-automatic method performs better than the automatic one, since it includes some manual corrections that are considered as the ground truth. However, the results obtained from the automatic approach are certainly positive, since the F-score surpasses 0.90. The major problem of this method is the segmentation of the first slices performed by the algorithm, which do not present many bone structures but have some internal organs areas to segment, thus relying mainly on the distance to the background. Other than that, the segmentation of the rest of the slices is nearly perfect. If we take the worst slice segmentations and we perform them manually, however, the results improve. Interestingly, taking the 12 worst slice segmentations, as we did in the second experiment with the semi-automatic algorithm using an acceptable F-score threshold of 0.90 (see Table 2), and replacing them with manual segmentations, the average F-score approaches 0.94, similar to the results of the semi-automatic approach in the same conditions. Hence, as a future work, we will consider the possibility of merging both algorithms by using an automatic process as default, and a semi-automatic one to correct the slice segmentations with the worst results.

4. Conclusion

Two different segmentation algorithms have been proposed to remove the internal organs from CT scans of live pigs, which is a key process required to compute their lean meat percentage. The first algorithm that has been presented is semi-automatic and uses a Dynamic Programming-based approach to find the best boundary for the internal organs, while the second one is fully automatic and uses distance maps and morphological operators. The traditional method to segment the internal organs is the manual segmentation, which usually takes hours in order to complete the whole segmentation for a single pig. In our case, both proposed algorithms take only few seconds or minutes to complete the same process with very similar results. The automatic approach is faster and prioritises robustness over accuracy, with an average response time between 40 and 50 s, and an average F-score of more than 0.90. On the other hand, the semi-automatic approach is preferred if the user wants to control the level of accuracy, since some manual corrections can be performed to improve the results. In this case, the response time to segment a single slice lies between 0.5 and 2 s, and assuming a 15% of manually corrected slices (about 12 slices), it provides an average F-score which surpasses 0.94.

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CHAPTER 7

Results and discussion

Previous chapters have presented the publications which are part of this document. In this chapter the results obtained from each publication will be summarised and a general discussion about these results will be carried out. As depicted in Figure 1.2, where the connection between the presented publications is made clear, the results will be divided in two main blocks: medical imaging applied to teaching, and medical imaging applied to meat industry.

7.1 Medical imaging applied to teaching

In the first block, two e-learning platforms have been developed, one related to the medical field, and the other one related to the veterinary field. The medical e-learning platform has been created based on the need of the medical students and medical professionals for having learning tools which are far more interactive and visual, noticeably increasing their motivation. In the case of medical students, to facilitate their learning process; in the case of medical professionals, to increase their participation in recycling courses, since it is usually poor in face-to-face courses.

Starting from the current platforms which could help us to achieve our goal, we have identified some shortcomings which we wanted to solve with the design and implementation of a new platform focused on radiology: the RadEd platform. From the teacher's side, we noticed the need for a simple and fast content creation process as well as some tools to evaluate and monitor students, while the learners' requirements were focused on interactive and engaging ways to learn without place and time restrictions. To evaluate the functionalities of the RadEd platform, it has been compared to other web-based radiology platforms. Table 7.1 summarises the evaluated platforms, including RadEd, and their features, which have been selected upon our needs. To obtain more detailed information about this comparison as well as the interfaces of the RadEd platform, see Chapter 2 and Chapter 3.

Regarding the principal differences between the RadEd platform and the other evaluated platforms, we can mainly highlight the following features:

- **Content creation.** Some platforms do not allow to add new cases, or the procedure to do so is considerably complex and it requires the user to have specific knowledge, while other platforms provide this feature only as a theory case. Furthermore, there are few platforms which offer a high exercise customisation level while allowing an appropriate classification both for the theory and the practical contents. Analysing these problems, then, RadEd presents a content creation process which provides all these features.

	MyPACS [Weinberger 2002]	COMPARE [Grunewald 2003]	ELERA [Grunewald 2004]	ExamWeb [Lewis 2013]	KICLA [Rowe 2014]	USRC [Burbridge 2015]	RadStax [Colucci 2015]	**RadEd** [Xiberta 2016]
Content								
Practice-based	-	-	+	+	-	+	-	+
Cases searching	+	-	+	+	+	-	-	+
External resources	-	-	-	-	-	-	-	+
External links	-	+	+	-	-	-	-	+
Learning functionalities								
Presentation-based	+	-	-	-	-	-	+	+
Test exercises	+	-	+	+	-	-	-	+
Interactive exercises	-	-	-	-	-	+	-	+
Help messages	-	+	+	+	-	+	-	+
High exercise customisation	-	-	-	+	-	-	-	+
Assessment strategies	-	-	-	+	-	-	-	+
Image interaction								
Image-based	+	+	+	-	+	+	+	+
MPR or 3D	-	-	-	-	-	-	+	-
Labels	+	-	-	-	-	+	+	+
Annotations	+	+	-	-	-	+	-	+
Zoom & pan	+	+	-	-	-	+	-	+
General features								
Cross-browser	+	-	+	-	+	-	-	+
Software independent	-	+	-	+	-	-	+	+
No installation requirements	+	+	+	+	-	+	+	+
Collaborative learning	+	-	-	+	+	-	-	-
User-friendly interface	-	-	+	+	-	+	+	+
No software knowledge	-	-	+	+	+	-	-	+
Multilanguage	-	-	-	-	-	-	-	+

Table 7.1. Summary of the evaluation of the main web-based radiology e-learning platforms.

- **Learning functionalities.** Leaving aside the platforms which do not provide exercises at all, the other ones are mostly divided between those which provide guessing exercises, i.e. hiding and showing information, and those which have a higher degree of interaction providing multiple-choice exercises. However, almost no platforms offer interactive exercises which go beyond this feature, and the few that do so do not allow the automatic correction of these exercises, nor they have any correction strategies. RadEd allows several types of interactive exercises which are automatically corrected, and it is designed to incorporate new types easily.

- **Image interaction.** Since the purpose of the evaluated platforms is focused on the learning in radiology, most of them are image-based. Nevertheless, few of them allow a high level of image interaction, such as zooming and adding labels and annotations, and those which allow it do not use these features to solve exercises. Moreover, almost no platform makes use of visual representations higher than 2D, such as MPR and 3D visualisations. RadEd, although it still only uses 2D representations, offers a high level of image interaction and uses such features in its exercises, such as the location exercises, where the user has to mark a specific area of the image.

- **Accessibility.** All the evaluated platforms have some accessibility problems, either because they are not cross-browser, or because they require some plug-ins to work properly. Furthermore, although it may be a minor problem, none of them have the option to change the language. One of the main objectives of the RadEd platform is that it can be used by everybody without place and time restrictions, so that it is multilingual, cross-browser, and it does not need any specific plug-in.

The advantages of these characteristics have also been tested in a real context, with the participation of almost 250 users, between students and medical professionals, who enrolled and completed a radiology course using the RadEd platform and answered a survey about its functionalities. The results, detailed in Chapter 3, demonstrate that the level of satisfaction with the platform is remarkably high, either for its capability to improve the learning and the content creation processes, as required by teachers, or for the high level of image interaction that achieves a higher motivation amongst learners. In fact, from the 10 scoring questions of the survey, all of them achieve an average satisfaction value of about 75% or more.

The evaluation of the RadEd platform has also made it possible to fix the existing errors in the platform, as evidenced by the results obtained in the different phases of the pilot test. In other words, the results of the second phase, in which some improvements suggested by the users of the first phase were included, are significantly more satisfactory than the results from this first phase. Therefore, this difference in the results prove that it is helpful to keep a place where users can express their opinion with respect to the platform, and indicate the errors they may have found.

In addition, the results also show that one of the main objectives of the RadEd platform development has been achieved, since the participation of the learners in this kind of courses has increased. According to the survey, almost half of the learners had participated in none or few online courses before completing this one, whereas after completing it almost all of them would recommend it. Actually, the participation in face-to-face courses of the same kind is usually very low, and sometimes it is mandatory. In our case, with an online and voluntary course, the participation has been proved to be far higher.

Finally, the results have also shown that, although the availability of a mobile version of the platform is considered to be useful (almost two thirds of the users consider so), hardly any of the users have taken advantage of it. Hence, the preferred device to access the platform and interact with the images is, obviously, a bigger screen such as the one from a computer, since there is more space available and the images can be better visualised. However, being able to access the platform from the mobile phone can also be useful in some circumstances, even though it is not the priority device.

With all the knowledge and the results from the evaluation of the RadEd platform, Chapter 4 focuses on medical imaging applied to veterinary teaching. If the needs of medical students and medical professionals with regard to the interactive tools they can use have been previously explained, in the case of veterinary science these problems are still more noticeable. There are very few graphical and interactive resources which are able to improve the learning process of medical imaging applied to veterinary science. Indeed, there are generally few virtual tools for this discipline.

Gathering these needs, then, a new web-based e-learning platform has been created with the purpose to facilitate all these processes: the IVET platform. Following the same steps as in the previous platform, and to evaluate the new tool we have designed, it has been compared to other virtual veterinary platforms, although the comparison has had to be much more general taking into account that there are almost no platforms of this kind. Table 7.2 summarises the evaluated platforms, including IVET, listing a set of more general features. To obtain more detailed information about this comparison as well as the interfaces of the IVET platform, see Chapter 4.

Regarding the principal differences between the IVET platform and the other evaluated platforms, we can mainly highlight the following features:

- **Learning functionalities.** Almost half of the platforms do not offer any type of exercise at all, and only one of them provides interactive exercises; that is, exercises which are not multiple-choice questions. Moreover, only some of these platforms allow the possibility to access the statistics of the solved exercises. In the case of IVET, multiple-choice questions are supported, but also those exercises where the image interaction is fundamental, such as 2D location exercises, where the user has to mark a specific area of the image; MPR location exercises, where the user has to move all 3 planes to place the intersection point to its corresponding location; and 3D location exercises, where the user has to select a 3D object amongst the ones presented in the exercise. The access to the complete statistics of the exercises is also an option provided by the IVET platform.

- **Image interaction.** Almost all platforms assign a highly important role to images, but not all of them allow basic operations such as zooming. Approximately half of

	[Theodoropoulos 1994]	[Phillips 2001]	[Malinowski 2003]	[Dale 2005]	[Linton 2005]	[Ertmer 2007]	[Grizzle 2008]	[Tawfiek 2011]	[Pop 2013]	[El Sharaby 2015]	[Raffan 2017]	**IVET**
Learning functionalities												
Theory	+	+	-	+	+	+	-	+	+	+	+	+
Test exercises	+	-	-	-	-	+	+	+	+	-	+	+
Interactive exercises	-	-	-	-	-	+	-	-	-	-	-	+
Statistics	-	-	-	-	-	+	+	-	+	-	-	+
Image interaction												
Image-based	+	+	+	+	+	+	+	+	-	+	+	+
MPR or 3D	-	+	+	+	+	-	-	+	-	-	+	+
Zoom & pan	-	+	+	-	+	+	-	+	-	+	+	+
General features												
Web-based	-	-	-	+	-	+	+	-	+	+	-	+
Cross-browser	-	-	-	-	-	-	+	-	-	+	-	+
Software independent	-	-	-	-	-	-	+	-	-	+	-	+
Community support	-	+	-	-	-	+	-	-	-	-	-	-
Suggestions area	-	-	+	-	+	+	-	-	-	+	-	-

Table 7.2. Summary of the evaluation of the main veterinary e-learning platforms.

them also support visualisations which go beyond 2D, but the vast majority use a technique which consists in showing multiple 2D images from different angles in order to create a 3D effect; only one platform really uses 3D models which can be rotated freely. The IVET platform, however, uses 2D images, MPR visualisations, and also 3D models over which the user can zoom, pan and rotate. Besides, it is the only platform that gives a great importance to medical imaging, and to everything which can be learned from it.

- **Accessibility.** Many of the evaluated platforms are not web-based, and some of them are even delivered on CD-ROM. Furthermore, some of the web-based platforms are not cross-browser or they require the installation of some plug-ins, thus restricting the access to those users who do not have the appropriate requirements. IVET is accessible from all modern browsers and it does not require any plug-in, since it takes advantage from the benefits of HTML5 and the integration of WebGL to show all the visualisation types with which it works, including MPR visualisation and 3D models.

- **Social components.** Few platforms have an integrated community support system or a place where the users can suggest improvements for the application. The IVET platform does not integrate these features either, although it is intended to design a communication channel between learners and teachers, and also a system to collect suggestions.

7.2 Medical imaging applied to the meat industry

After briefly presenting and discussing the results of the first main block, corresponding to medical imaging applied to teaching, the next step is to focus on the second main block, which is centred on the application of medical imaging to another field: the meat industry.

When dealing with this field, one of the main goals is to find efficient and effective methods to classify the quality of animals. In this sense, one of the most important parameters is the lean meat percentage (LMP) of the animal, since it is one of the most evident indicators of its quality. This parameter can be manually obtained by classifying the tissues of the animal once it is dead, but it is a very slow process and it does not allow to follow up the evolution of the animal, since the method requires to slaughter it. As a solution to these problems, some algorithms have been designed to obtain the LMP value from medical images, thus accelerating the process and avoiding, in some cases, the slaughter of the animal.

In Chapter 5 we have presented an algorithm to compute the LMP value of a pig from medical images corresponding to its carcass. It is a fast, accurate and automatic algorithm, and it is also robust to the data variation which may exist between different scanners or between different images of the same scanner. To achieve this robustness, it is based on a partial volume model that determines where to assign the voxels which have values that lie between two pure tissues. Table 7.3 summarises the obtained re-

Dissection methodology	Method	R^2	RMSEP	Correlation compared to	P-value
Simplified	Proposed approach (weight)	0.9333	0.9676		
	Thresholding (Th.) (weight)	0.8875	1.2588	Proposed approach (weight)	0.0032
	Th. with bone filling and skin detection (ThBS) (weight)	0.9394	0.9227	Proposed approach (weight)	0.5381
	Proposed approach	0.9396	0.9203	Proposed approach (weight)	0.0564
	Proposed approach (skin as lean)	0.9016	1.1764	Proposed approach	0.0001
	Proposed approach (distortion)	0.9291	0.9976		
	Th. (distortion)	0.7857	1.7377	Proposed approach (distortion)	< 0.0001
	ThBS (distortion)	0.8576	1.4155	Proposed approach (distortion)	0.0004
Full	Proposed approach (weight)	0.9709	0.8973		
	Thresholding (Th.) (weight)	0.9595	1.0490	Proposed approach (weight)	0.2860
	Th. with bone filling and skin detection (ThBS) (weight)	0.9814	0.7148	Proposed approach (weight)	0.1351
	Proposed approach	0.9726	0.8725	Proposed approach (weight)	0.4776
	Proposed approach (skin as lean)	0.9467	1.2081	Proposed approach	0.0013
	Proposed approach (distortion)	0.9594	1.0604		
	Th. (distortion)	0.8385	2.1100	Proposed approach (distortion)	< 0.0001
	ThBS (distortion)	0.9002	1.6574	Proposed approach (distortion)	0.0045
Virtual (no distortion)	Proposed approach (distortion)	0.9773	0.6473		
	Th. (distortion)	0.8816	2.0884	Proposed approach (distortion)	< 0.0001
	ThBS (distortion)	0.9125	1.6310	Proposed approach (distortion)	< 0.0001

Table 7.3. Summary of the correlations and errors from the evaluated LMP computation methods, including the p-values of the comparison between them (p-value obtained from the Steiger's test).

sults, where the proposed approach refers to the method that uses the partial volume model, based only on volume (and not on weight), and that considers the skin of the animal as a new tissue instead of considering it as lean meat. To obtain more detailed information about the results, see Chapter 5.

With these results, therefore, three interesting properties of the proposed approach can be highlighted:

- **Good results under normal conditions.** Under normal conditions, i.e. without distortion, the results of the proposed approach are as acceptable as the ones of the method which gets the highest correlation, since there are no significant differences between them. Hence, the proposed approach can be established as the standard method to compute the LMP value.
- **Skin as a new tissue.** The detection of skin as a new tissue, and not as part of the lean meat, allows us to obtain a better approximation of the LMP value.
- **Better results in distorted images.** When the images are distorted, the proposed approach clearly gets the best results, presenting significant differences with respect to the other methods.

Based on these properties, then, we can assert that the proposed approach, as it has been defined, is the method which generally gets the best results with respect to the other evaluated methods.

So far, and considering all these methods, the classification process is based on assigning each voxel of the image into one particular tissue, since the voxels come from the images of a carcass, and in that case all of them are used to compute the LMP value. However, if a live animal is scanned instead of a carcass, a previous process is needed before starting the classification of voxels, since the internal organs of the animal, which are not needed to compute the LMP value, and do not appear in a carcass scanning because they have already been manually extracted before, are also represented in the medical images.

In Chapter 6 we have presented two algorithms to segment and remove the internal organs of live pigs medical images. One of the algorithms is semi-automatic and is able to achieve results with a high level of accuracy, while the other algorithm is fully automatic and is able to segment all the medical images in very little time. Table 7.4 summarises the obtained results, showing the mean F-score value and the approximate computational time for each algorithm. To obtain more detailed information about the results, see Chapter 6.

Analysing the results, we can evaluate and prioritise both algorithms according to their effectiveness and efficiency:

- **Effectiveness.** If we focus on the effectiveness, we can see how the semi-automatic algorithm obtains better results, with the highest F-score values. The automatic algorithm, on the other hand, also obtains highly satisfactory results, but the F-score values are lower. Obviously, this difference stems from the fact that the semi-

Measure	Semi-automatic	Automatic
Minimum F-score value	0.9383	0.8862
Maximum F-score value	0.9485	0.9134
Mean F-score value	0.9431	0.9040
F-score standard deviation	0.0032	0.0080
F-score coefficient of variation	0.0034	0.0089
Computational time	0.5–2 s per slice*	40–50 s (whole pig)

*Manual segmentation time not included.

Table 7.4. Summary of the F-score values and the computational time for the semi-automatic and the automatic segmentation methods (using the most suitable parameters) to remove the internal organs from live pig CT images.

automatic algorithm includes a manual segmentation process which increases the effectiveness of the algorithm.

- **Efficiency.** If we focus on the efficiency, we can see how the automatic algorithm is the fastest one, taking less than one minute on average to segment the internal organs of a whole pig. The computational time of the semi-automatic algorithm, i.e. the time required for the automatic part of the algorithm, is also quite low, but not as low as the automatic one. Besides, the computational time does not include the time required for the user to manually correct the inaccurate segmentations of the automatic part; this amount of time varies depending on the user, and may increase the total time up to a few minutes.

With this evaluation, then, we can conclude that the use of an algorithm or the other one will depend on the previous requirements, that is, the importance we may give to effectiveness or efficiency in each situation.

Overall, the results from each one of the presented publications indicate that some helpful contributions based on medical imaging techniques have been made to the research in both the teaching and the meat industry fields by improving the teaching methodologies or proposing new solutions to current problems.

CHAPTER 8

Conclusions

The development of medical imaging techniques has led to crucial advances in the field of medical diagnosis up to the point of being an indispensable tool for the medical professionals. These advances can be applied not only in clinical processes, but also in other fields such as education and meat science, which can take advantage from medical image visualisation and processing. Although some innovative e-learning environments have been already proposed in the context of education, they are mainly focused on specific material such as digital atlases and model explorations. The use of real medical imaging data is scarce, and interactive exercises are usually not provided. Moreover, the content creation process of most of these frameworks is arduous for teachers, and the learning material is often closed or not renewed. In the context of meat science, medical imaging data is used to determine the quality and the commercial value of the animals by means of image processing techniques, such as image thresholding segmentation to classify animal tissues into lean meat, fat and bone. However, finding the threshold values is not trivial, and these methods may be affected by data variability. Furthermore, the presence of internal organs in the medical images obtained from live animals can complicate the tissue segmentation and classification, since they are not considered when computing the lean meat percentage.

The purpose of this thesis is to present new strategies to approach the above-mentioned problems. To reach this objective, two e-learning platforms have been developed in order to reinforce the use of medical imaging data in the fields of medical and veterinary education, not only by offering multiple visualisation options, but also by integrating interactive exercises to motivate students' learning and participation. Special care has been taken to assist teachers in the creation of new learning content. As for the meat industry applications, a new robust and accurate method has been developed to quantify the lean meat content without being affected by the partial volume effect, and two segmentation algorithms have been implemented to remove the internal organs of live animals CT scans.

The next section explicitly describes the contributions made to the corresponding research fields, as well as the publications derived from them.

8.1 Contributions

Based on the global objective of this thesis, which aims to spread the use and take advantage from medical imaging techniques in the fields of education and meat science, several contributions have been made:

- Medical image visualisation techniques have been applied to improve the learning process in medicine.

  Taking into account the importance of medical imaging in the medical science, a solution has been proposed to increase its use in the teaching methodologies. A new web-based e-learning platform has been designed where images take the main role, including theory material and interactive exercises which are automatically corrected. The new environment has also focused on the content creation process, so that it is easy and fast for teachers to reuse and create new content. Both the undergraduate students and the medical professionals can take advantage of this teaching methodology, since it can be included in the medical curricula or adopted as a means to provide recycling courses. Although the platform is defined as a radiology education tool, it has been designed to be incorporated to any teaching methodology which makes use of medical imaging.

  This contribution, titled *A new e-learning platform for radiology education (RadEd)*, has been published in *Computer Methods and Programs in Biomedicine* [Xiberta 2016].

- The acceptance of the previous e-learning platform has been measured in a thorax radiology course for medical professionals in the context of continuing education.

  After the development of the web-based e-learning platform described in the previous contribution, an evaluation of its acceptance has been performed in order to confirm its ability to motivate the learners' participation. A face-to-face thorax radiology course has been transformed to an online one by using the new e-learning environment, and a survey has been provided to the learners to evaluate the course and the features of the platform. The results indicate that the new environment is highly accepted, valuing the interactivity of the platform and its ability to overcome the place and time restrictions.

  This contribution, titled *Measuring the acceptance of e-learning in continuing education courses for medical staff: the experience of a thorax radiology course*, has been submitted to *Computerized Medical Imaging and Graphics*.

- Medical image visualisation and segmentation techniques have been applied to improve the learning process in veterinary science and increase the support for new graphical resources.

  Considering the lack of medical imaging resources in the field of veterinary science, a new framework has been proposed to foster its use. A new web-based e-learning platform has been designed to support as many graphical resources as possible, including 2D images, 3D models and multiplanar visualisations. The graphical resources take a main role in the theory content provided by the platform, as well as in the interactive exercises, such as selecting the corresponding anatomical part of a whole 3D animal model. As for the teachers, the content creation process has been designed to be fast and comfortable, and the exercises are automatically corrected to avoid teachers perform the evaluation manually. A manual segmentation process to generate new 3D models from animal CT scans has also been described.

This contribution, titled *IVET, an Interactive Veterinary Education Tool*, has been submitted to *PLOS ONE*.

- Medical image processing techniques have been applied to improve the quality classification process of animal carcasses in the meat industry.

  Focusing on the image processing techniques applied to medical imaging data, a solution has been proposed to determine the quality of animal carcasses based on their CT scans. A new automatic pipeline has been developed to quantify the amount of each animal tissue, so that the lean meat percentage, which is a key parameter for the quality classification, can be computed. The new method is fast and accurate, and minimises the partial volume effect, so it is robust to data variability which may exist between two different scanners or between two different outputs of the same scanner. The results of the proposed approach have been compared to other thresholding-based approaches, always considering the manual dissection as the reference method. The proposed pipeline achieves the best results and is the less affected by data variability.

  This contribution, titled *Evaluation of an automatic lean meat percentage quantification method based on a partial volume model from computed tomography scans*, has been submitted to *Computers and Electronics in Agriculture*.

- Medical image processing techniques have been applied to improve the quality classification process of live animals in the meat industry.

  Being aware of the need to provide efficient and non-invasive techniques to determine the quality of live animals, a strategy has been developed which consists in removing the internal organs represented in the animal CT scans, which are not required to classify the animal tissues, but are usually confused with them. Two new segmentation algorithms have been proposed to remove the internal organs from live pig CT images: a semi-automatic and an automatic method. The semi-automatic method applies an iterative process to detect the internal organs' boundary by using previous information, and the user can check the correctness of the new boundary at the end of each iteration. The automatic method segments each CT scan individually, and uses distance maps and morphological operators such as dilation to find the best boundary for the internal organs. An analysis has also been performed to evaluate both algorithms and figure out which method is preferred in terms of accuracy and required time.

  This contribution, titled *A semi-automatic and an automatic segmentation algorithm to remove the internal organs from live pig CT images*, has been published in *Computers and Electronics in Agriculture* [Xiberta 2017].

8.2 Future work

Although the use of medical imaging in the fields of education and meat science has no limits, and new applications will keep on appearing in the future, with the exposition of the contributions the main objective of this thesis is considered to be achieved. However, focusing on these contributions, some future work can still be developed.

In the context of education, a wider support for 3D models can be achieved. Few current web-based environments allow their visualisation, and only surface models are supported, i.e. triangle meshes. The process of creating surface models is laborious because there are not accurate methods which can achieve a good result automatically, and a manual process is required at the end. Therefore, the amount of 3D models tends to be rather small. However, when dealing with volume models, i.e. voxel models, which use the medical imaging data directly obtained from the scanner, the inner part of the models can be observed and the segmentation process is not required, thus saving creation time. The visualisation of volume models is usually provided in desktop applications, but more research needs to be done to achieve a fluent interaction in a web-based environment, since the computational cost is still too high.

Related to the visualisation of volume models, the ability to visualise DICOM models directly would be of great interest for the web-based medical e-learning environments. By using DICOM information, case-based models with pathologies could be included as practical content to increase the content offer provided to the students. With the support for new graphical resources, therefore, new types of exercises can be designed which offer a higher degree of interactivity, increasing the students' motivation.

As for the e-learning features of the platform, a new strategy can be defined following the idea of an intelligent tutoring system which automatically proposes exercises to the students based on their results, i.e. offering exercises with a certain level of difficulty depending on the students' previous scores. Another interesting research line is the study of new interaction techniques by means of virtual and augmented reality. New interactive devices allow novel methods to simulate clinical processes in real environments, so that users' experience can be greatly improved.

In the context of meat science, some improvements can be done in the model used to classify the bone tissue from the CT scans of animal carcasses, so that it does not rely on a fixed threshold. Regarding the segmentation algorithms to remove the internal organs of live CT scans, they can be merged taking the automatic method as default, and using the semi-automatic one to correct the segmentations with the worst results. Then, the merged algorithm to remove the internal organs plus the new LMP quantification pipeline to classify the animal tissues could be used as a non-invasive method to determine the quality of live animals. Finally, the whole classification approach should be evaluated using different animal species other than pigs.

New advances in medical imaging will also contribute to new applications in the education and meat science fields. Medical imaging has been, is, and will be an indispensable tool to improve teaching methodologies and achieve more efficient and non-invasive methods in the meat industry.

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The Road goes ever on and on
down from the door where it began.
Now far ahead the Road has gone,
and I must follow, if I can,
pursuing it with eager feet,
until it joins some larger way
where many paths and errands meet.
And whither then? I cannot say.

—J.R.R. Tolkien