Knowledge-based Probabilistic Modeling for Tracking Lyrics in Music Audio Signals

Georgi Dzhambazov

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Director de la tesi:

Dr. Xavier Serra Casals

Music Technology Group

Dept. of Information and Communication Technologies

Universitat Pompeu Fabra Barcelona

The doctoral defense was held on ....., 2017, at the Universitat Pompeu Fabra and scored as .....

Dr. Axel Röbel

Thesis Committee Member

IRCAM, Paris, France

Dr. Matthias Mauch,

Thesis Committee Member

Queen Mary University of London, UK

Dr. Emilia Gómez

Thesis Committee Member

Universitat Pompeu Fabra, Barcelona, Spain

To the divine voice of nature that gifted the human voice with the amazing capability of singing

Preface

This thesis has been carried out between Oct. 2013 and April 2017 at the Music Technology Group (MTG) of Universitat Pompeu Fabra (UPF) in Barcelona (Spain), supervised by Dr. Xavier Serra Casals. All work has been conducted in collaboration with the CompMusic team at MTG. The work in Chapter 5.3 has been conducted in collaboration with Dr. Andre Holzapfel (KTH Royal Institute of Technology, Stockholm, Sweden).

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This thesis could not have been the same without the restless support of many mentors, influencers, and friends.

The most valuable piece of support came from the CompMusic team - for me a team notable for its friendly multicultural atmosphere. At the first place, CompMusic would not have been there without the vision of Dr. Xavier Serra. I am extremely grateful to him for believing in me and for his constant readiness to reach a hand and guide me. My personal thanks go to Dr. Sertan Şentürk for his patient in-depth explanations of Makam music concepts; Dr. Ajay Srinivasamurthy for his never-ending improvement advices and fruitful talks on graphical models; Rong Gong (the fellow singing voice explorer); Dr. Sankalp Gulati (the great entrepreneurial example), Rafael Caro Repetto (for the excellent music theory hints), Dr. Gopala Krishna Koduri (for providing me a place to stay in the first days).

Without my family my productivity would not have been the same. I am grateful especially to my mother for her ceaseless motivating words in this long journey.

Abstract

This thesis proposes specific signal processing and machine learning methodologies for automatically aligning the lyrics of a song to its corresponding audio recording. The research carried out falls in the broader field of music information retrieval (MIR) and in this respect, we aim at improving some existing state-of-the-art methodologies, by introducing domain-specific knowledge.

The goal of this work is to devise models capable of tracking in the music audio signal the sequential aspect of one particular element of lyrics - the phonemes. Music can be understood as comprising different facets, one of which is lyrics. The models we build take into account the *complementary context* that exists around lyrics, which is any musical facet complementary to lyrics. The facets used in this thesis include the structure of the music composition, structure of a melodic phrase, the structure of a metrical cycle. From this perspective, we analyse not only the low-level acoustic characteristics, representing the timbre of the phonemes, but also higher-level characteristics, in which the complementary context manifests. We propose specific probabilistic models to represent how the transitions between consecutive sung phonemes are conditioned by different facets of complementary context.

The complementary context, which we address, unfolds in time according to principles that are particular of a music tradition. To capture these, we created corpora and datasets for two music traditions, which have a rich set of such principles: Ottoman Turkish makam and Beijing opera. The datasets and the corpora comprise different data types: audio recordings, music scores, and metadata. From this perspective, the proposed models can take advantage both of the data and the music-domain knowledge of particular musical styles to improve existing baseline approaches.

As a baseline, we choose a phonetic recognizer based on hidden Markov models (HMM): a widely-used methodology for tracking phonemes both in singing and speech processing problems. We present refinements in the typical steps

of existing phonetic recognizer approaches, tailored towards the characteristics of the studied music traditions. On top of the refined baseline, we device probabilistic models, based on dynamic Bayesian networks (DBN) that represent the relation of phoneme transitions to its complementary context. Two separate models are built for two granularities of complementary context: the structure of a melodic phrase (higher-level) and the structure of the metrical cycle (finer-level). In one model we exploit the fact the syllable durations depend on their position within a melodic phrase. Information about the melodic phrases is obtained from the score, as well as from music-specific knowledge.Then in another model, we analyse how vocal note onsets, estimated from audio recordings, influence the transitions between consecutive vowels and consonants. We also propose how to detect the time positions of vocal note onsets in melodic phrases by tracking simultaneously the positions in a metrical cycle (i.e. metrical accents).

In order to evaluate the potential of the proposed models, we use the lyrics-to-audio alignment as a concrete task. Each model improves the alignment accuracy, compared to the baseline, which is based solely on the acoustics of the phonetic timbre. This validates our hypothesis that knowledge of complementary context is an important stepping stone for computationally tracking lyrics, especially in the challenging case of singing with instrumental accompaniment.

The outcomes of this study are not only theoretic methodologies and data, but also specific software tools that have been integrated into Dunya - a suite of tools, built in the context of CompMusic, a project for advancing the computational analysis of the world's music. With this application, we have also shown that the developed methodologies are useful not only for tracking lyrics, but also for other use cases, such as enriched music listening and appreciation, or for educational purposes.

Resum

La tesi aquí presentada proposa metodologies d'aprenentatge automàtic i processament de senyal per alinear automàticament el text d'una cançó amb el seu corresponent enregistrament d'àudio. La recerca duta a terme s'engloba en l'ampli camp de l'extracció d'informació musical (Music Information Retrieval o MIR). Dins aquest context la tesi pretén millorar algunes de les metodologies d'última generació del camp introduint coneixement específic de l'àmbit.

L'objectiu d'aquest treball és dissenyar models que siguin capaços de detectar en la senyal d'àudio l'aspecte seqüencial d'un element particular dels textos musicals; els fonemes.

Podem entendre la música com la composició de diversos elements entre els quals podem trobar el text. Els models que construïm tenen en compte el context complementari del text. El context són tots aquells aspectes musicals que complementen el text, dels quals hem utilitzat en aquest tesi: la estructura de la composició musical, la estructura de les frases melòdiques i els accents rítmics. Des d'aquesta prespectiva analitzem no només les característiques acústiques de baix nivell, que representen el timbre musical dels fonemes, sinó també les característiques d'alt nivell en les quals es fa patent el context complementari. En aquest treball proposem models probabilístics específics que representen com les transicions entre fonemes consecutius de veu cantanda es veuen afectats per diversos aspectes del context complementari.

El context complementari que tractem aquí es desenvolupa en el temps en funció de les característiques particulars de cada tradició musical. Per tal de modelar aquestes característiques hem creat corpus i conjunts de dades de dues tradicions musicals que presenten una gran riquesa en aquest aspectes; la música de l'opera de Beijing i la música makam turc-otomana. Les dades són de diversos tipus; enregistraments d'àudio, partitures musicals i metadades. Des d'aquesta prespectiva els models proposats poden aprofitar-se tant de les dades en si mateixes com del coneixement específic de la tradició musical per

a millorar els resultats de referència actuals.

Com a resultat de referència prenem un reconeixedor de fonemes basat en models ocults de Markov (Hidden Markov Models o HMM), una metodologia abastament emprada per a detectar fonemes tant en la veu cantada com en la parlada. Presentem millores en els processos comuns dels reconeixedors de fonemes actuals, ajustant-los a les característiques de les tradicions musicals estudiades. A més de millorar els resultats de referència també dissenyem models probabilistics basats en xarxes dinàmiques de Bayes (Dynamic Bayesian Networks o DBN) que respresenten la relació entre la transició dels fonemes i el context complementari. Hem creat dos models diferents per dos aspectes del context complementari; la estructura de la frase melòdica (alt nivell) i la estructura mètrica (nivell subtil). En un dels models explotem el fet que la duració de les síl · labes depén de la seva posició en la frase melòdica. Obtenim aquesta informació sobre les frases musical de la partitura i del coneixement específic de la tradició musical. En l'altre model analitzem com els atacs de les notes vocals, estimats directament dels enregistraments d'àudio, influencien les transicions entre vocals i consonants consecutives. A més també proposem com detectar les posicions temporals dels atacs de les notes en les frases melòdiques a base de localitzar simultàniament els accents en un cicle mètric musical.

Per tal d'evaluar el potencial dels mètodes proposats utlitzem la tasca específica d'alineament de text amb àudio. Cada model proposat millora la precisió de l'alineament en comparació als resultats de referència, que es basen exclusivament en les característiques acústiques tímbriques dels fonemes. D'aquesta manera validem la nostra hipòtesi de que el coneixement del context complementari ajuda a la detecció automàtica de text musical, especialment en el cas de veu cantada amb acompanyament instrumental.

Els resultats d'aquest treball no consisteixen només en metodologies teòriques i dades, sinó també en eines programàtiques específiques que han sigut integrades a Dunya, un paquet d'eines creat en el context del projecte de recerca CompMusic, l'objectiu del qual és promoure l'anàlisi computacional de les músiques del món. Gràcies a aquestes eines demostrem també que les metodologies desenvolupades es poden fer servir per a altres aplicacions en el context de la educació musical o la escolta musical enriquida.

(Translated from English by Oriol Romaní Picas)

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Chapter 1

Introduction

The way music is created, shared, distributed and listened to has been recently changing rapidly due to advancements in Information Technology. Music Information Retrieval (MIR) is a research subfield of music technology that aims to advance in automatic music processing. Some of the subjects addressed in MIR research include building computational models for describing music structures and phenomena, as well as their temporal progression.

Any musical instrument along with carrying a melody, is characterized also by an unique timbre. Classes representing the perceived 'timbral colour' of the singing voice can be described by abstract categories, such as 'mellow', 'harsh'. This reflects a quality described as 'instrumental' timbre by musicologists [Durga, 1978]. Still, the belonging of a singing excerpt to one particular colour class is rather subjective and varies from one listener to another. This means that there may not be a mutual agreement on where the time positions of transitions between these classes are.

Few instruments, including singing voice, have their timbre continuously vary in time, premising frequent timbral alterations. Unlike other instruments though, the singing voice has a unique characteristic: its ability to articulate actual lyrics. Lyrics are one of the most important musical aspects. They carry a message or a story and attract the attention of the listener. She/he will naturally follow the lyrics while listening to the melody of the main singing voice.

Phonemes - the building block of words - can be considered as a discrete number of timbral classes, wherein each class has a characteristic spectral template. The ability to articulate phonemes is an innate characteristic of human speakers. In fact, singers articulate by means of given vowels even

when not singing with actual lyrics. The transitions between consecutive phonemes can be considered as slow gradual changes of timbre as opposed to the short-term timbral fluctuations, which are rather related to the instability of the human vocal tract. That is to say, the timbre of singing voice, in addition to carrying the identity and 'instrumental quality', is the reason why we distinguish a particular phoneme in a given time instant. Therefore, despite varying continuously, the singing voice timbre can be considered to belong to one of a discrete set of phonemes at a particular point in time. Unlike the transitions among classes of 'instrumental' timbre, the exact time positions, in which singers transition from one phoneme to another, can be distinguished by most listeners unambiguously. For brevity, in the rest of this work we will refer to the aspect of singing voice timbre that makes humans distinguish between the identity of different phonemes as 'phonetic timbre'.

The research carried out in this dissertation focuses on the acoustics of the lyrics of singing voice in polyphonic music and their relation to written lyrics. Sung lyrics can be studied from many different perspectives, whereas this work takes an MIR viewpoint, aiming at the analysis of temporal changes of lyrics content with an end goal of automatic synchronization between sung and written lyrics.

1.1 Scientific Context

Singing voice processing is still one of the most challenging subfields of MIR: Allegedly, none of the problems related to the singing voice could be considered nearly solved. Challenging remain especially the problems of singing voice detection; transcription of the singing melody and transcription of the lyrics. The timbre of singing voice has multiple functions: Apart from articulating actual phonemes and representing the 'instrumental quality', singers use some timbral aspects to stand out from the rest of the accompanying instruments [Sundberg and Rossing, 1990]. Despite all these, there is not much work on describing the singing voice timbre in a computational way. Some of the problems related to timbre are summarized in Goto [2014] as 'vocal timbre analysis' and include automatic lyrics processing of voice, singer identification, comparison of timbral similarity.

Looking at MIR in general, there is still a wide gap between what can be automatically extracted from audio recordings and the semantically meaningful high-level musical concepts, which listeners associate with singing [Wiggins, 2009]. A possible reason for this semantic gap might be that the approach usu-

ally taken is bottom up: low-level features are extracted and then high-level concepts are inferred by aggregating these features. In such approaches often high-level musical knowledge is not reflected in the computational model itself. Most MIR research outcomes have been validated against eurogenetic music and do not generalize to other music cultures of the world. Applying state of the art methods for analysis of non-eurogenetic[1] music yields suboptimal results [Serra, 2011]. The lack of explicit modeling of music knowledge becomes a more evident disadvantage for non-eurogenetic music compositions, because they are characterized by their own specific music principles. In fact most music to the east of Europe has elaborate rhythmic and melodic framework. Thus extending state of the art approaches by fusing all music-specific concepts, relevant for a given task, would exploit the full potential of the studied music. With this end goal in mind, the project CompMusic[2] (Computational Models for the Discovery of the World's Music) was envisioned [Serra et al., 2013]. Art music of five different cultures are being studied in the project: Hindustani (North India), Carnatic (South India), Turkish-makam (Turkey), Arab-Andalusian (Maghreb) and Beijing opera (China). The art Makam music of Turkey, a focus of this study, proliferated in the Ottoman Empire and continues its legacy mainly in modern Turkey. In this thesis we will refer to it as Ottoman Turkish Makam Music (OTMM)[3].

In particular for singing voice, in current MIR research little work focuses on methods, which model sung lyrics together with its interdependence on complementary musical aspects like, for example, the progression of a melodic phrase. One possible reason for that could be that such a model is hard to design and develop, because it has to be considerably generic to represent such interdependencies for any music genre in the broad sense. In contrast to that, for each of the music traditions of CompMusic there is a well-defined framework of specific music principles. Therefore it may be more feasible to develop a singing voice model that represents jointly phonetic timbre and these music principles for a particular music tradition. This is mainly because these principles for a one music tradition could be summarized into a model in a much more straight-forward way, than for multiple genres of music.

The work covered in this thesis has been developed to focus on OTMM. A

[1] The term Eurogenetic is coined in Holzapfel et al. [2014] to avoid the misleading division music into Western and non-Western. It designates the discussed theoretical constructs are motivated by the European common practice period.

[2] http://compmusic.upf.edu

[3] For the sake of compliance, this naming is adopted from a related computational study - Şentürk [2016]

personal motivation for me is that OTMM has nature very akin to the traditional music of Bulgaria - the music with which I have grown. Being the official music of the Ottoman Empire, it has influenced enormously all Balkan music, and to a rather high extent Bulgarian traditional music. This made me naturally understand and appreciate its musically rich melodic and rhythmic framework throughout the research conducted in this thesis.

1.2 Motivation

1.2.1 Why consider complementary context?

The progression of lyrics in singing is not an isolated phenomenon: lyrics have an inherent correlation with other music phenomena. In an abstract sense lyrics can be imagined as the 'flesh' and the musical facets as the 'music skeleton': the lyrics progress, driven by the transitions of the 'skeleton' music phenomena, such as melodic events and rhythmic events. In this respect, studying the temporal aspects of sung lyrics also requires describing the relations of the lyrical units to the temporal progression of underlying musical events. In this work we will refer to *unit of lyrics* (or *lyrical units*) as a general concept that stands for different linguistic granularity: lyrics line, a phrase of words, word, syllable, phoneme.

These relations jointly unfold in time to form a *complementary musical context* of the sung lyrics. By *complementary musical context* (or simply *complementary context*) we will refer to any musical facet, manifesting in events simultaneously to the transitions of lyrical units and having an influence on them[4]. In this work we suggest to divide the complementary context of lyrics into three hierarchical levels with respect to its time granularity: the overall structure of the composition (coarse-level), the structure of a melodic phrase (middle-level) and the structure of a metrical cycle (fine-level).

Each facet of the complementary context manifests itself as the time progression of concrete musical events: Firstly, at the highest context level, the overall structure of the composition determines the highest-level of lyrics units: lyrics lines. The transition from current structural section (e.g. verse, chorus) to another one can be considered a musical events, which signals the transition

[4]We adopted the term *musical context* from Mauch [2010], where it is introduced for the task of chord estimation to serve a similar function. The authors use it to represent any musical facet, which is complementary to the harmonic content of chords - the main facet being tracked. We decided to use *complementary* instead of *musical* to emphasize the fact it is complementary to phonetic timbre.

to another lyrics line (or whole lyrics paragraph). Then on the middle level of context, the position of a lyrics syllable in a melodic phrase influences its duration. Singers may prolong or shorten syllables, in order to align them with accents of the melodic phrase. On an even finer context granularity, the transitions between syllables are aligned with the accents of the metrical cycle.

These interdependences become even more important in OTMM, which has some very specific principles of the main musical facets. In OTMM, the musical concepts are based on a well-grounded theory. Also, as already mentioned, the sung melodic phrases of in OTMM music, are rich in expressive elements. From all these reasons, OTMM provides an excellent framework to incorporate domain-specific knowledge into a context-aware model of sung lyrics.

The well-grounded theory of OTMM also paved the way to computational work on some of these aspects, including among others predominant melody extraction [Atlı et al., 2014]; relation of metrical accents and vocal note onsets [Holzapfel, 2015]; score-informed structural section discovery [Şentürk et al., 2014]. In this context, we can benefit from those studies and use their outcomes as facets of complementary context.

1.2.2 Why lyrics-to-audio alignment?

In this thesis, we will focus on the concrete problem of lyrics-to-audio alignment (LAA). LAA aims to automatically synchronize the lyrics in their two representations: sung in an audio recording and written as text. An audio recording and its corresponding lyrics are input to a LAA system. It estimates their temporal relationship, providing as output the start and end timestamps of the phoneme sequence, comprising the lyrics. Among all research questions, related to sung lyrics defined in the context of MIR, we chose to work on LAA for several reasons.

Firstly, the accuracy of a LAA system provides a quantitative way to measure the influence of the complementary context on the transitions in the phonetic timbre of singing voice. From this perspective, we only focused on one aspect of singing voice timbre: the slow timbre changes, which account for the transitions between consecutive phonemes. In addition, automating the LAA has numerous user applications. Building a piece of work with market potential is also a major motivation behind this research. Some applications of context-aware LAA include karaoke-like lyrics visualization, automatic thumbnailing and enriched music listening.

Note that some related singing voice language content modeling tasks like singer identification and language identification are not the goals of this thesis, because they can be solved by solely signal processing methods, wherein the use of complementary context does not necessarily provide a clear advantage.

1.2.3 Why predominant singing voice?

Characterizing the lyrics content of singing when accompanying instruments are present is challenging. One of the reasons for this is that the audio spectrum is a mixture of many different sources, which for computers are not easily separable from each other. This complexity is significantly mitigated in music traditions, which are centered around the singing voice, wherein the number of accompanying instruments is often small. That is why, being a largely vocal-centered tradition, OTMM provides a feasible context to validate the modeling developed in this study.

In addition to all the reasons listed above, a strong motivation to pursue this research is that, to our knowledge, this is the first work that designs a computational model of lyrics by considering (relatively) comprehensively the facets of its complementary context.

1.3 Opportunities and Challenges

Computational modeling of the singing voice has been focused to a large extent on transcribing the perceived melodic pitch, leaving other musical facets, among which is sung lyrics, less investigated. In the broad area of computational analysis of the language content of the singing voice, MIR researchers have explored tasks such as singing language identification, LAA, keyword spotting, lyrics transcription Goto [2014]. In total, however, there have been very few studies per each of these particular lyrics-related tasks.

The topics related to tracking sung lyrics in particular have been approached mostly by adopting the phonetic recognizer paradigm from speech recognition [Fujihara and Goto, 2012]. The main idea is that for each phoneme a separate acoustic model is created, which describes the overall timbre of the phoneme [Rabiner and Juang, 1993]. However, compared to speech, singing voice has several substantially different acoustic characteristics. Among them, the presence of accompanying instruments poses a major challenge to automatic lyrics tracking. The spectral peaks of instrumental sounds might occlude the spec-

tral content of voice, resulting in missing or distorted key singing timbral characteristics.

1.3.1 Challenges of Makam music

In contrast to to western music, in non-eurogenetic traditions of music a special type of interaction (termed heterophony) is present. The consequence of heterophony is that the harmonics of singing voice spectrum are interwoven with the harmonics from the spectrum of other instruments. In particular, certain harmonics of the voice can overlap with those of accompanying instruments, and thus be distorted by the energy of the harmonics of these instruments. Applying most hitherto singing voice extraction techniques to OTMM will not result in optimal estimation of phonetic timbre. A reason for this is because existing works have been focused on music with very small degree of heterophony. Therefore a model for lyrics tracking, based on the traditional way of extracting phonetic timbre can easily loose track in music with heterophonic voice-instrument interplay. For this reason, we expect that the use the complementary context, complementary to phonetic timbre can provide the 'stepping stones' to the process of lyrics tracking.

1.3.2 Opportunities of Makam music

Due to the heterophonic characteristics of OTMM, vocal melody contours can be extracted quite reliably. Several temporal phenomena of singing voice, such as note onsets, vibrato, glissando are evident from the melodic contours. Therefore, the contextual information from events, present in the melodic contours, can be rather reliably obtained automatically.

Modeling lyrics is coupled with the particular language: the pronunciations of the phonemes of any language form an unique set of sounds. Therefore classical approaches on modeling speech are trained and tested on material from the same language. Being a relatively new research field, lyrics modeling follows to a large extent this paradigm. Switching to another target language in this sense would require the complete replacement of the lyrics model with one of the new target language. Building such a model might be a bottleneck, mainly because it depends on the availability of annotated speech/singing corpus (for complete justification see the Background section). This thesis, although focused on OTMM music, aims at building an approach that is not restricted to one specific language. An important motivation for this are the similar characteristics of the traditions within the CompMusic project (in

particular being vocal-centered), whereas language is one of the few differing aspects.

One interesting characteristic of singing in OTMM is that sung vowels could be prolonged to a significant extent, when compared to vowels in eurogenetic music, in particular eurogenetic popular music. This lowers the quotient of consonants (a big portion of the language-specific sounds) from the total singing duration and thus mitigates their significance. This allows focusing on modeling of the acoustics of vowels, which makes it easier to adapt the constructed model of lyrics to another language.

When this PhD was started, OTMM was the only CompMusic tradition, for which an extensive collection of machine-readable musical scores was available. Music scores provide important contextual information complementary to lyrics, including but not limited to boundaries of structural sections, note durations and metric cycles. Exploiting the information in the musical score to its full extent is a major opportunity, in alignment with the goal of CompMusic to pursue a data-driven study on a music tradition.

1.4 Research Objectives

In alignment with the goals of CompMusic, the goal of this thesis is to build a culture-specific computational approach, which is meaningful for a concrete music repertoire. We have focused on OTMM due to the reasons listed above. While CompMusic addresses four other music traditions, we study the influence of one particular aspect of complementary context in only one tradition: Beijing Opera.

This thesis exploits computational approaches for analysis of music recordings. The approaches applied are taken from the fields of signal processing and machine learning. Signal processing is needed to extract the phonetic timbre of lyrics from the audio signal. The recorded audio is the primary source of information together with the given lyrics. Using complementary context, the proposed alignment model outputs words together with their aligned timestamps (Fig. 1.1). Two separate phonetic recognizers are created: One represents the influence of the structure of melodic phrases on syllable transitions. Another one represents the influence of the structure of the metrical cycle. Depending on the nature of the complementary context, different additional data sources or domain knowledge are explored.

A supervised learning method represents the temporal aspect of the singing voice of sequential transiting from a phoneme to another one. It is an extension

around the concept of hidden Markov models (HMMs) [Rabiner and Juang, 1993]. HMMs are preferred because their probabilistic generative nature can describe adequately the temporal progression of the singing voice. The degree of temporal variability is particularly increased by the expressive singing style of OTMM and Beijing opera.

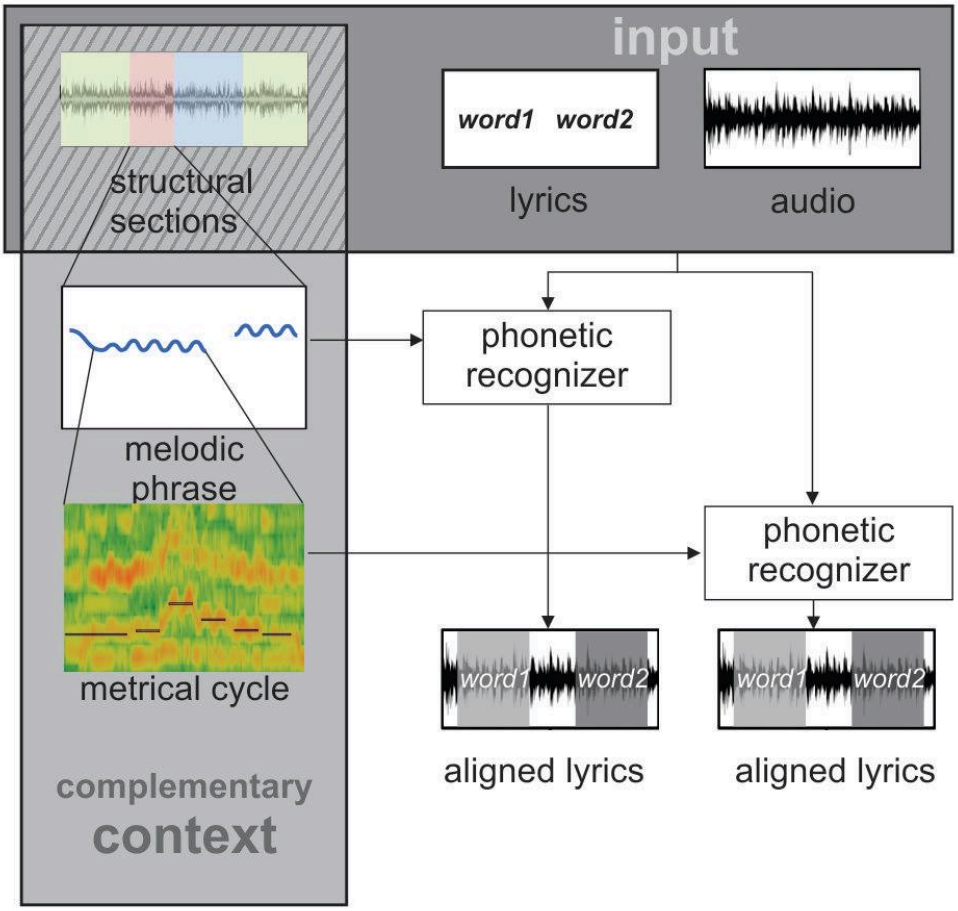


Figure 1.1: Use of different facets of complementary context in the automatic lyrics-to-audio alignment. Structural segmentation of a musical recording into melodic phrases is considered a 'black box'. The audio signal of the obtained musical phrases, along with its corresponding lyrics, is input to two separate phonetic recognizers. Both of them perform alignment of the audio signal to lyrics. Timestamps of aligned lyrics units are output.

1.4.1 Broad research objectives

Create a data-driven computational approach to describe transitions between sung lyrics that is aware of specific complementary context

The goal is to address these bits of knowledge from the complementary context, which have a clear influence on the slow changes of the singing voice timbre, related to the transitions between consecutive phonemes. The way music events evolve in time for a given music tradition can be expressed as a set of music principles. As a result of the work of computational musicologists, such principles specific to a music tradition have been aggregated in terms of concrete patterns and constraints. We aim to create a music-specific machine learning method of tracking sung lyrics, which benefits from the knowledge, compacted in these music patterns. The model has to jointly represent them and their influence on the transitions between consecutive units of lyrics. More precisely, such a joint model will allow the transitions of phoneme timbre be conditioned not only on the acoustic timbral features, but also on the simultaneously occurring complementary context events.

Probabilistic graphical models provide an effective framework to integrate complementary context knowledge in terms of the components of the model. In this thesis, we will extensively use dynamic Bayesian networks (DBNs) - a particular graphical model that can represent not only dependencies between concepts, but also their temporal progression [Murphy, 2002]. The phonetic recognizer baseline provides a probabilistic framework, which allows to be extended easily to a DBN. We suggest a method that captures the influence on the lyrics transitions of each considered facet of complementary context. To this end, we represent events from complementary context as components in a DBN and their influence on the lyrics as a hierarchical dependence between the components.

The complementary contexts relevant for phonetic transitions, which we explore in this study, are:

- structure of the composition (coarse-level)
- structure of a melodic phrase (middle-level)
- structure of the metrical cycle (fine-level)

We do not aim to explicitly model the influence of the structure of the music composition on lyrics. Instead, the segmentation of a recording into its sections

is obtained from an external method, which is considered as a 'black box'. Each obtained section contains one or more melodic phrase. We use *melodic phrase* as a generic term to represent a musically meaningful melodic entity, usually delimited by an instrumental break and usually corresponding to a lyrics line.[5]. The audio signal of each obtained melodic phrase, along with its corresponding lyrics line, is input to the proposed phonetic recognizers (see Fig. 1.1). We aim at building a separate phonetic recognizer with middle-level context and a separate one with fine-level context, each of which is a DBN. The middle-level one considers the influence of the structure of a melodic phrase on the transitions between consecutive syllables. In particular, we focus on representing how the position of a lyrics syllable in a melodic phrase influences its duration. As to the fine-level context, we aim at studying how phoneme transitions interact with the position of the accents in the metrical cycle (i.e. the metrical accents). In an initial step we estimate the timestamps of the vocal note onsets (the initial time segments of sung tones), in a manner informed by the metrical accents. Then the goal is to represent how the transition to a consecutive sung syllable is conditioned on the transition to a consecutive note onset.

Since some of these complementary context relations to lyrics have not been previously strictly formalized in a computational study, a major effort of this thesis is conceptualizing them in terms of compact bits of probabilistic knowledge.

Develop a method for lyrics-to-audio alignment

The proposed contextual models are designed with the intention to be generic enough and applicable in different end-tasks in the broader research area of sung lyrics. Having in mind the time limitation of this study, we focused on the particular task of LAA as a way to evaluate the performance of the proposed generic model. However, we expect that due to the ubiquity of the addressed facets of complementary context, the behaviour of our model that we asses on LAA will be comparable on neighbouring tasks including keyword spotting and lyrics recognition.

As a baseline for LAA we chose phonetic recognizer approach, adopted from speech-to-text alignment, based on HMMs. HMMs not only have proven to be the most successful strategy for LAA, but they also provide an appropri-

[5]The term *melodic phrase* is used intentionally instead of a *melodic motif*, which usually stands for a short segment/pattern being a part of a complete melodic phrase

ate temporal probabilistic framework, which we can extend for representing complementary context.

The alignment method, designed in this thesis, is evaluated mainly with singing in Turkish language. Nevertheless, to assure its application to other music genres we aim at devising ways for the easy transfer of the built models of Turkish phonemes to other languages. An ideal solution would be a universal language-independent model of a superset of phonemes representing a set of all languages of interest. Having in mind the reasonable differences between the languages in the CompMusic traditions, this is an elaborate linguistic task, outside the scope of this work. In contrast, the approach commonly taken in existing work is rebuilding a complete model for each language in turn. Training models of phonemes in singing is in fact a laborious task (see Background Chapter) and in general not a flexible strategy. Instead, we set as a reasonable objective to find an adequate scheme for mapping the phoneme models among two different languages. To our knowledge, there has been no work so far in computational modeling of sung lyrics addressing the problem of inter-language phoneme mapping.

Evaluate the contribution of each piece of complementary context knowledge for modeling sung lyrics

Using LAA as a concrete end task allows evaluating the contribution of any particular facet of complementary context in a quantitative way and comparing them.

The novelty of the presented models is that they suggest a strategy of how to integrate facets of complementary context into the main alignment step. Some of the context facets explored in this work have also been addressed in previous work on LAA [Fujihara and Goto, 2012]. However their relation to phonetic timbre is not represented explicitly in the main alignment model. Often knowledge from complementary context is part of a preprocessing or postprocessing step relative to the main alignment step (see Background Chapter). With the exception of Fujihara et al. [2011], almost no work has evaluated the contribution of these separate steps. To address this research vacuum, we compare the alignment accuracy for each different piece of complementary context and the baseline phonetic recognizer, agnostic to any complementary context.

Explore extensions and generalizations of the music-specific models to other traditions in the context of CompMusic

Working in tradition-specific context, there is a danger that the devised models become overfitted to the unique characteristics of the music tradition. To avoid that, the model should not reflect cases, unique for OTMM, but instead induce patterns that are applicable also to other musics with similar characteristics.

When a song is performed, the degree of deviation from the musical score for OTMM is arguably the least, compared to other CompMusic traditions. For example, in Beijing opera the duration of sung syllables frequently deviates to a bigger extent from the score and could span a very long time interval. To proof the transferability of some of the proposed models outside of OTMM, we evaluate on material from another music tradition. We focused on a particular aspect of complementary context - the structure of a melodic phrase, for a particular tradition - Beijing opera. Comparing the application of the syllable-duration aware model for two traditions also serves to quantitatively evaluate if a facet of complementary context contributes to a different degree for each of them (see Chapter 4).

1.4.2 Contributions

In pursuing the above presented goals we build methodologies, which can be seen as concrete technical and scientific contributions:

1. We extend the existing state of the art phonetic recognizer scheme for tracking sung lyrics in a way that involves selected facets of complementary context knowledge. We conceptualize the interaction of phoneme transitions and these facets in a compact way as probabilistic dependencies. These dependences are represented as hidden variables in a DBN.

2. We suggest several implementation strategies for detection with the proposed DBNs. In some cases the topology of a DBN becomes relatively complex, because of, for example, the big number of hidden variables. This makes the inference with DBNs computationally demanding and thus model simplifications are required:

    a) integrate the musical-context knowledge in the inference method, instead of being hidden variable

    b) reduce the range of the state-space exploiting all available musical-context-knowledge

c) integrate the musical-context knowledge as a modification of the transition model

3. We develop a clean and modular software framework, which can be easily used to reproduce or extend the outcomes of the research, conducted in this thesis.

1.5 Outline

The thesis is organized into six chapters, wherein the main contributions are contained in Chapters 4 and 5. Chapter 2 covers the research background, summarizing the principles of the musics studied: OTMM and Beijing Opera. It also overviews the state of the art in the methodologies used in lyrics-to-audio alignment. A focus is put on describing the pipeline of a phonetic recognizer alignment approach. Finally, the chapter outlines related research on DBNs - the main probabilistic model, used throughout the thesis. Chapter 3 presents the developed baseline system for lyrics to audio alignment, which is also based on a phonetic recognizer. Refinements in some of the recognizer steps, which makes it tailored to OTMM, are discussed. Chapter 4 describes the first core proposal of the thesis, a lyrics-to-audio alignment system that considers some context facets complementary to lyrics, in particular the structure of the sung melodic line. Chapter 5 presents a separate model for lyrics-to-audio alignment that considers another facet of complementary information, the accents in the metrical cycle of music. Finally, Chapter 6 concludes the thesis with a review of the key findings and a summary of the contributions.

Chapter 2

Background

In Section 2.1.1 we first summarize some of the principles of OTMM, the main music tradition analysed in this thesis, which influence directly or implicitly the way phonetic timbre progresses in time. We put a focus among all principles on the ones related to the structural form of the compositions; the vocal melodic phrases of singing voice and their underlying metric patterns. Language, being one of the important aspects of lyrics, is reviewed in terms of the acoustic characteristics of the phonemes. Analogously, for Beijing opera we review the language and some relevant principles of complementary context (Section 2.1.2). We emphasize the structure of a melodic phrase, being the specific context facet we exploit later in Chapter 4.

Then in Section 2.2 we summarize the hitherto approaches to the LAA alignment problem whereby the focus is put on those based on the phonetic recognizer paradigm. Common shortcomings as well as opportunities for extension are identified.

Finally, after introducing briefly the concept of dynamic Bayesian networks (Section 2.3), we review in Section 2.4 particular examples of related work on sung lyrics, in which consideration of concepts of complementary context, complementary to phonetic timbre, proved to be beneficial.

2.1 Background on the music traditions

As *complementary context* in this thesis we refer to any musical events that occur simultaneously to and are complementary to the transitions of the phonemes. Most traditional musics have well-defined music principles and theory. In this section we recapitulate the particular principles that guide how the vocal melodic phrases are structured.

2.1.1 Ottoman Turkish makam music

In a large geographical region of Asia, north Africa and east Europe, there are numerous music traditions described around the concepts "makam/maqam/-mugam", which share similar practice and terminology. Ottoman Turkish makam music (OTMM) - the makam music tradition, which proliferated in the Ottoman Empire and continues its legacy principally in Turkey, is the focus of this thesis.

Language

Unlike modern Turkish, Ottoman Turkish is characterized by more loanwords from Arabic and Persian origin. The lyrics language for the şarkı compositions in our evaluation dataset spans both modern and Ottoman Turkish. The Turkish phonology comprises 38 distinctive phonetic sounds, 8 of which are vowels. There are no diphthongs, and when vowels come together, they retain their individual sounding. Lengthening of vowels is realized by a non-pronounced character ğ. However vowel lengths have a negligible importance in sung Turkish.

Principles of complementary context

Examples of complementary context principles can be organized by the levels of granularity, as we suggested in the Introduction Chapter.

Coarse-level: (structure of the composition) Vocal melodic phrases are organised in the course of the performance according to principles of the composition structure. The şarkı form adheres to a well-defined verse-refrain-like structure: a şarkı contains three vocal sections: zemin (verse), nakarat (refrain), meyan (second verse). They are preceded/surrounded by aranağme (an instrumental interlude) [Ederer, 2011]. Each section is rather short and contains usually one (or 2-3) melodic phrases. In a vocal section through

almost all its duration a singing voice is present, except for short instrumental interludes (at the end of a melodic phrase).

Middle-level: (structure of a melodic phrase) A melodic phrase in the şarkı form represents a musically-meaningful and complete segment of the melodic line. In this work we did not exploit any OTMM-specific principles of the melodic phrase, because their correlation to the lyrics transitions was not obvious. Instead, we utilized information about musical note events from complementary source of music representation - the music scores. OTMM has been predominantly an oral tradition for centuries. Since early 20th century, a score representation extending the traditional Western music notation has been used as a complement to the oral practice. The scores contain not only notes, but also the lyrics organized into sections. Karaosmanoğlu et al. [2014] presented a machine-readable score collection, in which melodic phrases are annotated into smaller melodic units (motives). A melodic unit in this collection corresponds roughly to a metrical cycle.

Fine-level: (structure of the metrical cycle) The metric structure in OTMM is explained by *usul*. A certain *usul* roughly defines the metrical cycle, and it can be described by a group of strokes with different velocities, which imply the beats and downbeats in the rhythmic pattern. Some of the common usuls include *düyek* with 8/8 time signature; *aksak* (9/8); curcuna (10/8). In contrast to the eurogenetic music, a metrical cycle can be rather long and have a complex rhythmic pattern with an odd number of beats. The number of pulses (finest metrical accents) in an usul cycle might be up to 120. The progression of the events in a melodic phrase is correlated tightly to the underlying metric pulsation. Studies on symbolic music data showed that the likelihoods of vocal note events are influenced by the their position in a metrical cycle [Holzapfel, 2015].

Singing style

OTMM is predominantly a voice-centered tradition. This implies not only that singing voice is the source of predominant melody. It also entails that in performances the vocal melodies are rich in expressive embellishment. Embellishments of the melodic line is, in fact, a fundamental aesthetic aspect of OTMM. Singers typically perform simultaneous variations of the same melody in their own register, a phenomenon commonly referred to as heterophony. In particular the vocal lines are especially embellished, because this way singers can 'stand out' from the instrumental mix and show their virtuosity.

The melody lines of singing voice are not flat: skilled singers can control the variation of their voice's pitch to articulate expressive figures such as portamentos, vibratos and melismas. Examples of singers very versed at that are Zeki Müren, Melihat Gülses, Kani Karaça. Melodic phrases have often a 'slow start' - the first tone is approached after a long portamento or a slur [Ederer, 2011]. Detecting the exact onset timestamp of vocal onsets is hard because of the 'slow start' effect. A further challenge is the ambiguity of note transitions - the transitions to another note are often 'enriched' by melismas.

For a comprehensive introduction on the concepts of OTMM from a computational point of view, the interested reader is referred to [Şentürk, 2016, Section 2.1].

2.1.2 Beijing opera

Beijing opera (also known as Jingju) is a form of Chinese opera that emerged in 18th century.

Language

The language of Jingju is standard Mandarin with some slight dialect. In Mandarin, there is no notion of words, but written language is grouped instead into a syllables. Each syllable represents a unique object and therefore has a dedicated character. Lyrics are represented as a sequence of Mandarin characters. Therefore it makes sense naturally that LAA is evaluated on the syllable level. When referring to Jingju we will use the term *syllable* as equivalent to one written character. In Mandarin each syllable is divided into three constituent parts: head (initial part), belly (middle part) and tail (final part) [Duanmu, 2000]. The belly, the middle part can be a pure vowel, diphthong or triphthong. A syllable head (always a consonant) and a tail (a group of consonants) are both optional.

Principles of complementary context

Coarse-level: (structure of the composition) Lyrics in Jingju are a central musical facet. Lyrics come from poetry and are thus commonly structured into couplets. Each couplet has two lyrics lines and can be considered a structural section. The lyrics describe the story of the act and thus never repeat, even though some melodic motives could recur.

Meter is another musical facet that creates the impression of progression in the structure of an aria. Each aria can have one or more metrical pattern (*banshi*):

it indicates the mood of the story and is correlated to tempo[Wichmann, 1991]. Usually an aria starts with a slow *banshi* which changes a couple of times to one with faster tempo. In this way the overall tempo of the aria increases gradually up to the fastest tempo to express more intense mood at the culmination point of the aria.

Middle-level: (structure of a melodic phrase) In contrast to OTMM, in Jingju machine-readable music scores are rarely available. In fact actors, learn to sing by imitating a master artist. To this end the durations in scores play a secondary role, after the example of the master actor. During time, as part of the practice of imitation, specific principles for the structure of the melodic phrase have emerged.

We consider as a melodic phrase a segment of the vocal line, that corresponds to a line of the lyrics. in Jingju to a lyrics line (sentence) is usually divided into 3 syllable groupings, called *dou.* Each lyrics line can be considered a melodic phrase. Interestingly, in Jingju there exist some rules of the durations of the *dous*, which serve as guidance to actors. A *dou* consists of 2 to 4 syllables [Wichmann, 1991, Chapter III]. To emphasize the semantics of a phrase, or according to the plot, an actor has the option to sustain the vocal of the *dou*'s final syllable. There is also some guidances about the number of *dous.* If a poetry line of the lyrics has 10 syllables, a rule of thumb is that it consists of 2 3-syllable dous, followed by a 4-syllable dou. Respectively, if a poetry line has 7 syllables, it is a rule of thumb that it consists of 2 2-syllable dous, followed by a 3-syllable dou. These rule-like relations present a clear example of some music-specific knowledge that could be probabilistically modeled in a lyrics tracking approach as a complementary source of information.

Another typical characteristic of Jingju is the relatively long durations of sung vowels. The vowel(s) in the belly part bear(s) the main tone of the melody and as such can be prolonged substantially for artistic purposes.

2.2 Background on Lyrics-to-Audio Alignment

Although humans are very versed in making sense of the lyrics, sung in songs, for machines the task of automatically tracking lyrics is very challenging. LAA refers to the automatic synchronization between sung lyrics and their written representation. One of the ultimate goals of research in sung lyrics is the automatic transcription of lyrics (a.k.a. lyrics recognition) from a mixture of singing voice and accompaniment [from Fujihara and Goto, 2012]. The recognition of ordinary speech in noisy environments itself only recently started reaching satisfactory results. From this perspective it is not realistic at this stage to strive for reasonable results of automatic lyrics recognition. Despite the few research attempts, none of them has succeeded in achieving satisfactory performance with instrumental-accompanied musical signals [Mesaros and Virtanen, 2010, McVicar et al., 2014]. In this context, LAA can be seen as a stepping stone to disentangling the puzzle of lyrics recognition, because while tackling LAA we could gain precious insights of general validity to lyrics-related tasks. LAA relates to lyrics recognition much in the same way speech-to-text alignment relates to speech recognition.

2.2.1 Evaluation metrics

The accuracy of alignment can be evaluated at different granularity, which depends on the application. In this sense the accuracy is measured in different level of entities, which we will refer to in what follows as lyrical units. A unit could be either phoneme, syllable, word, lyrics line/phrase, or complete lyrics paragraph/section. When generating subtitles for music videos, for instance, line- or phrase-level alignment might suffice. On the contrary, when precise alignment is required, as in the case of automatic generation of highlights for karaoke, syllable- or even phoneme-level is required.

Being a rather under-researched problem, there has not been established a standard evaluation metric. There have been proposed several metrics, whereby each one has been used in only one or two works.

Average absolute error/deviation Initially utilized in Mesaros and Virtanen [2008], the absolute error measures the time displacement between the actual timestamp and its estimate at the beginning and the end of each lyrical unit. The error is then averaged over all individual errors. Evaluation was carried on timestamps at boundaries of lyrics lines. The authors themselves note that an error in absolute terms has the drawback that the perception of an error with the same duration can be different depending on the tempo

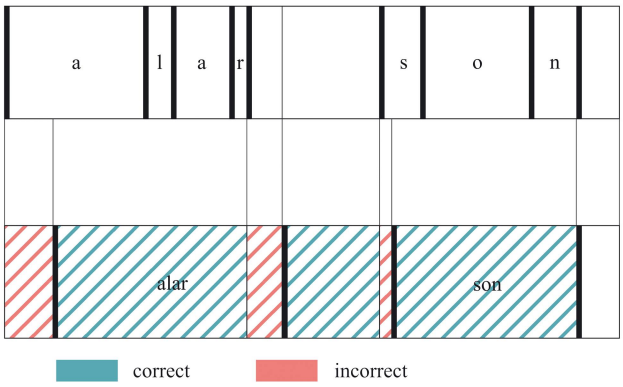


Figure 2.1: Evaluation by percentage of correct segments

of the song. The granularity of the lyrical units was refined in Mauch et al. [2012], where alignment was evaluated on the word level and further in Chang and Lee [2017] on the syllable level.

Percentage of correct segments The perceptual dependence on tempo is mitigated by measuring the percentage of the total length of the segments, labeled correctly to the total duration of the song - a metric, suggested by Fujihara et al. [2011, Figure 9]. Figure 2.1 illustrates the metric by an example.

The granularity, on which the authors evaluated, was lyric lines. This metric can be seen as a special case of the frame clustering metric for evaluating structural segmentation proposed in the work of Levy and Sandler [2008]. This is essentially the same as the percentage of correct segments if we consider a lyrical unit acting as a 'section'. Despite being rather unbiased by tempo and rather strict, the percentage of frames does not give a very intuitive estimate from a perceptual point of view, because the correlation to the extent of the absolute error is not obvious.

Percentage of correct estimates according to a tolerance window A metric that takes into consideration that displacements from ground truth below a certain threshold could be tolerated by human listeners, was suggested in Mauch et al. [2012]. The authors evaluate the mean percentage of start time estimates $\hat{t_i}$ that fall within τ seconds of the start time t_i of the corresponding ground truth lyrics unit:

$$\rho_\tau^k = \frac{1}{N_k} \sum_{word\, i} 1_{|\hat{t}_i - t_i| < r} \times 100$$

where k is the count of words in a given song. The final metric is computed averaging ρ_τ^k over all songs.

In that particular work evaluation was carried out on the level of words, and τ was set to 1 second. Later in alignment was evaluated for both words and syllables. Further, the authors investigated more elaborately the influence of the its window τ, ranging tolerance values from 0 to 2 seconds.

2.2.2 Phonetic recognizer overview

A complete overview of recent LAA approaches can be found in Fujihara and Goto [2012, Literature Review]. Here we review only the approaches based on what the authors call a 'phonetic recognizer', because it is the alignment strategy, which has resulted in most promising results. The core machine learning algorithm used in phonetic recognizers is HMMs. They are suitably representing the time-changing nature of lyrics, because HMMs can model time-contiguous, non-overlapping events.

The task of automatically converting spoken speech into text is known as automatic speech recognition (ASR) and has been one of the most well researched acoustic processing research problems. The typical way speech recognition is approached is by building a model for each phoneme based on the characteristics of its timbral acoustics [Rabiner and Juang, 1993]. The acoustic properties of spoken phonemes can be induced by the spectral envelope of speech.

An end-task, related to ASR is the automatic alignment between speech and its written transcript, also known as text-to-speech alignment. The classical approach of alignment is conducted by using the so called 'forced alignment' method: a transcribed piece of text is expanded to a network of phonetic models and matched to an audio recording of a speaker speaking this particular text. Each phonetic model represents the acoustic characteristics of the phoneme and is used to compare the likelihoods of feature vectors, extracted from the audio. A phonetic model is usually a HMM consisting of 1 up to 3 states representing the initial, middle and final acoustic state of a phoneme. The audio is aligned to the phonemes by finding the most likely path for the extracted sequence of feature vectors in the phoneme network [Rabiner and Juang, 1993].

When the vocal recordings are a cappella (a.k.a. monophonic) LAA can be considered a special case of text-to-speech alignment, which is essentially solved. Since the forced alignment technique was originally developed for clean speech, the presence of accompanying instruments and non-vocal sections pose a challenge to migrating it as-it-is to accompanied singing. Therefore, accompaniment attenuation and the detection of singing voice (a.k.a. vocal detection) are mandatory prerequisites before executing the actual alignment. A LAA that is based on phonetic recognizer with forced alignment comprises a sequence of typical steps, depicted in Figure 2.2.

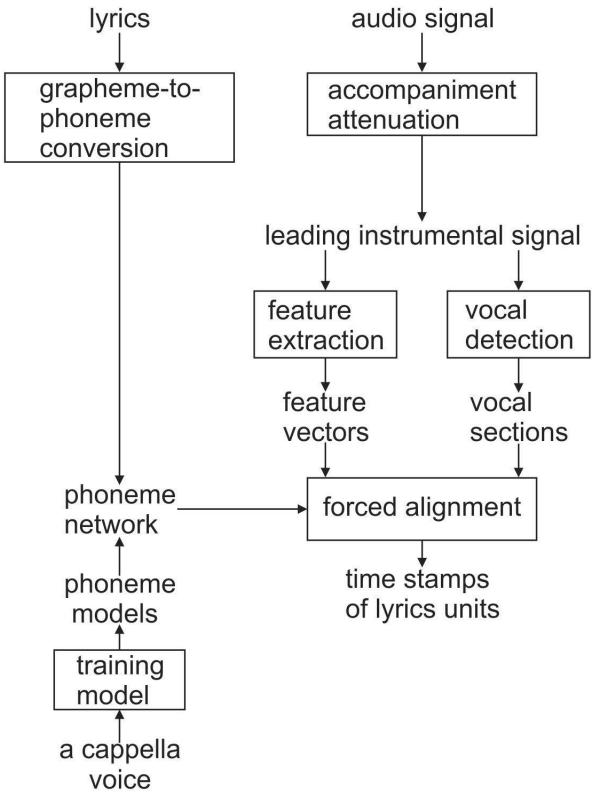


Figure 2.2: Typical steps of lyrics-to-audio phonetic recognizer approach

The goal of accompaniment attenuation (AA) is to isolate from the mixture signal the spectral content, which has its origin in singing voice, while attenuating the rest of the spectrum, generated by accompanying instruments.

Singing Voice Detection (SVD) a.k.a. as vocal detection has an aim to identify

Author	Features	Training approach	>1 language
Mesaros	MFCC	Speech + adaptation	N
Fujihara	MFCC	Speech + singer adaptation	Y
Kruspe	MFCC+PLP	Singing	N

Table 2.1: Seminal LAA works based on the phonetic recognizer approach. These are respectively: Mesaros - Mesaros and Virtanen [2008]; Fujihara - Fujihara et al. [2011]; Kruspe - [Kruspe and Fraunhofer, 2016]

time intervals of the complete audio signal, in which singing voice is present. In the context of LAA the presence entails that it is a leading voice, compared to backing vocals, because written lyrics represents the sung content of only the main vocal.

Since AA and SVD can be considered separate problems on their own, in some related work existing prior methods are adopted. Then lyrics lines are expanded to a sequence of phonemes based on language-specific grapheme-to-phoneme rules. In this way, the HMMs are concatenated into a phoneme network. Phonetic models are trained on acoustic characteristics of material from either clean speech or a cappella singing.

In what follows we take a reviewing journey through the subsets of existing approaches from Table 2.1, staying some time at each of these steps and scrutinizing how some of the approaches address it. Notably, the approach of Kruspe and Fraunhofer [2016] is trained on a cappella singing, which excludes the need of both the AA and SVD steps.

2.2.3 Accompaniment attenuation

Compared to a cappella, the automatic alignment of lyrics in singing voice signal accompanied by various instruments, is much more challenging. The phonetic models trained on features, extracted from unaccompanied voice represent entirely the singing voice properties. In polyphonic mixture of voice and accompaniment, however, the vocal properties are interfered from the instrumental sounds. Spectral peaks from harmonics of accompanying instruments might occlude the harmonic components of voice. This means that some timbral characteristics, pivotal for distinguishing the vowel identity, can be distorted. In this setting, the phonetic models, trained on a cappella singing voice lose their discriminative power. To address this problem researchers have come up with techniques that isolate as much as possible the spectral

content, which has its origin in singing voice, while attenuating the rest of the spectrum.

In Fujihara et al. [2011], Mesaros and Virtanen [2008] a method for segregating the predominant melodic line is utilized: First the spectral components that are multiples of the fundamental frequency of the vocal melody (also known as harmonic partials) are extracted from the sound mixture. Then they could be optionally refined and eventually grouped together to form the vocal signal. In the end, the vocal content is resynthesized from these by means of a sinusoidal model. At the core of representing singing voice content in polyphonic mixtures is a model, capable of representing the complex interactions between the vocal harmonic partials and other instrumental sources in the mix. Several strategies of harmonic modeling have been proposed [Serra, 1989, Yeh and Roebel, 2009]. A key challenge to such models is how to tackle partials from two different sources that have spectral overlap. Yeh and Roebel [2009] describes the expected amplitude of two overlapping partials based on the assumption that the partials overlap at the same frequency.

A drawback of the harmonic modeling presented above is that unvoiced consonant regions are not detected due to their lack of predominant pitch. Fujihara et al. [2011] suggest as a solution a method for fricative (unvoiced consonants) detection. In the alignment stage the time intervals, for which the presence of fricative sounds is unlikely, are forbidden to be matched to fricatives (actually only 'sh') from the phonemes network. A slight improvement in alignment accuracy was registered, supposedly because phoneme gaps in the middle of lyrics phrases were shorter than they were without fricative detection. However, since alignment accuracy was measured on lyrics phrase level, the effectiveness of the proposed fricative recognition method could not be fully evaluated.

The importance of the accompaniment attenuation method has been confirmed by comparing the alignment performance when disabling it. The phrase-level accuracy was improved by 4.8 absolute percent when MFCCs were extracted from the vocal segregated signal compared to when extracted directly from the polyphonic mix. Apart from that, the quality of the attenuation process can be objectively judged with the metrics used for evaluation of source separation on the segregated vocal (ideally vocal-only) signal. It is however hard to interpret how much the quality of attenuation affects the subsequent processing. To our knowledge no study has taken efforts in carefully examining the correlation of the degree of attenuation on the alignment accuracy, despite it being an important element in dealing with real-world

accompanied singing.

2.2.4 Singing voice detection

In early LAA approaches (including the work of Mesaros and Virtanen [2008]) no automatic singing voice detection method was applied. Instead the authors annotate manually structural sections (verse, chorus, bridge) with singing voice present. The sections durations range from 9 to 40 seconds. Then the assumption is made that in all vocal sections the predominant source is the voice. This permits to apply the harmonic modeling melody extraction strategy of accompaniment attenuation, presented in the previous section without the need of explicitly determining if the source of the main melody is voice or another instrument. Short instrumental interludes are accommodated by training a model for instrumental accompaniment, which ideally will get activated in such interludes.

2.2.5 Acoustic Features

The timbre of singing voice is described by its harmonic partials. The timbral properties of a sung note depend on the distribution of the energy of its harmonic partials, whereas more energy is concentrated in harmonics around formant frequencies.

Formant frequencies

The formant frequencies represent resonances of the vocal tract and cavities, and can be controlled to some extent by changing the length and shape of the vocal tract, and the shape and position of the tongue and lips [from Mesaros, 2012]. Formant regions are ordered according to their energy with first formant (F1) representing the spectral frequency region with highest energy. Findings in singing research have indicated that the two lower order formants (F1-F2) are most important for understanding spoken speech, whereas higher order ones (F3-F5) are related to the identity of the singer. The first formant is known to change with varying the jaw opening, while the second is correlated to the tongue shape. The vowels of speech are determined by specific combinations of F1 and F2, which are relatively stable for a vowel and among different speakers [Sundberg and Rossing, 1990].

Mel frequency cepstral coefficients

MFCCs are reliable descriptor of phonetic timbre. Usually the first 12 mel-frequency cepstral coefficients (MFCCs) and their difference to the previous time instants are used.

Ideally the efforts on reducing the influence of accompanying instruments can be mitigated by focusing on designing features that capture phonetic timbre in a way robust to background instruments. There has been some efforts recently to use end-to-end learning: for example encouraging results for singing voice detection were presented in Schlüter [2016]. Hopefully in the future insights from this approach can be adopted to recognizing not only if bits of spectral content originated from singing voice, but also its phonetic class. However, since no such features are yet designed, the working strategy for recognition of phonemes remains to extract features after the accompaniment has been reduced from the original polyphonic mix.

2.2.6 Decoding with HMMs and Forced Alignment

Since HMMs are not only the main machine learning algorithm behind the phonetic recognizer approaches, but also can be considered a special case of dynamic Bayesian networks, which we rely on in our own method, we will now give a very brief overview of HMMs.

HMMs are probabilistic finite-state automata, where transitions between states $x_k \in 1, ..., S$, where S is the number of states, are ruled by probability functions. The states in a phonetic recognizer are the phonemes. Transition probabilities are assumed to depend only on a finite number of previous transitions.

$$P(x_k|x_{k-1}, x_{k-2}, ...) = P(x_k|x_{k-1}) \tag{2.1}$$

This is known as the Markov property, i.e. the current state directly depends only on a limited number of previous states (in this example only one). The specification of the righthand side in 2.1 is known as the state transition model, which can be expressed in a stochastic transition matrix (A_{ij}), where $a_{ij} = P(x_k = j \,|\, x_{k-1} = i)$. For two given phonemes, the transition matrix describes the probability of the one following the other. Transitions can be trained from annotated data or hand-crafted by imposing some musically-meaningful constraints.

States (in our case the time phases of the phonemes) are not observable. Instead we observe features (in our case phonetic timbre), which are modeled as random variables Y_t and are assumed to depend exclusively on the current state, i.e. the observations' distribution is $P(y_k|x_k)$. The emission probabilities, can be trained to maximize the probability of emitting a given set of observation sequences and although traditionally modeled by GMMs, could be virtually any (usually generative) machine learning model, which can express its output in terms of class probabilities. A complete discussion on theory and applications of HMMs can be found in [Rabiner and Juang, 1993].

2.2.7 Phoneme network

The goal of the grapheme-to-phoneme conversion is to create a phoneme transcription out of the word sequence, comprising the input lyrics. The conversion is carried out using a set of the phonemes from a phonetic alphabet, based on a pronunciation dictionary, prepared by linguists.

As inherited from HMM-based speech recognition, it is assumed that the observed feature sequence is generated from an HMM. Traditionally, a 3-state HMM model for each phonemes is trained, as well as for a silent pause. An HMM has left-to-right topology, which corresponds to how the acoustics of the voice evolve sequentially in time from an initial, through a middle and to a final state. Mesaros and Virtanen [2008] adopted the 3-state paradigm and trained for each state a 10-mixture Gaussian distribution fitted on the feature vector The resulting phoneme network is a super-HMM, concatenated from the HMMs of the individual phonemes in the sequence. At inter-phoneme transitions, the network 'forces' only a single possible transition: to the following phoneme from the transcript. The only exception are special case phonemes for short silent pauses, which can be optionally skipped.

Cross-language modeling

As a rule of thumb the phoneme models, used in the recognition are trained from the same target language to assure the integrity of the models. However, often there might not be enough training material for the language of interest, which opens a necessity for finding a cross-language phoneme mapping strategy as an alternative. As a matter of fact cross-language mapping has been important research direction in speech recognition for long time, but only recently some substantial results were achieved for the particular task of speech synthesis [Sun et al., 2016]. One of the few LAA researches using phonemes trained on a different language was done by Fujihara et al. [2011]. To be able

to align English songs the authors mapped English phonemes to their closest approximates from a set of Japanese phoneme models. This resulted in sub-optimal alignment results though due to the different language phonetics: In Japanese all vowels are pure, part of monophthongs, which is a clear limitation for the more complex acoustic characteristics of English diphthongs.

2.2.8 Training procedure

In the absence of enough singing material with annotated phonemes, phonetic models are trained on a big corpus of speech with annotated sentences. Later these phonetic speech models are adapted to match the acoustic characteristics of clean singing voice using a small singing dataset with annotated phonemes. The adaptation techniques are borrowed from research carried on adapting universal speech models to characteristics of a particular speaker.

Training on speech

Compared to speech, singing voice evinces more complex frequency and dynamic characteristics: fluctuation of fundamental frequency (F0) and loudness of singing voices are far stronger than those of speech sounds [Sundberg and Rossing, 1990]. The fundamental frequency of women in speech is between 165 and 200 Hz, while in singing it can reach 1000 Hz. This is much higher than the normal for speech value range of the first formant (500 Hz). In such cases the first formant moves higher in frequency, so that it corresponds approximately to the fundamental frequency, while the second formant might also move higher. Therefore the first two formants of singing voice are less stable than speech and harder to predict. In addition, some skillful singers are capable of changing drastically their position by moving their vocal cavity, tongue and lips. On top of that, compared to speech, some phenomena including vibrato and singer's formant are present only in singing. To address all these discrepancies an adaptation of the acoustic properties of spoken phoneme models is needed.

Mesaros and Virtanen [2008] proposed to borrow a technique from speech recognition that adapts an universal speech model to the speech for a particular speaker. They used the method Maximum Likelihood Linear Regression (MLLR). In Fujihara et al. [2011] after applying a MLLR, another statistical adaptation technique - the Maximum a posteriori (MAP) transform - was run. MAP shifts the mean and variance components of the Gaussians of the each spoken phoneme model in an acoustic space towards the characteristics of the corresponding sung phoneme. An advantage of the MAP transform

compared to other adaptation techniques is that it allows the manipulation of each phoneme model independently.

Training on singing voice

Another fundamental difference between speech and singing voice is that the time a vowel is held in singing is much longer and much varying than in speech. In a recent study Kruspe [2015b] compared the accuracy of recognition of individual phonemes with model trained on speech and a model trained on the same speech modified with 'sing-like' transformations: In turn pitch shifting, time-stretching and vibrato addition were applied on the same data. The author obtained 18% correctly classified audio frames with the model with all three modifications jointly, improving from the baseline of 12% with the speech model. Furthermore, result showed that a significant accuracy improvement was observed mainly due to time-stretching. The adaptation strategy presented above might compensate to a certain extent for most of the acoustic difference, except arguably for the variation of phoneme durations. One reason might be that when sung vowels are prolonged their transitions to neighbouring phonemes have more variability than in speech, too.

A bottleneck for training on actual singing is the lack of phonetically annotated singing material. Kruspe and Fraunhofer [2016] proposed a viable strategy for annotation: they trained monophone one-state HMMs on a speech corpus, wherein each observation model is a GMM. Then they preselected around 6000 recordings of full songs from the DAMP dataset from Stanford University[1]. DAMP is a huge collection of a cappella popular music, sung by amateur singers with lyrics available, but not aligned whatsoever. The authors aligned the a cappella audio on the phoneme level to its lyrics by means of forced alignment with the fitted speech-trained GMMs. The aligned phoneme timestamps have been fed as if they were manual annotations into a 3-hidden-layer Multi-Layer Perceptron (MLP) with sigmoid activation function. On material from DAMP the resulting model reached a remarkable phoneme recognition of 25% of correctly classified frames compared to 12% with a model trained only on the speech dataset. Results on the word-level alignment were however not reported.

[1] https://ccrma.stanford.edu/damp/

In summary, the problem of LAA has been quite researched. However:

1. Each of the presented approaches is trained on material from the language, on which it was tested. This means each time an aligner for a new language (for example Turkish) is required, reuse of existing work as a baseline is not feasible without a modification/adaptation of the acoustic model. This problem is inherited from speech-to-text alignment.

2. In most approaches the extracted acoustic features are agglomerated into classes (phonemes and non-vocal states) in a bottom-up fashion, without considering the dependence of simultaneously occurring melodic and rhythmic musical events. It is not very good idea to rely only on timbral features trained from material, which might have quite some mismatch with the test dataset. This mismatch is further aggravated by the artifacts of extracting only the vocal content in the case of polyphony. A crucial limitation of existing alignment methods is that lyrics are tracked with hidden Markov models, which have only one latent variable. It can represents the state of lyrics being in one of all possible phonemes or in a non-vocal region. One hidden state does not have the expressivity to represent sufficiently well the influence of interrelated concepts of the *complementary context* (as we defined it in the Introduction chapter). Therefore the forced alignment step itself has limited knowledge of simultaneous events of the complementary context. As a result, it is integrated as a preprocessing or postprocessing step relative to the main alignment step. For example, the events of transition of one structural section to the next are used to manually segment a whole recording into sections and then alignment is run separately on each segment Mesaros and Virtanen 2008.

3. There is (almost) no reproducible work on LAA with accompaniment.

2.3 Background on dynamic Bayesian networks

A probabilistic graphical model is a probabilistic model that expresses conditional dependence between random variables using a graph. HMMs can be considered a probabilistic graphical model with a single hidden random variable. A bayesian network is a probabilistic graphical model that represents a set of random variables and their (conditional) dependencies with a directed acyclic graph.

A dynamic Bayesian network (DBN) is an extension of Bayesian networks that can relate variables over time [Murphy, 2002]. To build a meaningful model of sung lyrics we have at our disposal sequential data from audio features, as well as complementary context events that are interrelated to phonetic timbre in terms of musical patterns or rules. DBNs hence provide an effective and explicit way to encode dependence relationships between phonetic timbre and different pieces of complementary context, addressed in this work. Excellent resources on graphical probabilistic models and inference is Koller and Friedman [2009] and for Bayesian models in time, in particular, is [Barber et al., 2011].

Research by Whiteley et al. [2006] introduced DBNs to music computing. The authors emphasize the fact that DBNs can natively model higher-level musical qualities more intuitively and efficiently than an HMM.

2.3.1 Inference in DBNs

Inference with in probabilistic models refers to the operation, in which we estimate the probability distribution of one or more unknown variables, given that we know the values of other variables.

Exact inference in DBNs, in its simplest form involves marginalizing over variables to obtain the distribution over the required set of variables, achieved by direct marginalization, factoring, variable elimination and other techniques [D'Ambrosio, 1999]. However, in practice exact inference is complex and without closed form solutions. Therefore, in this thesis a viable workaround taken is to reduce the proposed DBNs, without losing their encoded dependence between musical phenomena, to HMMs and resort to the Viterbi decoding.

2.4 Background on sung lyrics with complementary context

In what follows we review existing studies on sung lyrics, in which knowledge from complementary context contributed to improvement in accuracy. We have organised these studies broadly according to the levels of granularity of complementary context, to which we comply in this thesis. As some approaches can be considered to benefit from more than one level, we do not aim at strict subdivision, but rather at laying out the background in a structured way, which we can start off extending systematically, to address the goals of this thesis.

2.4.1 Coarse-level context

An experimental evaluation of the relation of structure and sung lyrics remains outside the scope of this study. Instead, we utilize automatic segmentation of complete song recording into its structural segments as a preprocessing step to LAA. However, in a future work, it is desirable to incorporate structural information into the phonetic recognizers, proposed in this thesis.

The use of music structural information has provided guidance for alignments on the higher-level in previous works [Lee and Cremer, 2008, Wang et al., 2004]. Lee and Cremer [2008] showed that the results of rough structure segmentation can be used for paragraph-level alignment of lyrics. First a structural segmentation of the audio recording is performed using acoustic features. Then the chorus section is determined by a clustering method, whereas the vocal ones are determined by a SVD method. The resulting sections are aligned to the hand-labeled lyrics paragraphs by means of dynamic programming.

2.4.2 Middle-level context

Musical chords are a piece of complementary context parallel to lyrics in the granularity of a lyrics lines. Mauch et al. [2012] proposed the integration of textual chord information into the baseline phonetic recognizer approach of Fujihara et al. [2011], which we described above. The authors assume that the complete chord annotation is provided together with lyrics in the format of song sheets, which can be obtained from web-sites such as *UltimateGuitar*. The song sheet provides chord annotations anchored to words. To handle the ambiguous mapping of the word-level annotation to the finer-level of syllables, Mauch suggests a 'a flexible chord onset' strategy: To allow a chord change in any of the syllable of its corresponding word, for each syllable alternative paths

is constructed in the syllable-HMM network . The syllable-HMM-network can be unambiguously expanded to a phoneme-HMM-network.

In this setting, since the phoneme sequence is fixed, a hidden phoneme state h determines several possibilities with equal likelihood for a hidden chord state c, which can be represented as a DBN The combined transition probability is 'inherited' from the trained phoneme transitions. In addition to the baseline phoneme emission y^m an emission feature y^c for chroma is added, which are combined in one mutual observation probability on inference. The approach greatly improves the word-level accuracy of the baseline, from 46.4% to 87.5 % in terms of the percentage of correct estimates according to a tolerance window of 1 second.

Chang and Lee [2017] described a method to deal with both syllable- and word-level lyrics-to audio alignments of accompanied music recordings in Korean and English. The approach is to discover repetitive acoustic patterns of vowels in the target audio by referencing vowel patterns appearing in lyrics.

2.4.3 Fine-level context

Few works for tracking lyrics in singing voice have proposed a method that represent features, describing phoneme timbre jointly with other melodic characteristics [Fujihara et al., 2009].

Fujihara et al. [2009] concurrently estimates the phoneme classes and fundamental frequency of singing voice from recordings with instrumental accompaniment. They suggest the use of probabilistic spectral templates of singing voice, that represents both phoneme identity and the predominant f0. No temporal progression from one template to the next is modeled though. An important advantage of the approach is that the templates can be trained directly from the polyphonic mix without segregating the predominant voice or affecting the instrumental accompaniment, which is often a necessity in other studies. Accuracy for phoneme estimation is evaluated in terms of the ratio of the number of frames that are correctly estimated to the total number of frames. Frames taken into consideration in this calculation were only the five Japanese vowels a,e,i,o,u. The ratio of 55 % for a baseline with GMMs and MFCCs was increased to 60.1 % with the proposed model, which is arguably the best vowel recognition system in accompanied singing.

In [Korzeniowski, 2011] a hidden state space is proposed that combines the typical 3-state left-to-right HMMs for phonemes with the note state space introduced in Orio and Déchelle [2001]: each note has 3 states corresponding

to its temporal phases attack, sustain and release. The goal of the study is to improve automatic score-to-audio alignment by integrating information from the lyrics timbre, available in parallel to the score. However, due to the humongous state space, result of the the cartesian combination of the note and phoneme state space, the authors were not able to implement this strategy. Instead they used the note HMM and incorporated vowel information as additional feature (together with pitch, loudness, etc.) via the observation probabilities of the states.

Summarizing, almost none of the related work that considers complementary context is based on the proved to be most successful LAA strategy - phonetic recognizer. The only exception is the approach of Mauch et al. [2012], which is however limited to music traditions, for which the concept of chords is applicable. Due to the heterophonic interaction of accompaniment instruments with singing voice for traditions like OTMM the harmony does not occur in the form of chords and we cannot benefit from this work.

Chapter 3

Baseline Lyrics-to-audio Alignment Model

3.1 Introduction

In this chapter we depict our lyrics-to-audio alignment (LAA) baseline system. It is a phonetic recognizer, based on phoneme HMMs. To date most of the studies on LAA are based on the phonetic recognizer approach, as described in Section 2.2. The goal is to describe the key elements of the baseline approach, which are not related to complementary context. In this way we 'set the scene' for the methodologies that consider context - the main contribution of this thesis. They will be the focus of the following two chapters. To this end, in this chapter we go through the key steps of a phonetic recognizer and describe which existing methodologies we plugged in. Some of these are tailored to the specific characteristics of OTMM (see Section 2.1.1). In particular, we explain how we utilized a method for linking structural sections of the composition to their respective audio segments in a recording. Further, we describe the benefit of a predominant melody extraction method. We comment on tuning their parameters. We present in more details the construction of the phoneme network from the lyrics transcription, for which some rules for Turkish language are required.

A major contribution of this chapter is a strategy to represent phonemes in Turkish language by mapping them to phonemes in English. This enables the use of a reliable model for English as a viable replacement for Turkish, for which the available training material is scarce. We also describe the datasets used to evaluate the LAA methods, presented throughout this thesis. Com-

piling datasets, representative of the music tradition and the key facets of complementary context, is an important effort of this study.

We start the chapter by describing the evaluation datasets, comprising both a cappella and multi-instrumental recordings from OTMM (Section 3.2). We then introduce our choices for each of the steps of the standard phonetic recognizer in Section 3.3. We describe the construction of the phoneme network in Section 3.3.2. In Section 3.4, we present a comparison of three strategies to train the acoustic model for Turkish language. Finally, in Section 3.5 we discuss the alignment results by evaluating the baseline model on the presented datasets.

3.2 Datasets

In this thesis we have evaluated the proposed lyrics tracking approaches on a dataset of selected recordings from OTMM repertoire. To this end we prepared two datasets: *multi-instrumental lyrics OTMM dataset,* which encompasses original studio recordings with accompaniment of multiple instruments, and an *a cappella lyrics OTMM dataset,* which contains solo signing voice. Additionally, we compiled a *multi-instrumental vocal onsets OTMM dataset* with annotations of vocal note onsets containing performances with well-perceived percussive accents. In all datasets we payed special attention to annotating carefully the timestamps of the music events, in which complementary context manifests.

3.2.1 *Multi-instrumental lyrics OTMM dataset*

The *multi-instrumental lyrics OTMM dataset,* which we compiled, consists of 13 performances with a soloing singer - 5 with male and 8 with female one. The performances are from 11 compositions in the şarkı form and have total duration of 19 minutes. They are drawn from the *CompMusic* corpus of OTMM repertoire [Uyar et al., 2014] and have varying recording quality, including historic recordings not necessarily with good studio quality. Music scores are provided in a custom machine-readable format, called *symbTr,* complying with the *humdrum* notation philosophy [Karaosmanoğlu, 2012]. These scores contain annotations of the structural sections of the şarkı form. The words in a section are further split adopting the division into melodic phrases, proposed by Karaosmanoğlu et al. [2014]. What the authors call a musical phrase represents a musically-meaningful motif of the melodic line. A phrase spans roughly the same number of metrical cycles depending on the tempo (1

total #sections	#phrases per section	#words per phrase
75	2 to 5	1 to 4

Table 3.1: Phrase and section statistics for the OTMM dataset

or 2 cycles). This corresponds to up to 4 words depending on their length. A melodic phrase often also contains short instrumental motives before or after the vocal line. If an original phrase boundary splits a word we have modified it to include the complete word, in order to assure appropriate evaluation on word or phrase level. Table 3.1 presents statistics about phrases. The total number of words in melodic phrases are 732.

The performance recordings contain the annotations of the boundaries of segments corresponding to the score sections, which have been done in the study of Şentürk et al. [2014]. We annotated further the melodic phrase boundaries using the *Praat* annotation tool. Whenever needed, we split or merged some melodic phrases with outlier duration so that phrases within a recording have approximately equal duration [1].

3.2.2 *A cappella lyrics OTMM dataset*

Due to the lack of appropriate a cappella material in the şarkı form, we recorded especially for this study an a cappella version of the *accompanied vocal OTMM dataset*.

The vocal parts of the *multi-instrumental lyrics OTMM dataset* have been sung by professional singers, especially recorded for this study, A performance has been recorded while listening to the original recording, whereby instrumental sections are left as silence. This assures that the order, in which sections are performed, is kept the same. This assures that the generated timestamps are valid for the accompanied version, too. Although each recorded singer has some peculiar time advances and delays of given syllables, the recordings are to a very high degree in-sync with the originals. We carefully checked that by listening simultaneously to both the original and the a cappella version. The annotated phrase boundaries are available at [2].

[1] The dataset is available at http://compmusic.upf.edu/turkish-sarki

[2] The audio and the annotations are available under a CC license at http://compmusic.upf.edu/turkish-makam-acapella-sections-dataset

Additionally, the singing voice for 6 recordings (with a total duration of 10 minutes) from the dataset has been annotated with MIDI notes inferred by the music score[3]. On annotation special care is taken to place the note onset on the time instant, when voiced sound starts. If a syllable starts with an unvoiced phoneme, the onset is placed at the beginning of the vowel (see Figure 5.3). In addition, as onset is considered the point in time in which a transition to a new note is started, because slurs and portamentos are common in OTMM [4].

3.2.3 *Multi-instrumental vocal onsets OTMM dataset*

Unlike the previous two datasets, being designed for LAA, we compiled *the multi-instrumental vocal onsets OTMM dataset* to be used for note onset detection of singing voice in multi-instrumental recordings. We utilize it for automatic note onset detection, informed by underlying metrical accents. To that end, all recordings have clearly audible percussive strokes, at some of the beats in a metrical cycle. Except for vocal onsets, timestamps of beats are also annotated. It is a subset of the dataset, presented in Holzapfel et al. [2014], including only the recordings with singing voice present. It is divided into training and test dataset. The test dataset comprises 5 1-minute excerpts from recordings with solo singing voice for each of two meter classes, referred to as usuls in Turkish makam: the 9/8-usul aksak and the 8/8-usul düyek. All excerpts are manually annotated with beats, downbeats and vocal note onsets[5]. Interestingly, each usul has a characteristic pattern of beat positions, on which percussive strokes are hit. For example, in aksak the beats 1,3,4,5,7 and 9 have strokes. Musicians observe these patterns rather conservatively.

The training set spans around 7 minutes of audio from each of the two usuls, annotated also manually with beats and downbeats. Due to the scarcity of material with solo singing voice, several excerpts with choir sections were included.

3.2.4 *A cappella lyrics Jingju dataset*

The dataset has been especially compiled for this study and consists of excerpts from 15 arias, chosen from the *CompMusic* corpus of Jingju arias Repetto and Serra [2014]. It has total duration of 67 minutes and comprises two female

[3] Creating the annotation is a time-consuming task, but we plan to annotate the whole dataset in the future

[4] Onset annotations are available at http://compmusic.upf.edu/node/233

[5] The dataset is available at http://compmusic.upf.edu/otmm-vocal-onsets-dataset

#sentences per aria	9.2
#syllables per sentence	10.7
avrg sentence duration (sec)	18.3
avrg syllable duration (sec)	2.4

Table 3.2: Sentence and syllable statistics for the Jingju dataset

singers. For a given aria were present two versions: a recording with voice plus accompaniment and an accompaniment-only one. From these, we generated a cappella singing by subtracting manually the instrumental accompaniment from the complete version [6]. Table 3.2 presents the average values per sentence and syllable.

Each aria is annotated on different event granularities: from the *banshi* type, through boundaries of lyrics sentences, down to boundaries of syllables and boundaries of phonemes. Annotations are carefully done by native Chinese speakers and a Jingju opera musicologist[7]. The phoneme set has 29 phonemes and is derived from Chinese pinyin, and represented using the x-sampa standard[8]. To assure enough training data for each model, certain underrepresented phonemes are grouped into phonetic classes, based on their perceptual similarity.

3.3 Steps of the phonetic recognizer

An overview of the steps of the proposed approach can be seen in Figure 3.1. These steps comply with the typical steps of a generic phonetic recognizer approach (presented in Fig. 2.2 of the Background Chapter). In what follows we discuss in details the design choices and the preferred solutions for each step.

3.3.1 Structural segmentation

Being a challenging problem itself, a full-fledged SVD is outside the scope of this study. We instead divided manually each audio recording into sec-

[6] The resulting monophonic singing is perceived as clean as if it were a cappella, having slightly audible artifacts from percussion on the non-vocal regions

[7] These are the *CompMusic* team members Rong Gong, Yile Yang and Rafael Caro Repetto

[8] Annotations are made available at http://compmusic.upf.edu/node/286

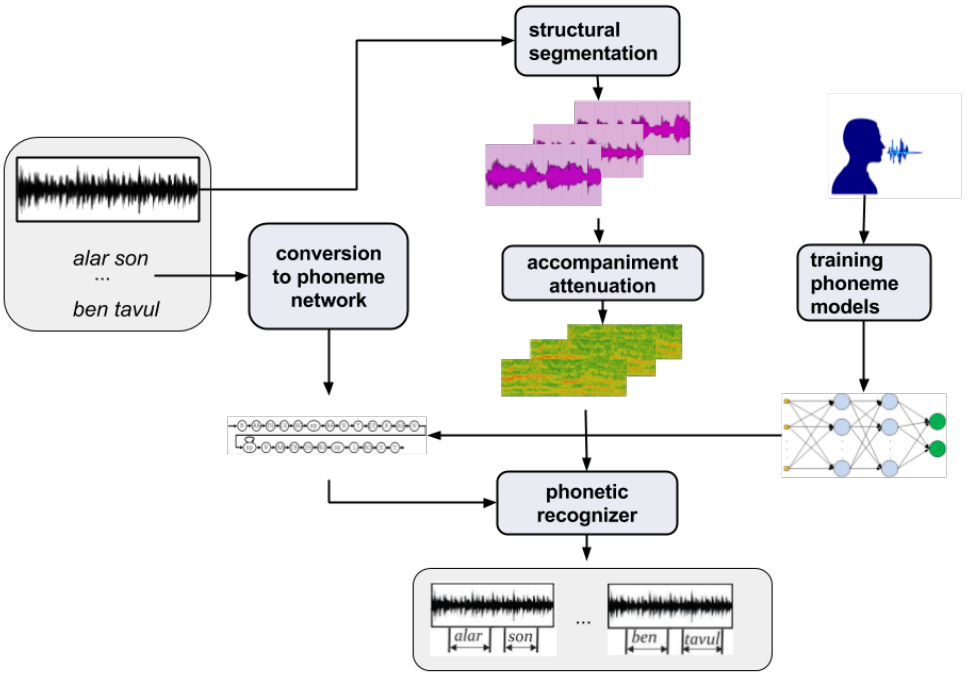


Figure 3.1: Overview of the steps of the baseline lyrics-to-audio alignment system

tions (e.g. zemin, nakarat, meyan) as indicated in the music score, whereby instrumental-only sections were discarded. In the şarkı form each vocal segment corresponds to a structural section (zemin, nakarat, or meyan). We assign manually to each segmented vocal section its corresponding lyrical line, in order to assure correct lyrics.

All alignment throughout this thesis is performed on an audio recording and text for each vocal section separately. LAA on complete audio recordings was not desirable due to the unpredictability of the sections order and addition of improvisation sections during performance.

To verify the feasibility of automating the structural segmentation, we utilized a method for linking score sections to their beginning and ending timestamps in a recording with Makam singing [Şentürk et al., 2014]. Due to the high accuracy of this method, almost all sections are mapped correctly with minor section boundary displacements. We showed that integrating section link-

ing as a preprocessing step yields estimated section boundaries that are not detrimental to matching the correct lyrics sections [Dzhambazov et al., 2014].

3.3.2 Accompaniment attenuation

It is rather infeasible to successfully track the phonemes in multi-instrumental music signals by using the models, trained solely on a cappella singing. The harmonic partials in unaccompanied singing are relatively straightforward to extract because they form clear intensity peaks in the spectrogram. A simple intensity-peak-picking strategy is however prone to failure in accompanied singing, because of the interference with instrumental harmonic partials. To handle this case many harmonic partial extraction methods were proposed (see Section 2.2.3).

Such a method requires as input a melody contour, generated by a melodic source. We first extract the vocal contour of the singing voice. Then, based on it, its harmonic partials are derived from the spectrum. Then the vocal harmonic partials are resynthesized into an interpolated vocal spectrum $\bar{X}_t$. Finally, we extract acoustic features from $\bar{X}_t$ instead of the original polyphonic spectrum.

Singing voice melody extraction

To extract the contour of the predominant singing voice in music with instrumental accompaniment, we utilized the algorithm, described in Atlı et al. [2014]. It is a method for extraction of the melody of a predominant instrument. It relies on the basic methodology of Salamon and Gómez [2012], but modifies the way in which the final melody contour is selected from a set of candidate contours, in order to reflect the specificities of OTMM:

1. It chooses a finer bin resolution of only 7.5 cents that approximately corresponds to the smallest noticeable change in Makam melodic scales.

2. Unlike the original methodology, it does not discard time intervals where the peaks of the pitch contours have relatively low magnitude. This accommodates time intervals at the end of the melodic phrases, where Makam singers might sing softer.

In addition to generating f0 values, the algorithm performs in the same time a predominant source detection: it returns zero for f0 in regions with no dominant melody. The melody contour obtained this way has its origin not only

from singing voice but also from accompanying instruments. This happens in short instrumental interludes, where an accompanying instruments carries the main melody.

Harmonic model

We utilized the harmonic model of Serra [1989] to filter the spectral peaks corresponding to the the harmonic partials of the singing voice. The spectral peaks are computed at the expected location of harmonic partials at multiples of the fundamental frequency $f^n \approx h_n f^0$, where h_n is the harmonic index (3.1). Parabolic interpolation refines the exact frequency locations. We estimated $\bar{X}_t$ with a relatively huge number of harmonics (30), in order to preserve as much as possible the phoneme identity information.

$$Yh[k] = \sum_{r=1}^{R} A_r W[k - r\hat{f}_0] \tag{3.1}$$

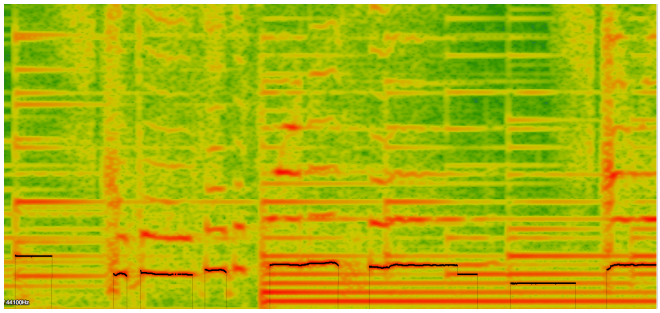
It should be noted that it is not an end goal of this study to segregate the singing voice from the polyphonic mix. Methods that are focusing on a good separation of the singing voice strive to obtain a representation of the vocal content with the least amount of introduced artifacts. By contrast, in our case some artifacts may be acceptable as long as they do not distort significantly the distinction of the identity of vowels. Nevertheless, as a benchmark, we carried out a study, in which we evaluated the quality of voice segregation using the harmonic model [Dzhambazov and Serra, 2016].

Resynthesis

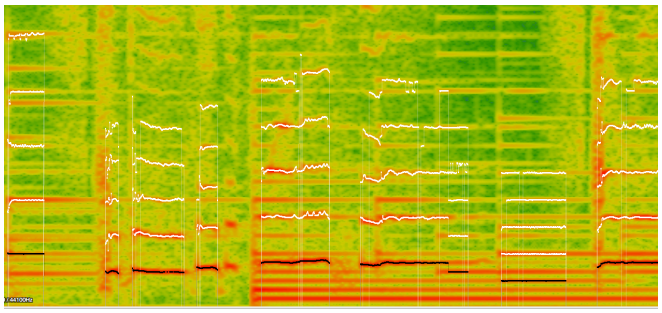
The interpolated vocal harmonic partials are resynthesized by means of a constant overlap add resynthesis with the *sms-tools* package[9]. Despite being distorted by energy leaks from instruments, the interpolated partials seem to preserve well the overall spectral shape of the singing voice, including the formant frequencies, which encode the phoneme identities. The resynthesis allowed us to listen and verify that vocals are still to a large extent intelligible.

Note that melody resynthesis usually results in singing voice with perceivably worse intelligibility of the phonemes than the original signal. Some unvoiced

[9] http://mtg.upf.edu/technologies/sms



(a) Extracted predominant melody



(b) Detected harmonic partials with the harmonic model, based on the predominant melody

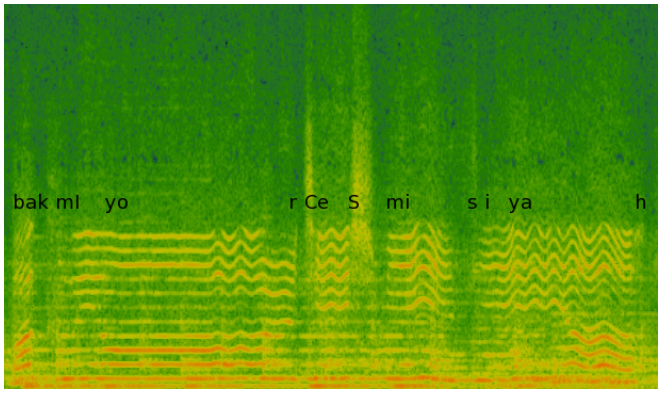
Figure 3.2: Example of extracting harmonic partials of predominant voice with the harmonic model

consonants are dropped, as well as some artifacts are introduced. However, for computers, which are not as versed as human listeners in distinguishing among sources, the accompaniment reduction is an imperative step.

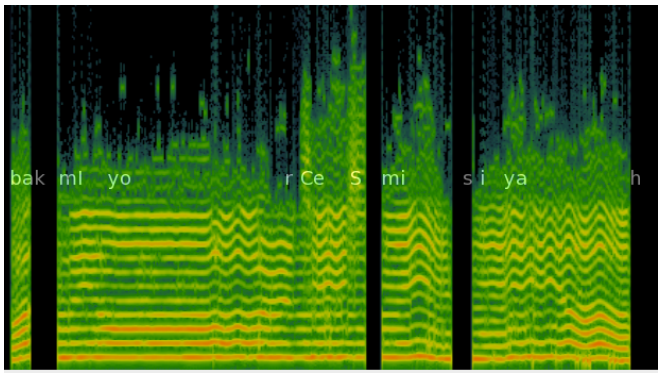
An example for the audio segment with the lyrics phrase *bakmıyor çeşmi siyah* can be seen in Figure 3.3b.

3.3.3 Acoustic Features

MFCCs have several parameters, that could be tuned according to the application use case. A standard for extracting MFCCs for the characterization of singing voice are the default parameters of the HMM toolkit (htk), which



(a) Original spectrogram



(b) Resynthesized singing voice. Note that some unvoiced consonants are replaced with silences

Figure 3.3: An example of the resynthesized harmonic partials for the lyrics phrase *bakmıyor çeşmi siyah*

is tailored to speech recognition. We adopted these to assure consistency to previous work (see Table 3.3).

3.3.4 Phoneme network

The phonetic recognizer is a HMM, wherein the states of the HMM represent the sequence of phonemes from the phoneme transcription of the lyrics. As we described in Section 2.2.7 the goal of the grapheme-to-phoneme conversion is to create the phoneme transcription out of the word sequence, comprising the input lyrics for a particular vocal section.

TARGETKIND = MFCC_0_D_A_Z
TARGETRATE = 100000.0
WINDOWSIZE = 250000.0
USEHAMMING = T
PREEMCOEF = 0.97
NUMCHANS = 26
CEPLIFTER = 22
NUMCEPS = 12
HIFREQ=8000

Table 3.3: Parameters of MFCC extraction (in the HMM toolkit format)

A phonetic recognizer HMM can be represented as a DBN with a single hidden state for the current phoneme (Figure 3.4). In all DBN diagrams in this thesis we use circles and squares to denote continuous and discrete variables, respectively. Also gray nodes and white nodes represent observed and hidden variables, respectively. Although in initial experiments we trained a 3-state-HMM per phoneme, in most of the work in this study a single-state HMM was preferred. Preliminary experiments revealed that the alignment accuracy with 3-states is not noticeably better than that with one state. In this section we present the derivation of the phoneme network for Turkish language, in alignment with the focus of this chapter on the OTMM music. While in general the derivation of the phoneme network used for Jingju is following the same principles, some Mandarin-particular details are discussed in Section 4.5.1.

Graphene-to-phoneme conversion

The words are expanded to phonemes based on a phonetic alphabet, designed for each particular language. For this sake linguists have developed the international phonetic alphabet (IPA) - a language-independent notation system of phoneme sounds [10]. For each language exists one or several options for an alphabet of machine-readable representation of IPA. For Turkish we have adopted the alphabet METUbet, proposed for one of the speech recognition state-of-the art systems for Turkish [Özgül Salor et al., 2007, Table 1]. METUbet is very easy to interpret, because of its intuitiveness. All latin written characters are mapped to their corresponding latin phoneme, while the characters ç, ş, ı, ö, ü unique for Turkish language, are mapped to capital

[10] https://en.wikipedia.org/wiki/International_Phonetic_Alphabet

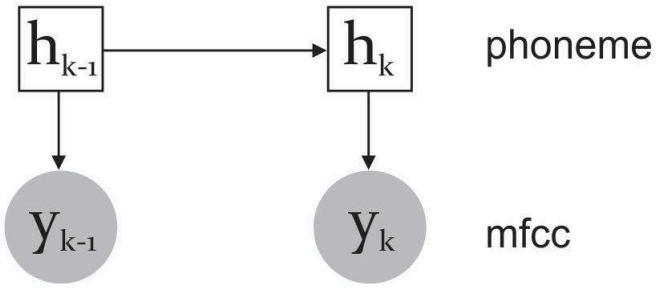


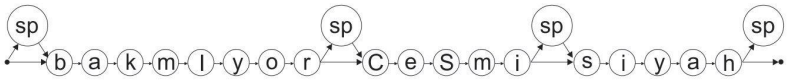
Figure 3.4: DBN for the baseline phonetic recognizer: a hidden state represents the phoneme state. Circles and squares denote continuous and discrete variables, respectively. Gray nodes and white nodes represent observed and hidden variables, respectively.

letters - respectively C, S, E, OE, UE. The unpronounced ğ is omitted from the transcript, whereas g is represented as GG.

After the grapheme-to-phoneme conversion optional filler silence tokens are inserted in between words. A silence model represents short non-voiced time intervals, when singing voice is not active to accommodate silent pauses or breaths between words. Using METUbet the lyrics phrase *bakmıyor çeşmi siyah* is expanded to a phoneme sequence seen in Figure 3.5a. Square brackets denote zero or one occurrence of a token, and vertical bars denote alternatives. Its corresponding phoneme network is depicted in Figure 3.5b.

[sp] b a k m I y o r [sp] C e S m i [sp] s i y a h [sp]

(a) Phoneme sequence for the lyrics phrase *bakmıyor çeşmi siyah*.



(b) Phoneme network for the lyrics phrase *bakmıyor çeşmi siyah*.

Figure 3.5: An example of the phoneme sequence and phoneme network for the phrase *bakmıyor çeşmi siyah* for a cappella voice. The phoneme set used is the Turkish METUbet

Handling accompaniment artifacts

The phoneme network for accompanied singing ideally should be identical to the a cappella one presented above. In practice however, some of the phonemes in the accompaniment attenuation process are not accurately resynthesized. To address such cases, we build the network in a flexible way.

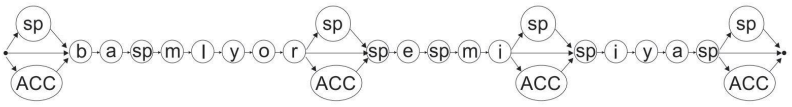
Except for silences, another filler model for non-vocal parts is introduced: a model for the instrumental background. We assume that the stochastic characteristics of the background music could be approximated by those of the instrumental-only regions in a music recording. We trained therefore a GMM for accompaniment instruments (ACC) from the time intervals, which are not annotated as words in the test dataset. It has a substantial amount of mixtures (40) to be able to capture the diverse timbral characteristics of background instruments. It is integrated as a single-state-HMM in the phoneme network. Setting the filler models as optional lets the phonetic recognizer activate the ACC model, depending on whether sound from background instruments was re-synthesized by the sinusoidal model, due to short regions, detected falsely as being vocal (see accompaniment attenuation step). In addition, this also accommodates potential instrumental leaks due to automatically detected boundary timestamps of vocal sections, displaced from the actual boundaries of sung lyrics.

A side effect of the resynthesis is that non-voiced consonants are not synthesized, which leaves short time intervals of silence. Looking carefully at Figure 3.3b one can notice that the time intervals for most METUbet unvoiced consonants: *k*, *S*, *s*, and *h* are converted into silences. Fujihara et al. [2011] suggested to tackle this problem by incorporating a separate method for detection of unvoiced consonants in the musical audio. The strategy we used instead is replacing unvoiced consonants by silence in the phoneme sequence. For example, for the phrase *bakmıyor çeşmi siyah* it will look accordingly in Figure 3.6a.

Figure 3.6b presents its corresponding phoneme network. We evaluated the contribution of this simple resynthesis handling strategy by comparing to the performance of alignment between the resynthesizes audio and the phoneme network of Figure 3.5b that is meant for a cappella singing. The results (see Table 3.6) outlined a slight improvement with the accompaniment aware network. We inspected carefully the flawed alignment cases with the a cappella

[sp|ACC] b a sp m I y o r [sp|ACC] sp e sp m i [sp|ACC] sp i y a sp [sp|ACC]

(a) Phoneme sequence for the lyrics phrase *bakmıyor çeşmi siyah*.



(b) Phoneme network for the lyrics phrase *bakmıyor çeşmi siyah*.

Figure 3.6: An example of the phoneme sequence and phoneme network for the phrase *bakmıyor çeşmi siyah* when accompanying instruments are present. The phoneme set used is the Turkish METUbet

phoneme network. This revealed that sometimes when there is a fricative in the vicinity of an inter-word *sp* (for example the *ş* from *çeşmi* following the *sp* between *bakmıyor* and *çeşmi*) the Viterbi would confuse the model of *sp* with the MFCCs for the fricative sound, due to the similarity of the phoneme acoustics of the two. This means that usually a couple of phoneme models (ç and e in this example) are assigned falsely to the MFCCs frames of the inter-word silence, which is extended in longer time than it should be. Respectively sometimes instead of such 'delays' os the *sp* model there are premature 'jumps' due to the same fricative confusion. In contrast, when there are leaks of accompaniment sounds, the added ACC model helps in distinguishing between the fricative and silence/ACC.

3.4 Training the acoustic model

To represent the probability $p(y_k|x_k)$ of observing the MFCC feature vector y_k at a time instant k, given a phoneme x_k, a classifier of the different phonemes is needed. In essence, for a phonetic recognizer a hidden variable is the current phoneme class x_k(see Figure 3.4). The phoneme classifier has to represent the acoustic specificities between the different phoneme classes. In this Section we present how to train GMMs and MLPs - two types of classifiers. In short, we refer to the phoneme models as the *acoustic model*.

3.4.1 Gaussian mixture models

As presented in Section 2.2.7 the GMMs until recently have been the de facto choice of phonetic timbre classifier. GMMs have the ability, given enough mixtures, to approximate arbitrarily shaped densities. It is reasonable to as-

sume that each mixture represents a broad class of a phonetic timbre event. Another major reason to be utilized for representing phonetic timbre is that by means of the so called *embedded reestimation* technique it is relatively straightforward to train the GMM parameters even from material with no phoneme annotations. Embedded reestimation is an generalization of the Expectation Maximization algorithm over time-series of feature vectors and has an efficient implementation in the HMM toolkit (*htk*) [Young, 1993]. Applying *htk* we fitted a 9-component GMM for each phoneme on feature vectors extracted from a dataset of Turkish speech Özgül Salor et al. 2007. It encompasses diverse speech recordings totaling to approximately 500 minutes. Preliminary experiments confirmed that the trained models can successfully recognize withheld material from the same dataset.

To address the acoustic differences between speech and singing an adaptation of the trained GMMs to singing material is needed. However due to lack of sufficient adaptation material we did not perform any adaptation. Instead of that we explored the option of using neural networks for the observation model.

3.4.2 Multilayer perceptron neural networks

Recent work on keyword spotting in English a cappella singing showed that a MLP trained on singing-like material results in much better accuracy, compared to a GMM, trained on speech Kruspe [2015b].

This motivated us to take the opportunity to consider the deep MLP model the authors trained from amateur singers in their subsequent work - [Kruspe and Fraunhofer, 2016]. We introduced their training procedure in Section 2.2.8 and will refer to their model as *MLP-English*. The *MLP-English* has 3 hidden layers with sigmoid activation function. The layers have respectively 1024, 850 and 1024 neurons and have as input the first 13 MFCCs, extracted with the *htk* extraction parameters, described in 3.3.3 plus their deltas and accelerations. This results in a 39-dimensional feature vector. The phonetic alphabet used is the English-specific encoding of IPA from Carnegie Mellon University (CMU)[11].

Since we did not have as many Turkish singing voice phoneme annotations sufficient for training a deep MLP, we simply adapted the *MLP-English* to Turkish. We exploited two cross-language phoneme mapping strategies: direct mapping and fuzzy mapping

[11] http://cmusphinx.sourceforge.net/

METUbet	IY	AA	UE	E	LL	I	O	M	U	OE	NN	VV
CMU	iy	aa	y	eh	l	ax	ao	m	uw	ow	n	v

METUbet	Z	C	ZH	H	CH	B	D	GG	F	KK	P	S	RR
CMU	z	jh	zh	hh	ch	b	d	g	f	k	p	s	r

Table 3.4: Direct mapping of English CMU phonemes to Turkish METUbet. Upper row vowels and liquids. Lower row all the rest consonants.

Direct cross-language mapping

As observation probability for each Turkish phoneme we substituted the probability of an English phoneme from the output layer of the *MLP-English*. The mappings we used are listed in Table 3.4.

To most phonemes in Turkish corresponds an English phoneme that represents a sound with perceivably the same acoustics. The only two Turkish phonemes not existing in English are OE and UE, for which we experimented with different mappings and ended up with respectively *ow* and *y* as most optimal.

Fuzzy cross-language mapping

A more reasonable alternative to enforcing a phoneme to be represented by exactly one phoneme from another language is a weighted sum of the acoustics of a set of similar phonemes. Such types of 'fuzzy' many-to-one mapping strategy has been proposed for speech synthesis of a given speaker from her mother tongue to another language by Sun et al. [2016]. Adopting the core idea of their concept we trained GMM model in the steps presented in Figure 3.7. First the extracted MFCC features from a cappella vocal OTMM dataset are input to the *English-MLP* and a vector of the posterior probabilities $p(s_n|x_k)$ of the $n = 39$ English phoneme classes for each time frame k are generated (see left half of Figure 3.7). These phonetic posterior probabilities are commonly known as posteriograms. Then in a second stage, a new model is trained to capture the mapping relationships between the posteriograms $p(s_n|x_t)$ and the 38 Turkish phoneme classes. The posteriograms are fed into the classifier as if they were the acoustic feature vectors. While Sun et al. [2016] built another deep neural network, we preferred a 2-component GMM classifier, because GMMs could handle training material with data size as small as 30 minutes of phoneme-annotated singing. Note that arguably one could train GMMs by embedded reestimation to avoid the need of phoneme annotations. However we preferred carefully done manual annotations of phoneme boundaries to

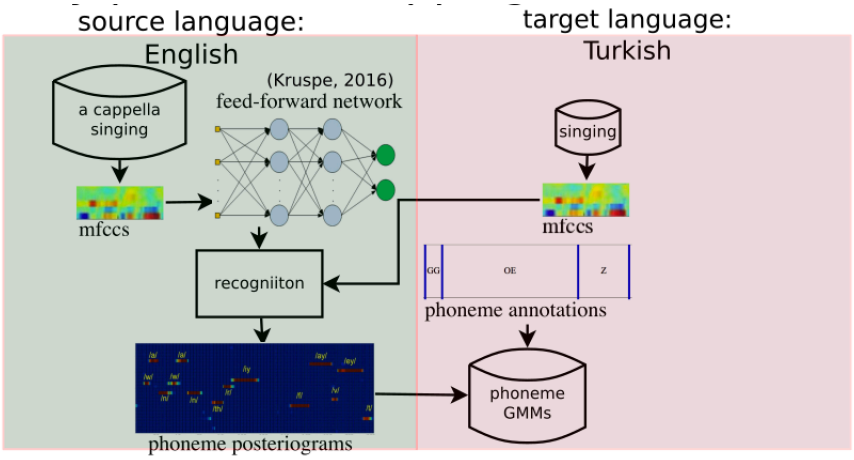


Figure 3.7: Cross-language phoneme mapping strategy from the source language (English) to the target language (Turkish). The English-MLP feed-forward network is trained on a huge singing voice dataset, whereas the GMMs are trained with phoneme annotations of a subset of the small *a cappella vocal Makam* dataset.

make sure proper mappings. Then on recognition the English posteriograms are generated in the same way as in training. Training of the GMMs was conducted with leave-one-recording-out cross validation.

We compared the two mapping strategies with the GMM model trained with Turkish by evaluating the percent of correctly identified phoneme time frames. The percent of correct frames has been used to evaluate the accuracy of the *MLP-English* model. This is done by setting to 1 the phonemes with maximum posterior probability for each time frame and zero to the rest of the phonemes. Then this sparse activation matrix is intersected with an oracle matrix, inferred from manually annotated phoneme boundaries.The first two models were evaluated on the whole phoneme-annotated subset of the *a cappella vocal OTMM dataset,* whereas the MLP-FuzzyM in the leave-one-recording-out cross validation manner.

The direct mapping of the *English-MLP* evidences a major improvement over the GMMs trained on speech (Table 3.5). It still scores reasonably worse than the reported 23 % in Kruspe and Fraunhofer [2016] on excerpts from the same English dataset with which it was trained. This large margin indicates that the direct mapping strategy may not be the most optimal one. Surprisingly the

model	% correct frames
GMM	9.8
MLP-DirectM	15.4
MLP-FuzzyM	9.2

Table 3.5: Percent of correctly identified phoneme frames for the 3 different phoneme models utilized: GMM trained from Turkish speech, *MLP-English* model mapped directly to Turkish phonemes, *MLP-English* model mapped by the proposed fuzzy phoneme mapping strategy.

fuzzy mapping strategy did not yield improvement over the baseline GMM. We believe that the explanation lies in the very small size of the training singing dataset with phoneme annotations. We attribute the remarkable improvement of the English-to-Turkish directly mapped model to the big learning capacity of a deep feedforward neural network.

3.5 Experiments

We compared the performance of the baseline phonetic recognizer for OTMM with different variants of the acoustic model: with GMM models and direct mapping to English-phonemes MLP. Experiments are carried out on the *a cappella lyrics OTMM dataset* (Section 3.2.2) and the *multi-instrumental lyrics OTMM dataset* (Section 3.2.1). To assess the effectiveness of the accompaniment attenuation (AA) step, we aligned the multi-instrumental recordings from the *a cappella lyrics OTMM dataset* with and without AA. We presents also results of the GMM with instrumental accompaniment and omitting the AA step. When accompanying instruments are present, we employed the modified phoneme network, which can handle possible artifacts from the AA step (see Section 3.3.4).

3.5.1 Evaluation metrics

Throughout this thesis, we evaluate the LAA by the metrics *average absolute error* and *accuracy (percentage of correct segments)*, introduced in Section 2.2.1.The alignment error and accuracy are computed at boundaries of the lyrics phrases, as manually annotated.

	accuracy	error
a cappella GMM	70.2	1.14
a cappella direct mapping	79.2	0.57
accompanied GMM (no AA)	52.1	2.15
accompanied GMM (no accompaniment handling)	63.2	1.98
accompanied GMM	67.5	1.26
HMM+adaptation Mesaros and Virtanen [2008]	-	1.4
HMM+ singer adaptation Fujihara et al. [2011]	85.2	-

Table 3.6: Comparison of performance of the baseline phonetic recognizer with different variants of the acoustic model. Evaluation is performed on both a cappella and accompanied singing from OTMM. Alignment accuracy and alignment error on the boundaries of lyrics phrases and reported on total for all recordings.

3.5.2 Discussion

Table 3.6 lists results for the different system variants and steps of the recognizer.

We observed that a problem is that alignment performs poorly towards the end of longer sections, which results in outliers of huge magnitude.

Although coming from different genre and language, we compare our alignment results to the best hitherto alignment systems for English pop songs [Mesaros and Virtanen, 2008] and for Japanese pop [Fujihara et al., 2011]. These are abbreviated in Table 3.6 respectively as *HMM + adaptation* and *HMM + singer adaptation*. In these works alignment is evaluated also on the level of a lyrical line/phrase. Our baseline approach differs from both works essentially in that they conduct speech-to-singing-voice adaptation. In comparison, we did not perform any adaptation of the original speech model. Adaptation data of clean singing voice for a particular singer might not always be available and thus does not allow the system to scale to data from unknown singers. Our baseline's best error on the multi-instrumental material is comparable to the system of Mesaros and Virtanen [2008], but still far from the accuracy of Fujihara et al. [2011]. The most possible explanation is the acoustic mismatch between our phoneme GMMs and the characteristics

of singing voice. This is confirmed by the rather low results on a cappella singing. Training phoneme acoustics merely on speech is clearly suboptimal. The high score of the *English-MLP* confirms that training on singing voice is a big advantage.

Moreover, Fujihara et al. [2011] trains a SVD module on data selected from material with same acoustic characteristics as the test data. The SVD module showed to notably increase the average accuracy of 72.1 % for a baseline to accuracy of 85.2 % for their final system. Investigating our results with low accuracy revealed that false positives of our AA module is a considerable reason for misalignment. Unlike Fujihara et al. [2011], we did not tailor the parameters of the harmonic model (built for Western popular music) to the specificities of our test dataset.

3.6 Summary

In this chapter we described our lyrics-to-audio alignment (LAA) baseline system. It is a phonetic recognizer, based on phoneme HMMs. We described the choices of the key steps of the phonetic recognizer, which are not related to modeling complementary context. Phoneme observation modeled as GMMs, trained on Turkish speech proved to be not the most optimal acoustic model. The alignment accuracy on a cappella (70.2 %) is rather low; whereas on multi-instrumental recordings (67.5%) is below the state of the art on LAA on English pop songs (85.2 %). The most possible explanation is the acoustic mismatch between our phoneme GMMs and the characteristics of singing voice. To address this mismatch, we proposed a strategy of mapping a state-of-the-art model for English, trained on English pop songs, to Turkish. We explored two different mapping strategies. The simpler direct mapping increased significantly the alignment accuracy (79.2 %). To our knowledge, this is the first work on computational modeling of sung lyrics, addressing the problem of inter-language phoneme mapping.

All the experiments presented in the following two thesis chapters are carried out with phoneme GMMs. This is because the mapping strategies were explored once the *English-MLP* became available (towards the end of this study[12]). However, the validity of the experiments in this thesis is not negatively influenced by that. Since the ultimate goal is to show that musical-context-aware modeling outperforms the baseline approach presented in this chapter, the absolute score of the baseline itself is of lesser importance.

[12] August 2016

Chapter 4

Lyrics-to-audio Alignment with Middle-level Complementary Context

4.1 Introduction

In this chapter we propose how to improve the baseline lyrics-to-audio alignment method by considering some context facets, complementary to lyrics. We focus on one particular middle-level facet - the structure of the sung melodic line. To this end, we study the influence of the structure of the sung melodic line on its lyrics. Studies of sheet music have indicated that there is a correlation between the accents of sung syllables and the accents in the melodic phrase [Nichols et al., 2009]. Singers may often prolong or reduce the duration of some syllables, in order to align them with the melodic accents.

Music scores provide important contextual information complementary to lyrics, including note durations. Nevertheless, the length of sung syllables could deviate considerably from the durations indicated in the music score. Singers in OTMM in particular tend to deviate from the music score to a significantly larger extent, in comparison to, for example, eurogenetic pop music or classical music. To address this, we propose an extension of the phonetic recognizer that models explicitly syllable durations. The proposed duration aware model is designed to accommodate duration variations. The major technical contribution of this chapter is the derivation an inference method for the model. Information about the durations is obtained from the music score. To our knowledge, this study is the first application of modeling of

music-score-induced duration for sung syllables.

To proof the transferability of the proposed explicit-duration model outside of OTMM, we evaluate on material from Jingju. The comparison to Jingju has an aim to quantitatively evaluate if the the duration knowledge contributes to a different degree for another music tradition. Jingju is a music tradition, characterized by sung syllables that span particularly long time intervals. Being a largely oral tradition, it rarely has machine-readable music scores. Instead, to determine how long to sustain a given syllable, actors follow specific principles for the structure of the melodic phrase. Therefore we apply the same core probabilistic model, whereby syllable durations are derived from these principles, instead of score. Among all the approaches presented in this thesis, this is the clearest example of an approach informed by music-specific knowledge.

The chapter is organized as follows: We start off by introducing existing computational approaches of lyrics tracking, which explicitly model durations of syllables (Section 4.2). In Section 4.3 we introduce the core probabilistic model. Then we describe the application of the inference in two different use cases: Firstly, in Section 4.4 we study how durations parsed from music scores in OTMM can be utilized as input reference syllable durations. Secondly, the core model is applied also to Jingju, for which reference durations are obtained from music-specific knowledge in the form of rules (Section 4.5).

4.2 Background on duration aware lyrics-to-audio alignment

The phonetic recognizer approach is based on phoneme HMMs. Standard HMMs have the drawback that they do not impose any restrictions on the waiting time in a state, resulting in geometric distribution. This does not correspond to the naturally occurring durations of phonemes in speech. Introducing restrictions on the state waiting time of the phoneme HMMs improves speech recognition results [Ferguson, 1980].

Unlike speech, for which the variation of the durations of the vowels is relatively small, sung vowels can have significantly bigger variations. HMMs are by far not capable to represent well vowels with long and highly variable durations. This is because the waiting time implied by a geometric distribution cannot be unlimitedly long [Rabiner, 1989]. Durations can be modeled instead by a duration-explicit hidden Markov model (DHMM) (also known as hidden semi-Markov model). In DHMMs the underlying process is allowed to be a semi-Markov chain with variable duration of each state [Yu, 2010].

The idea of the DHMM is that the actual waiting time in a state can be seen as being generated by any statistical distribution. Common choices are the gamma distribution or normal distribution, whereby the distribution's parameters can be set by using some a-priori knowledge about the waiting time. In this respect, DHMM provide a flexible methodology that allows the injection of some music-specific context knowledge, from which the expected waiting time of a phoneme can be derived. An approach to detect keywords from a cappella English pop songs exploiting knowledge about possible phoneme durations is presented in [Kruspe, 2015a]. The author used a DHMM with a gamma distribution, motivated by findings that gamma distribution represents well naturally observed phoneme durations in speech. The mean and variance of each phoneme is empirically estimated from a small portion of a cappella dataset. The precision of keyword detection increased when durations were limited. A limitation is that the learned phoneme parameters do not take into account the structure of the melodic phrase, i.e. they estimate the duration of a phoneme globally for given data. In addition, DHMMs have been shown to be successful for modeling other problems from the domain of music information retrieval. They have been successful in representing chord durations in automatic chord recognition [Chen et al., 2012].

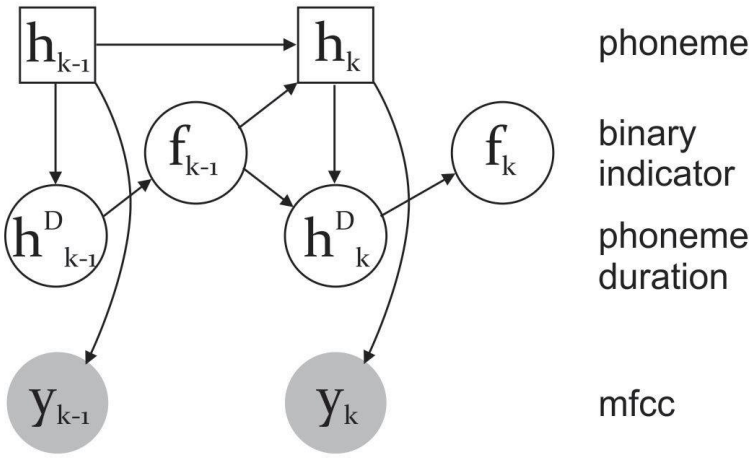


Figure 4.1: DBN representing the duration aware phonetic recognizer. A duration counter h^D keeps track of the waiting time in a phoneme state h. When h_D reaches 0, the binary indicator node f is fired, which triggers a change to next phoneme.

4.3 Duration aware probabilistic model

In this section we describe the core syllable-duration aware probabilistic model, presented first in Dzhambazov and Serra [2015]. In Figure 4.1 a DBN represented the duration time in a phoneme h explicitly as a duration counter variable h^D. When the duration counter expires (reaches 0), the indicator node f_k turns on, the current phoneme h_k can change state, and the next duration counter, h_k^D, is reset. The reason there is no h to f arc is that the duration termination process is deterministic [Murphy, 2002, Figure 2.22]. Inference in such a DBN with the Viterbi decoding will have time complexity of $O(TDH^2)$, where D is the maximal duration of the counter, T is the total time of a recording, and H is the number of phonemes in the phoneme network. In comparison to speech, the range of D for sung phonemes (especially in traditions like Jingju with reasonably long vowels) can cause an extremely big time complexity. In the case of forced alignment, however, it reduces to $O(TDH)$. Another limitation of the DBN is that due to the additional of a hidden counter variables h_D the size of the state space can become enormous.

To overcome that, we have adopted the idea of Chen et al. [2012] not to explicitly add the h^D to the model, but instead to extend the Viterbi decoding

to handle duration of states. Note that this does not reduce the time complexity. In what follows we describe a variation of Viterbi decoding method, in which maximization is carried over the most likely duration for each state. The duration counter is controlled by a normal distribution with mean derived from a lookup table of reference durations R_i, where i is the i^{th} phoneme in the phoneme network. The way the lookup table is constructed is related to how the complementary context is exploited and is the topic of sections 4.4 and 4.5

4.3.1 Parameter definitions

The Viterbi decoding is adapted from the procedure described in Chen et al. [2012]. We assume that the duration d for a state i may vary according to a normal distribution $P_i(d)$ with mean at the reference duration $d = R_i$ and standard deviation σ. We will use a separate global standard deviation σ_v for all vowels and a global one σ_c for all consonants. For the sake of representation simplicity, in the following equations we will use only one standard deviation σ. Now let us define:

R_{max} : $\max_i(R_i) + \sigma$

$b_i(O_k)$: observation probability for state i for feature vector O_k (comply with the notation of Rabiner [1989])

$\delta_k(i)$: probability for the path with highest probability ending in state i at time k (comply with the notation of Rabiner [1989, III. B]))

4.3.2 Recursion

The recursion step in the Viterbi algorithm is extended by adding the duration distribution $P_i(d)$ factor.

For $R_{max} < t \leq T$

$$\begin{aligned} \delta_k(i) &= \max_d \{\delta_{k-d}(i-1). \\ &\quad P_i(d)^{\alpha} \left[B_k(i,d)\right]^{1-\alpha}\} \end{aligned} \tag{4.1}$$

where

$$B_k(i,d) = \Pi_{s=k-d+1}^{k} b_i(O_s) \tag{4.2}$$

is the observation probability of staying d frames in state i until frame k. The domain of d comes from the normal distribution $(\max\{R_i - \sigma, 1\}, R_i + \sigma)$ and is reduced for states with reference duration $R_i < \sigma$.

A duration back-pointer is defined as

$$\begin{aligned} \chi_k(i) &= \arg\max_d \{\delta_{k-d}(i-1). \\ &\quad P_i(d)^\alpha \left[B_k(i,d)\right]^{1-\alpha}\} \end{aligned} \tag{4.3}$$

Note that in forced alignment the source state could be only the previous state from the phoneme sequence $i-1$, therefore the transition probabilities are omitted.

To be able to control the influence of the duration we have introduced a weighting factor α. Note that setting α to zero is equivalent to using a uniform distribution for $P_i(d)$.

4.3.3 Initialization

For $t \leq R_{max}$

$$\delta_k(i) = \max\{\delta_k(i)^*, \kappa_k(i)\} \tag{4.4}$$

where a reduced-duration delta $\delta_k(i)^*$ is defined in the same way as in Eq. (4.1) but

$$d \in \begin{cases} emptySet, & t \leq R_i - \sigma \\ (R_i - \sigma, \min\{t-1, R_i + \sigma\}), & else \end{cases} \tag{4.5}$$

reduces the duration to k when $k < R_i + \sigma$.

Lastly the probability of staying at initial state i at time k is defined as:

$$\kappa_k(i) = \pi_i P_i(k)^\alpha [\Pi_{s=1}^k (O_s)]^{1-\alpha} \tag{4.6}$$

for $k \in (1, R_i + \sigma)$.

4.3.4 Backtracking

Finally the decoded state sequence is derived by backtracking starting at the last state N and switching to a source state a number of $d = \chi_k(i)$ frames ahead according to the backpointer from Eq. 4.3.

4.4 Durations derived from music score

In this section we present an application of the duration aware model to singing from OTMM. Singers in OTMM tend to deviate from the music score to a significantly large extent. The goal of this study is to show that the duration aware models is capable to accommodate these duration variations. The lookup syllable duration table is constructed from information in the music score.

A general overview of the proposed approach is presented in Figure 4.2. As in all approaches presented in this thesis, first an audio recording is manually divided into segments according to the coarse level complementary context - the sections of the composition. In the case of Makam the boundaries of vocal section (one of zemin, nakarat, meyan) are indicated in the music score. An audio recording and its corresponding score are input. Relying on HMMs of phonemes the DHMM returns start and end timestamps of aligned lyrics phrases.

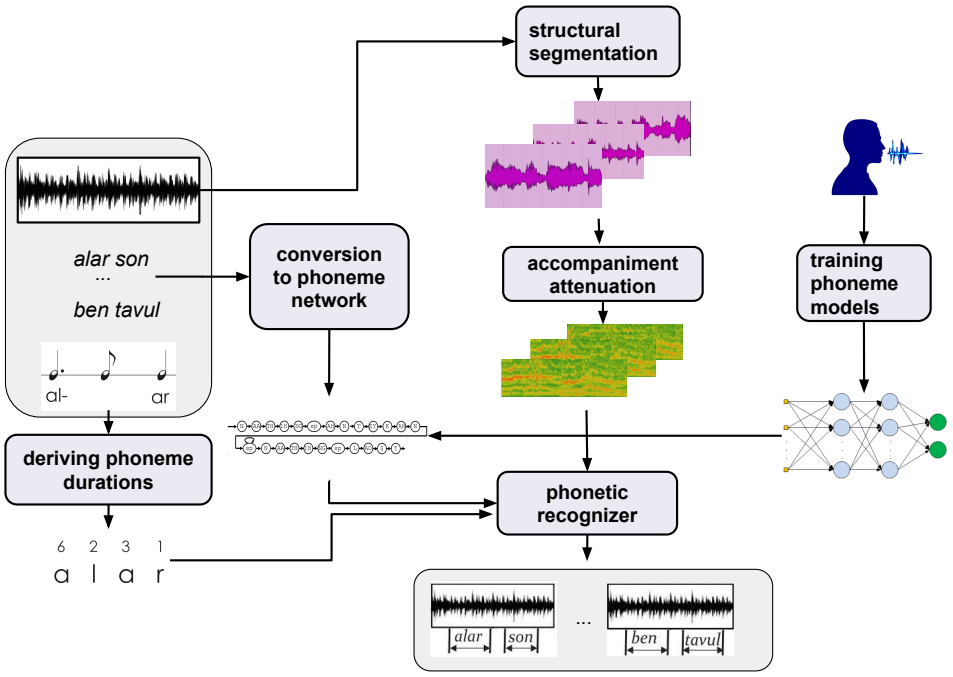


Figure 4.2: Overview of the steps of the lyrics-to-audio alignment system aware of phoneme durations. Durations are derived from the note values in the music score. The phonetic recognizer is a duration-explicit HMM

4.4.1 Deriving phoneme durations

For each lyrics syllable a reference duration is derived by summing the values of its corresponding musical notes (in units of 64th notes). Then the reference duration is spread among its constituent phonemes, whereby consonants are assigned constant duration and the rest is assigned to the vowel. Each consonants in a syllable is assigned a constant reference duration $R_i = 0.3$ seconds. To align a given recording the score-inferred lengths are linearly rescaled to match its musical tempo. After that scaling the unit of R_i becomes the number of acoustic frames.

4.4.2 Experiments

Alignment is performed on each manually divided audio section and results are reported per recording (on total for its sections). To assess the benefit

of the DHMM, results are compared to the baseline system, which is not aware of reference durations. Experiments are carried out on the *a cappella lyrics OTMM dataset* (Section 3.2.2) and the *multi-instrumental lyrics OTMM dataset* (Section 3.2.1).

We present results for the most optimal $\alpha = 0.97$. Most optimal standard deviations for vowels $\sigma_v$was found to be 0.7, while we fixed the one for consonants σ_c to 0.1 seconds, based on the fact that consonant durations do not vary significantly. These parameters were optimized by minimizing the alignment error on a separate development dataset of 20 minutes Turkish acapella recordings. To assure precision, we measured alignment of the development dataset on the word-level ground truth.

Evaluation metrics

Alignment accuracy is measured as the percentage of duration of correctly aligned regions from total audio duration (see Figure 2.1 for an example).

In addition, we define a metric *musical score in-sync* (MSI) to measure the approximate degree to which a singer performs a recording in synchronization with note values indicated in the musical score. Thus low accuracy of MSI indicates a higher temporal deviation from musical score. We compute MSI per a recording as the AA of score-inferred reference durations R_i compared to ground-truth, as if they were results after alignment.

Discussion

Table 4.1 presents comparison of the proposed DHMM system performance and the baseline system. It can be observed that modeling of durations with DHMM increases the accuracy by 10 absolute percent. One reason for this are cases of long vocals, in which the standard HMM switches to the next phoneme prematurely (due to its inability to stay long in a given state). In contrast, the duration-explicit decoding allows picking the optimal duration (which can be traced in an example in figure 4.3).

Figure 4.4 allows a glance at results per recording, ordered according to MSI. It can be observed that the DHMM performs consistently better than the baseline (with some exceptions, for which accuracy is close). Unlike the relatively stable accuracy for the a cappella case, when background instruments are present, the accuracy variates more among recordings.

For the sake of comparison, the alignment results of the best hitherto LAA systems for English pop songs [Mesaros and Virtanen, 2008] and for Japanese

System variant	alignment accuracy	alignment error
musical score in-sync	88.14	0.32
baseline a cappella	70.2	1.14
DHMM acapella	90.04	0.26
baseline polyphonic	67.46	1.26
DHMM polyphonic	77.74	0.63
HMM+adaptation Mesaros and Virtanen [2008]	-	1.4
HMM+ singer adaptation Fujihara et al. [2011]	85.2	-

Table 4.1: Alignment accuracy (in percent) for musical score in-sync; different system variants: baseline HMM and DHMM; state-of-the-art for other languages. Alignment accuracy is reported as total for all recordings. Additionally the total mean phrase alignment error (in seconds) is reported

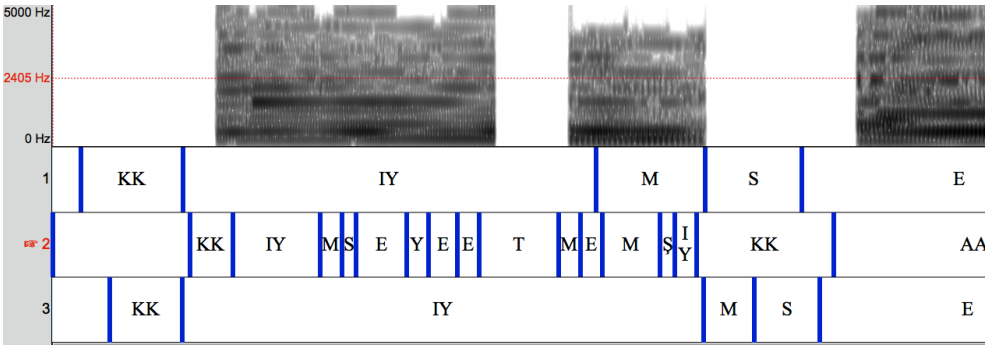


Figure 4.3: Example of decoded phonemes. *very top*: resynthesized spectrum; *upper level*: ground truth, *middle level*: HMM; *bottom level*: DHMM; (excerpt from the recording *Kimseye etmem şikayet* by Bekir Unluater)

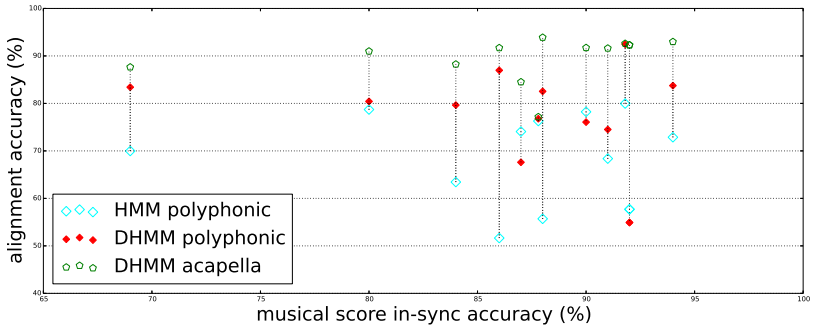


Figure 4.4: Comparison between results from DHMM (for both polyphonic and acapella) and the baseline HMM. Metric used is alignment accuracy. A connected triple of shapes represents results for one recording. Results are ordered according to *musical score in-sync* (on horizontal axis)

pop Fujihara et al. [2011] are also listed. These are abbreviated in Table 4.1 respectively as *HMM + adaptation* and *HMM + singer adaptation*. In these works alignment is evaluated also on the level of a lyrical line/phrase. Despite the lack of adaptation, our DHMM system yields results comparable to these reference approaches.

4.5 Durations derived from music knowledge

In Jingju the durations, indicated in scores are not so strictly observed as in OTMM. Instead as a reference usually serve the orally transmitted singing examples of master actors. During time, as part of this oral practice, specific rules have been formed: For example, if a poetry lyrics line has 10 syllables, a rule of thumb is that it consists of 2 3-syllable dous, followed by a 4-syllable dou. Respectively, if a poetry line has 7 syllables, it is a rule of thumb that it consist of 2 2-syllable dous, followed by a 3-syllable *dou* reference phoneme durations. These rules provide an excellent source to derive the phonemes reference durations for a duration-informed LAA. Therefore, we apply the duration aware probabilistic model (see 4.3), whereby syllable reference durations are derived from these principles, instead of the music score. The experiments in this Section are first presented in Dzhambazov et al. [2016b].

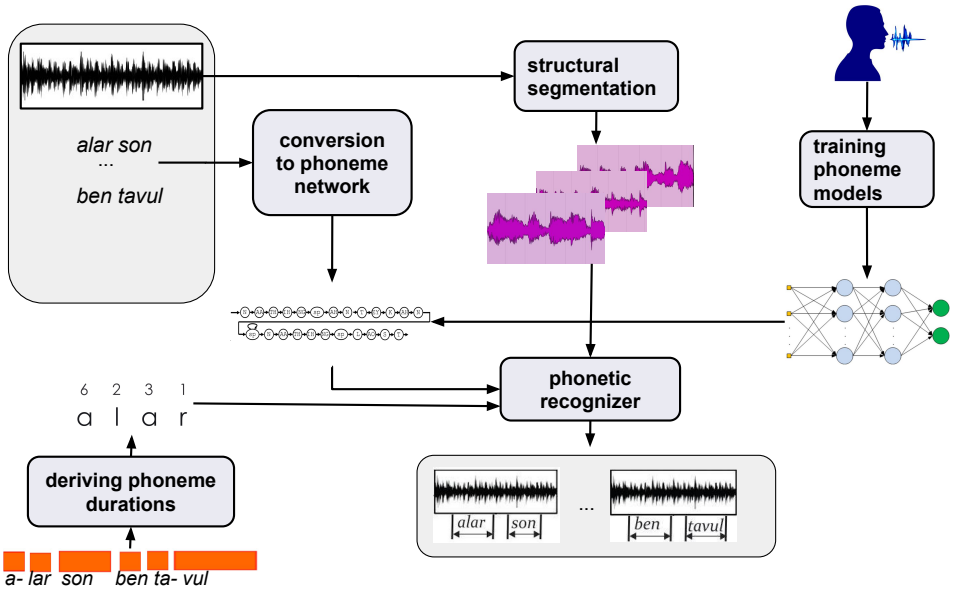


Figure 4.5: Overview of the steps of the lyrics-to-audio alignment system aware of phoneme durations. Durations are derived from music knowledge: the rules of durations of dous (syllable groups). The phonetic recognizer is a duration-explicit HMM

4.5.1 Steps of a phonetic recognizer

A general overview of the proposed approach is presented in Figure 4.5. As in all approaches presented in this thesis, first an audio recording is manually divided into segments according to the coarse level complementary context - the sections of the composition. In the case of Jingju as a section serves a lyrics line or a couplet (two lines). Because lyrics in Jingju are derived from poetry a lyrics line is in fact a lyrics sentence.

Training phoneme models The lyrics transcription in pinyin, divided into sentences for each aria, is expanded to phonemes based on grapheme-to-phoneme rules for Mandarin. A syllable-to-phoneme mapping table for Mandarin is used. Together with native Chinese speakers in the *CompMusic* team we created a mapping of pinyin syllables to the x-sampa phonetic alpha-

bet [1]. Due to the small amount of training material, and due to their relatively small ratio in total recording duration, most unvoiced consonants have been grouped into one class. Due to lack of publicly available Mandarin speech corpus, we trained the phoneme models on the Jingju a cappella dataset (3.2.4). To assure a reasonable amount of training data, we trained in a 3-fold manner, using 10 of the arias from the dataset. Each fold has 5 arias of around 40 minutes each. A mapping from the *MLP-English* to Mandarin was not endeavored, because it seemed infeasible due to the audibly significant differences in the acoustics of the Mandarin vowels. Diphthongs and triphthongs make the sound of vowels very dependent on the acoustic context.

The first 13 MFCCs and their delta and accelerations are extracted from 25ms audio frames with the hop size of 10ms from the a cappella singing. The extracted features are then fed to fit a GMM with 40 components for each phoneme. Phoneme-level annotations were used to train GMMs. Phoneme-level annotations were used to isolate the segments for each phoneme. For Jingju we prefer such a big number of mixture components to assure that it fits the varying acoustic conditions of the big number of diphtongs.

4.5.2 Music-knowledge-based durations

In Jingju an actor has the option to sustain the vocal of the *dou*'s final syllable. We will refer to the final syllable of a *dou* as *key syllable.* Therefore, reference phoneme durations are derived according to the *key syllables*, as follows:

Firstly, each *key syllable* in a *dou* is assigned longer reference duration, while the rest gets equal durations. Additionally, we observed in the dataset (see Section 3.2.4) that usually the last *key syllable* of the last sentence in a *banshi* is prolonged additionally. Thus we lenghtened additionally the reference syllable duration of these last *key syllables.* Figure 4.6 depicts an example. According to *dou* groups the 3rd, 6th and last syllable are expected to be prolonged. Note that these expectations often do not hold - in this example they do not hold for the 3rd syllable.

To apply the duration aware probabilistic model, we need to segment further the syllable reference durations down to phonemes reference durations R_i. To this end, the reference durations of syllables are divided among their constituent phonemes, according to the head-belly-tail division of syllables in Mandarin [Duanmu, 2000]. We assign consonants a fixed reference duration

[1] Part of the mapping (for diphthongs) rules can be found at https://github.com/georgid/AlignmentDuration/blob/noteOnsets/src/for_jingju/syl2ph.txt

$R_c = 0.3$ seconds, while the rest of the syllable is distributed equally among vowels. The reference durations R_i are linearly scaled to a reference number of frames according to the ratio between the number of phonemes in a lyrics line and the duration of its corresponding audio segment. In comparison to the model presented for OTMM, we opted for a separate standard deviation d_c for consonants, and d_v for vowels. Proper values for d_c and d_v assure that a phoneme sung longer or shorter than the expected R_i can be adequately handled.

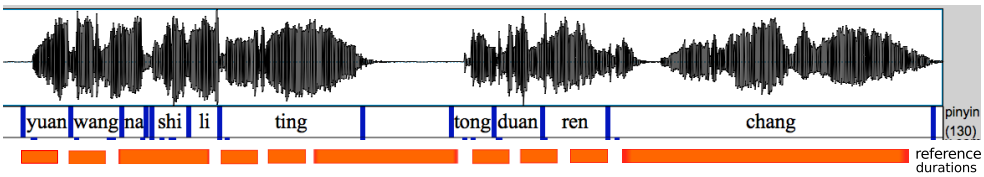


Figure 4.6: An example of 10-syllable sentence, being last in a *banshi* (before the *banshi* changes). Actual syllable durations are in pinyin, whereas reference durations are in orange parallelograms (below).

4.5.3 Experiments

Evaluation is carried on the dataset, presented in Section 3.2.4. Alignment accuracy is measured as the percentage of duration of correctly aligned regions from total audio duration (see Figure 2.1 for an example). In the context of this work a value of 100 means perfect matching of all Mandarin syllable boundaries from evaluated audio. Accuracy is measured for each manually segmented lyrics sentence and accumulated on total for all the recordings.

To define a glass ceiling accuracy, alignment was performed considering phoneme annotations as an oracle for acoustic features. Considering phoneme annotations, we set the probability of a phoneme to 1 during its time interval and 0 otherwise. We found that the median accuracy per a sentence of lyrics is close to 100%, which means that the model is generally capable of handling the highly-varying vocal durations of Jingju singing. Most optimal results were obtained with $\sigma_c = 0.7$; $\sigma_v = 3.0$

As a baseline we employed a standard HMM with Viterbi decoding with the *htk* toolkit Young [1993]. For both HMM and DHMM, because of the small size of the dataset, evaluation is done by cross validation on 3 folds with approximately equal number of syllables. Phoneme models are trained on 10 of the arias and evaluated on a 5-aria hold-out subset. Table 4.2 shows that the proposed duration model outperforms substantially the baseline alignment.

	oracle	baseline	DHMM
average	98.5	56.6	89.9
median per sentence	98.3	75.2	92.3

Table 4.2: Comparison of total oracle, baseline and DHMM alignment. Accuracy is reported as accumulate correct duration over accumulate total duration over all sentences from a set of arias.

Looking at oracle, one can conclude that reaching closer to it can be achieved in the future by improving the phoneme models, to capture phoneme identities in a more deterministic way.

4.6 Summary

In this chapter we proposed how to extend an HMM-based phonetic recognizer for lyrics-to-audio alignment by utilizing lyrics duration information as a cue, complementary to phonetic timbre. An advantage of the presented model is that it allows room for certain temporal flexibility to handle cases of significant deviation of sung vowels from the expected reference durations. We evaluated on material from two music traditions: OTMM and Jingju.

For OTMM reference phoneme durations are inferred from sheet music. The proposed model is tested on polyphonic audio recordings, as well as on an acapella dataset. Results show that the explicit modeling of phoneme durations outperforms a baseline approach, unaware of durations, by absolute 10 percent on the level of lyrics phrases. Information about durations can serves as a an important 'stepping stone' for the alignment process especially in the case of polyphonic audio, for which timbral features may not be deterministic enough. .

For Jingju we derived the expected syllable durations from music rules, specific for this music genre.

Chapter 5

Lyrics-to-audio Alignment with Fine-level Complementary Context

5.1 Introduction

In this chapter, we propose how to improve the baseline lyrics-to-audio alignment method by considering facets of fine-level context, complementary to lyrics. We focus on one particular fine-level facet - the accents in the metrical cycle (i.e. metrical accents). Metrical accents are an important mechanism that guides the structure of a melodic phrase. However, because it is not obvious to conceptualize the direct relation of metrical accents to syllable transitions. Instead, we investigate the relation of metrical accents to the positions of onsets (attacks) of sung notes in a melodic phrase. In this way, the influence of metrical events on syllable transitions is represented implicitly through its influence on note onsets, which are in turn influenced by metrical events. In this sense, metrical accents can be considered a facet of complementary context of lyrics.

With this motivation, we propose in the first part of the chapter a vocal onset detector that considers the simultaneously occurring accents in a metrical cycle. Vocal onset detection can be seen as a subtask of singing voice transcription. The model we propose extends a state of the art probabilistic model for beat tracking, in which a priori probability of a note at a specific position in the metrical cycle (i.e. metrical accent) interacts with the probability of observing a vocal note onset. Designing the transitions in the model in a

compact manner is the first major contribution of this chapter.

In the second part of the chapter, we address the relation of the phoneme transitions to simultaneously occurring vocal onsets. A well known fact is that when singing voice switches from the current syllable to another one, simultaneously with the change of timbre a vocal note onset is perceived. More precisely, the first voiced sound in a syllable bears the onset of a new note. Because such relations between vocal onsets and phonemes have not been previously formalized in a computational study, the second major contribution of this chapter is conceptualizing onset-aware phoneme transition rules. We propose also how to integrate these transition rules into the transition model of a HMM, which contributes to a more intuitive inference logic. To test the feasibility of the proposed model, we aligned lyrics to audio utilizing manually annotated onsets. Further, we explore how automatically detected vocal onsets can replace the onset annotations. Using automatic singing transcription to detect the vocal onsets instead of score-informed methods reduces the need of music scores. Evaluation is carried out on a cappella material from OTMM.

We start this chapter off by reviewing existing methods for singing voice transcription and existing methods for tracking metrical accents (i.e. beats) (Section 5.2). In Section 5.3 we explore how the accuracy of vocal onset detection can be increased by simultaneously tracking beats in a metrical cycle. Finally, in Section 5.4 we present a study of how the detected note onsets influence the transitions between consecutive phonemes. The novel phoneme transition rules and their integration into the transitions of a HMM are presented respectively in Sections 5.4.1 and 5.4.2.

5.2 Background

5.2.1 Automatic transcription of singing voice

The process of converting an audio recording into some form of musical notation is commonly known as automatic music transcription. Current transcription methods use general purpose models, which are unable to capture the rich diversity found in music signals Benetos et al. [2013]. In particular, singing voice poses a challenge to transcription algorithms because of its high degree of expressive elements such as soft onsets, portamento and vibrato. One of the core subtasks of singing voice transcription (SVT) is detecting note events with a discrete pitch value, an onset time and an offset time from the estimated time-pitch representation.

In recent years there has been a substantial amount of work on the extraction of pitch from both a cappella singing [Babacan et al., 2013, Molina et al., 2014] and predominant singing voice from polyphonic music [Salamon et al., 2014]. This has paved the way to an increased accuracy of singing voice transcription algorithms. One of the reasons for this is that a correctly detected melody contour is a fundamental precondition for SVT.

A probabilistic note HMM is presented in Ryynänen [2004], where a note has 3 states: attack (onset), stable pitch state and silent state. The transition probabilities are learned from data. Recently Mauch et al. [2015] suggested to compact the musical knowledge into rules as a way to describe the observation and transition likelihoods, instead of learning them from data. The authors cover a range with distinct pitch from lowest MIDI C2 up to B7. Each MIDI pitch is further divided into 3 sub-pitches, resulting in $n = 207$ notes with different pitch, each having the 3 note states. Although being conceptually capable of tracking onsets in singing voice audio with accompaniments, these approaches were tested only on a cappella singing. In multi-instrumental recordings, an essential first step is to extract reliably the predominant vocal melody. One of the few works dealing with SVT for polyphonic recordings Kroher and Gómez [2016], Nishikimi et al. [2016] rely on the algorithm of for predominant melody extraction Salamon and Gómez [2012]. Time deviations of sung vocal onsets from the onsets indicated in musical score are modeled in a probabilistic way in Nishikimi et al. [2016]. As a primary step of the note transcription stage, notes are segmented by a set of flamenco-specific onset detection rules, based on pitch contour and volume characteristics.

5.2.2 Beat Detection

Recently a Bayesian approach, referred to as the *bar-pointer* model, has been presented [Whiteley et al., 2006]. It describes events in music as being driven by their current position in a metrical cycle (i.e. musical bar). The model represents as hidden variables in a hidden Markov model (HMM) the current position in a bar, the tempo, and the type of musical meter.

The work of Holzapfel et al. [2014] applied this model to recordings from non-Western music, in order handle jointly beat and downbeat tracking. The authors showed that the original model can be adapted to different rhythmic styles and time signatures, and an evaluation is presented on Indian, Cretan and Turkish music datasets.

A modification of the bar-tempo state used in this work that optimizes its size, was later suggested by Krebs et al. [2015].

5.3 Beat-aware note onset detection

Metrical accents are a facet of complementary context that defines the rhythmic backbone of a melodic phrase. As such, metrical accents are an important mechanism behind the structure of a melodic phrase. Therefore it is worth studying how the transitions between syllables and words interacts with these accents. By *metrical accents* we will refer to notes that are emphasized as a result of the context of the musical meter. Naturally, accents occur on the beats, whereby downbeats (the first beat in a meter) will be perceived as being stronger accentuated. Detecting the times of vocal note onsets can benefit from automatically detected events from complementary musical facets, such as musical meter. In fact, the accents in a metrical cycle determine to a large extent the temporal backbone of singing melody lines. Studies on symbolic music data showed that the timestamps where vocal note onsets occur are influenced by the their position in a metrical cycle [Huron, 2006, Holzapfel, 2015]. .

Vocal onsets are usually soft, in contrast to some instruments with percussive onsets, which makes it hard to be automatically located. Vocal onset detection in multi-instrumental music is, in fact, one of the hardest MIR problems. Determining their exact onset timestamp is even harder in OTMM because of expressive singing phenomena: melodic onsets are often approached by slurs and melismas. Therefore any complementary information can be an important 'stepping stone' for increased detection accuracy.

In this section we make a hypothesis that the knowledge of the current position in a metrical cycle (i.e. metrical accent) can improve the accuracy of vocal note onset detection. To this end we propose a novel probabilistic model to jointly track beats and vocal note onsets.

5.3.1 Model Architecture

The proposed approach extends the beat and meter tracking model, presented in Holzapfel et al. [2014]. We adopt from that model the variables for the position in a metircal cycle (bar position) ϕ, the instantaneous tempo $\dot{\phi}$ and the rhythmic pattern r, related to the metrical cycle type. We also adopt the observation model, which describes how the metrical accents (beats) are related to an observed onset feature vector y_f. All variables and their conditional dependencies are represented as the hidden variables in a DBN (see Figure 5.1).

In this chapter we study how the *a priori* probability of a note at a specific

metrical accent interacts with the probability of observing a vocal note onset. To represent that interaction we add a hidden state for vocal note n, which depends on the current position in the metrical cycle. The probability of observing a vocal onset is derived from the emitted pitch y_p of the vocal melody.

In a DBN, an observed sequence of features derived from an audio signal $y_{1:K} = \{y, .., y_K\}$ is generated by a sequence of hidden (unknown) variables $x_{1:K} = \{x_1, ..., x_K\}$, where K is the length of the sequence (number of audio frames in an audio excerpt). The joint probability distribution of hidden and observed variables factorizes as:

$$P(x_{1:K}, y_{1:K}) = P(x_0)\Pi_{k=1}^{K} P(x_k|x_{k-1})P(y_k|x_k) \tag{5.1}$$

where $P(x_0)$ is the initial state distribution; $P(x_k|x_{k-1})$ is the transition model and $P(y_k|x_k)$ is the observation model.

5.3.2 Hidden variables

At each audio frame k, the hidden variables describe the state of a hypothetical bar pointer $x_k = [\dot{\phi}_k, \phi_k, n_k, r_k]$, representing the instantaneous tempo, the bar position, the note state, and a rhythmic pattern indicator, respectively.

Tempo state $\dot{\phi}$ and bar position state ϕ

The bar position ϕ points to the current position in the metrical cycle (bar). The instantaneous tempo $\dot{\phi}$ encodes how much bar positions the pointer advances from the current to the next time instant. To assure feasible computational time we relied on the combined bar-tempo efficient state space, presented in Krebs et al. [2015]. To keep the size of the bar-tempo state space small, we input the ground truth tempo for each recording, allowing $\dot{\phi}$ to deviate within ±10 bpm from it. Another motivation to limit the tempo in such a way is avoiding possible octave errors in the beat tracking, which would not be desirable for beat-aware note onset detection. This yields around 100-1000 states for the bar positions within a single beat (around 10K for usuls).

Note state n_k

The note states represent the temporal segments of a sung note. They are a modified version of these suggested in the note transcription model of Mauch et al. [2015]. We adopted the first two segments: attack region (A), stable pitch

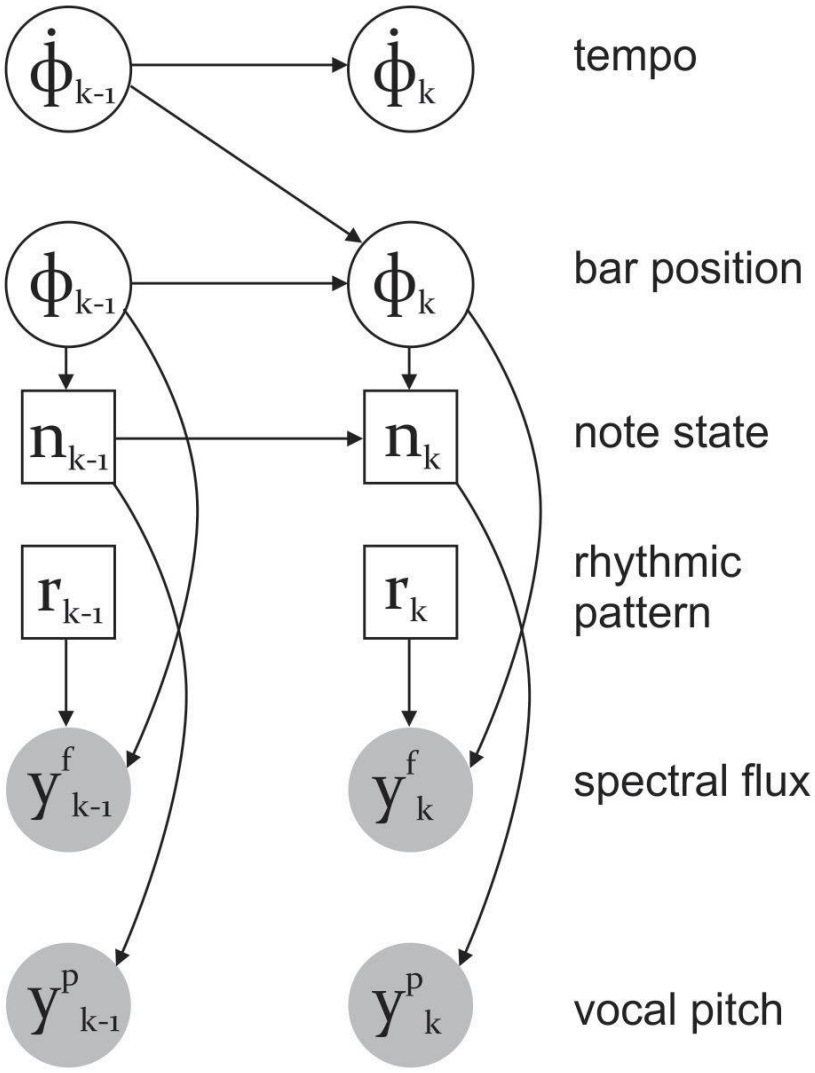


Figure 5.1: DBN for the proposed beat and vocal onset detection model.

region (S). We replaced the silent segment with non-vocal state (N). Because full-fledged note transcription is outside the scope of this work, instead of 3 steps per semitone, we used for simplicity only a single one, which deteriorated just slightly the note onset detection accuracy. Also, to reflect the pitch range in the datasets, on which we evaluate, we set as minimal MIDI note E3 covering almost 3 octaves up to B5 (35 semitones). This totals to 105 note states.

Rhythmic pattern r_k

A rhythmic patterns indicates the pattern of accents in a metrical cycle. For simplicity we use only one rhythmic pattern for each metric cycle. Let also $\theta(r)$ denote the number of beats in a rhythmic pattern r. Since the metrical type for each recording from the dataset is known a priori, a hidden state for the rhythm pattern is not modeled explicitly.

To be able to represent the DBN as a hidden Markov model, the bar-tempo efficient state space is combined with the note state space into a joint state space x. The joint state space is a cartesian product of the two state spaces, resulting in up to 10K x 105 = 1M states.

5.3.3 Transition model

Due to the conditional dependence relations in Figure 5.1 the transitional model factorizes as

$$\begin{aligned} P(x_k|x_{k-1}) = \quad & P(\dot{\phi}_k|\dot{\phi}_{k-1}) \times \\ P(\phi_k|\phi_{k-1}, \dot{\phi}_{k-1}) \times \quad & P(n_k|n_{k-1}, \phi_k) \end{aligned} \tag{5.2}$$

The tempo transition probability $p(\dot{\phi}_k|\dot{\phi}_{k-1})$ and bar position probability $p(\phi_k|\phi_{k-1}, \dot{\phi}_{k-1})$ are the same as in Holzapfel et al. [2014]. Transition from one tempo to another is allowed only at bar positions, at which the beat changes. This is a reasonable assumption for the local tempo deviations in the analyzed datasets, which can be considered to occur relatively beat-wise.

Note transition probability

The probability of advancing to a next note state is based on the transitions of the note-HMM, introduced in Mauch et al. [2015]. Let use briefly review it: From a given note segment the only possibility is to progress to its following note segment. To ensure continuity each of the self-transition probabilities

is rather high, given by constants c_A, c_S and c_N for A, S and N segments respectively (c_A=0.9; c_S=0.99; $c_N = 0.9999$). Let $P_{N_iA_j}$ be the probability of transition from non-vocal state N_i after note i to attack state A_j of its following note j. The authors assume that it depends on the difference between the pitch values of notes i and j and the difference can be approximated by a normal distribution centered at change of zero (Mauch et al. [2015], Figure 1.b). This implies that small pitch changes are more likely than larger ones. Now we can formalize their note transition as:

$$p(n_k|n_{k-1}) = \begin{cases} P_{N_iA_j}, & n_{k-1} = N_i \quad n_k = A_j \\ c_N, & n_{k-1} = n_k = N_i \\ 1 - c_A, & n_{k-1=}A_i \quad n_k = S_j \\ c_A, & n_{k-1} = n_k = A_i \\ 1 - c_S & n_{k=1} = S_i \quad n_k = N_j \\ c_S, & n_{k-1} = n_k = S_i \\ 0 & else \end{cases} \tag{5.3}$$

Note also that for the self-transitions in non-vocal states N_i it should hold that

$$c_N = 1 - \sum_i P_{N_iA_j} \tag{5.4}$$

.

In this study, we modify $P_{N_iA_j}$ to allow vacation in time, depending on the current bar position ϕ_k.

$$p(n_k|n_{k-1,}\phi_k) = \begin{cases} P_{N_iA_j}\Theta(\phi_k), & n_{k-1} = N_i \quad n_k = A_j \\ 1 - \Theta(\phi_k)\sum_i P_{N_iA_j}, & n_{k-1} = n_k = N_i \\ ... \end{cases} \tag{5.5}$$

where

$\Theta(\phi_k)$: function weighting the contribution of a beat adjacent to current bar position ϕ_k

The non-vocal self-transition probability is updated so that all non-vocal outbound transitions sum to 1. The transition probabilities in all the rest of the cases remain the same.

We explored two variants of the weighting function $\Theta(\phi_k)$:

Time-window redistribution In performance singers often advance or delay slightly note onsets in relation to the beats. The work Nishikimi et al. [2016] presented an idea of how to describe off-beat time-deviations of vocal onsets by stochastic distribution. Similarly, we introduce a normal distribution $N_{0,\sigma}$, centered around 0 to re-distribute the importance of beats over a time window around a beat. Let b_k be the beat, closest in time to a current bar position ϕ_k. Now:

$$\Theta(\phi_k) = [N_{0,\sigma}(d(\phi_k, b_k))]^w e(b_k) \tag{5.6}$$

where

$e(b)$: probability of a note onset co-occurring with the b^{th} beat in the metrical cycle (b $\in\theta(r)$)

w : sensitivity of vocal onset probability to beats

$d(\phi_k, b_k)$: the distance from current bar position ϕ_k to closest beat position b_k

Equation 5.5 means essentially that the original $P_{N_i A_j}$ is scaled accordingly to how close in time to a beat it is.

Simple weighting The transition probability $P_{N_i A_j}$ is modified only at beat positions, i.e. the weighting function is set to the peak of $N_{0,\sigma}$ only at bar positions corresponding to beat positions, and to 1 elsewhere.

$$\Theta(\phi_k) = \begin{cases} [N_{0,\sigma}(0)]^w e(b_k), & d(\phi_k, b_k) = 0 \\ 1 & else \end{cases} \tag{5.7}$$

5.3.4 Observation models

The observation probability $P(y_k|x_k)$ describes the relation between the hidden states and the (observed) audio signal. In this work we make the assumption that the observed vocal pitch and the observed metrical accent are conditionally independent from each other. This assumption may not hold in cases when energy accents of singing voice, which contribute to the total energy of the signal, are correlated to changes in pitch. However, for music with percussive instruments the importance of singing voice accents is diminished to a significant extent by percussive accents. Now we can rewrite Eq. 5.1 as

$$P(x_{1:K}, y^f_{1:K}, y^p_{1:K}) = P(x_0)\Pi_{k=1}^{K} P(x_k|x_{k-1})P(y^f_k|x_k)P(y^p_k|x_k) \tag{5.8}$$

This means essentially that the observation probability can be represented as the product of the observation probability of a metrical accent $P(y^f_k|x_k)$ and the observation probability of vocal pitch $P(y^p_k|x_k)$.

Accent observation model

In this paper for $P(y^f_k|x_k)$ we train GMMs on the spectral flux-like feature y^f, extracted from the audio signal using the same parameters as in Krebs et al. [2013] and Holzapfel et al. [2014]. The feature y^f summarizes the energy changes (accents) that are likely to be related to the onsets of all instruments together. The probability of observing an energy change depends on the position in the bar and the rhythmic pattern, $P(y^f_k|x_k) = P(y^f_k|\phi_k, r_k)$

Pitch observation model

The pitch probability $P(y^p_k|x_k)$ reduces to $P(y^p_k|n_k)$, because it depends only the current note state. We adopt the idea proposed in Mauch et al. [2015] that a vocal note state emits pitch y^p according to a normal distribution, centered around its average pitch. The standard deviation of stable states and the one of the onset states are kept the same as in the original model, respectively 0.9 and 5 semitones. The melody contour of singing is extracted in a preprocessing step. We utilized an algorithm, extended from Salamon and Gómez [2012] and tailored to Turkish makam. Each audio frame k gets assigned a pitch value and probability of being voiced v_k Atlı et al. [2014]. Based on frames with zero probabilities, one can infer which segments are vocal and which not. Since correct vocal segments is crucial for the sake of this study and the voicing estimation of these melody extraction algorithms are not state of the art, we preferred to rely on manual vocal annotations and thus assigned $v_k = 0$ for all frames, annotated as non-vocal.

For each state the observation probability $P(y^p_k|n_k)$ of vocal states is normalized to sum to v_k (unlike the original model which sums to a global constant v). This leaves the probability for each non-vocal state be $^{1-v_k}/_{n}$.

5.3.5 Learning model parameters

Accent observation model

We trained the accent probability patterns $P(y_k^f|\phi_k, r_k)$ on the training subset of the *multi-instrumental vocal onsets OTMM dataset* (see section 3.2.3). For each usul we trained one rhythmic pattern by fitting a 2-mixture GMM on the spectral-flux-like feature vector y^f. Analogously to Holzapfel et al. [2014] we pooled the bar positions down to 16 patterns per beat. The feature vector is normalized to zero mean, unit variance and taking moving average. Normalization is done per song.

Probability of note onset

The probability of a vocal note onset co-occurring at a given bar position $e(b)$ is obtained from studies on sheet music. Many notes are aligned with a beat in the music score, meaning a higher probability of a note at beats compared to inter-beat bar positions. A separate distribution $e(b)$ is applied for each different metrical cycle. For the düyek and aksak usuls $e(b)$ has been inferred from a recent study Holzapfel [2015, Figure 5. a-c]. The authors used a corpus of music scores, on data from the same corpus, from which we derived the dataset. The patterns reveal that notes are expected to be located with much higher likelihoods on those beats with percussive strokes than on the rest.

5.3.6 Inference

With manually annotated beats

We explored the option that beats are given as input from a preprocessing step (i.e. when they are manually annotated). In this case, the detection of vocal onsets can be carried out by a reduced model with a single hidden variable: the note state. The observation model is then reduced to the pitch observation probability. The transition model is reduced to bar-position aware transition probability $a_{ij}(k) = p(n_k = j|n_{k-1} = i, \phi_k)$(see Eq. 5.5). To represent this time-dependent self-transition probabilities we we utilize time-varying transition matrix. It falls in the general category of variable-time HMMs (VTHMMs) Johnson [2005]. The standard transition probabilities in the Viterbi maximization step are substituted for the bar-position aware transitions $a_{ij}(k)$

$$\delta_k(j) = \max_{i \in (j, j-1)} \delta_{k-1}(i)\, a_{ij}(k)\, b_j(O_k) \tag{5.9}$$

Here $b_j(O_k)$ is the observation probability for state i for feature vector O_k and $\delta_k(j)$ is the probability for the path with highest probability ending in state j at time k (complying with the notation of Rabiner [1989, III. B]

Full model

We obtain the most optimal state sequence $x_{1:K}$ by decoding with the well-known Viterbi algorithm. A Beat is detected when the bar position variable hits one of $\theta(r)$ positions of beats within the metrical cycle. A vocal note onset is detected when the state path enters an attack note state after being in non-vocal state.

Note that the size of the state space poses a memory requirement. A recording of 1 minute has around 10K frames at a hopsize of 5.8 ms. To use Viterbi thus requires to store in memory pointers to up to 4G states, which amounts to 40G RAM (with uint32 python data type).

5.3.7 Experiments

Vocal detection is evaluated on 5 1-minute excerpts from each of the two usuls from the *multi-instrumental vocal onsets OTMM dataset* (see Section 3.2.3), totaling in 10 minutes of audio. The hopsize of computing the spectral flux feature, which resulted in most optimal beat detection accuracy in Holzapfel et al. [2014] is $h_f = 20\,ms$. In comparison, the hopsize of predominant vocal melody detection is usually of smaller order i.e. $h_p = 5.8\,ms$ (corresponding to 256 frames at sampling rate of 44100). Preliminary experiments showed that extracting pitch with values of h_p bigger than this values reasonably deteriorated the vocal onset accuracy. Therefore in this work we used hopsize of 5.8 ms for the extraction of both features. The time difference parameter for the spectral flux computation remains unaffected by this change in hopsize, because it can be set separately.

As a baseline we run the algorithm of Mauch et al. [2015] with the 105 note states, we introduced in Section 5.3.2[1]. The note transition probability is the original as presented in Eq. 5.3, i.e. not aware of beats. Note that in Mauch et al. [2015] the authors introduce a post-processing step, in which onsets of consecutive sung notes with same pitch are detected considering their

[1]We ported the original VAMP plugin implementation to python

meter		beat Fmeas	P	R	Fmeas
düyek	Mauch	-	33.1	31.6	31.6
	Ex-1	-	40.4	39.5	39.0
	Ex-2	86.4	37.8	36.1	36.1
aksak	Mauch	-	42.1	36.9	37.9
	Ex-1	-	48.4	39.1	43.0
	Ex-2	72.9	45.0	39.0	40.3

Table 5.1: Evaluation results for Experiment 1 (shown as Ex-1) and Experiment 2 (shown as Ex-2). Mauch stands for the baseline, following the approach of Mauch et al. [2015]. P, R and Fmeas denote the precision, recall and f-measure of detected vocal onsets. Results are averaged per usul.

intensity difference. We excluded this step in all system variants presented, because it could not be integrated in the proposed observation model in a trivial way. This means that, essentially, in this paper cases of consecutive same-pitch notes are missed, which decreases somewhat the recall compared to the original algorithm.

Evaluation metrics

Beat detection Since improvement of the beat detector is outside the scope of this study, we report accuracy of detected beats only in terms of their f-measure. This serves solely as reference to existing work[2]. The f-measure can take a maximum value of 1, while beats tapped on the off-beat relative to annotations will be assigned an f-measure of 0. We used the default tolerance window of 70 ms, also applied in Holzapfel et al. [2014].

Vocal onset detection We measured vocal onset accuracy in terms of precision and recall. Unlike a cappella singing, the exact onset times of singing voice accompanied by instruments, might be much more ambiguous. To accommodate this fact, we adopted the tolerance of $t = 50\,ms$, used for vocal onsets in accompanied flamenco singing by Kroher and Gómez [2016]. Note transcription accuracy remains outside the scope of this study.

[2]Note that f-measure is agnostic to the phase of the detected beats, which is clearly not optimal.

Experiment 1: With manually annotated beats

As a precursor to evaluating the full-fledged model, we conducted an experiment with manually annotated beats. This is done to test the general feasibility of the proposed note transition model (presented in 5.3.3), unbiased from errors in the beat detection.

We did apply both the simple and the time-redistribution weighting schemes for $\Theta(\phi_k)$, presented respectively in Eq. 5.7 and in Eq. 5.6. In preliminary experiments we saw that with annotated beats the simple weighting results in much worse onset accuracy than the time-redistributed one. Therefore the experimental results reported are conducted with the latter weighting scheme.

We have tested different pairs of values for w and σ from Eq. 5.5.The onset detection accuracy peaked at w=1.2 and $\sigma = 30\,ms$. Table 5.1 presents the accuracies compared to the baseline. Inspection of detections showed that the proposed model added some onsets around beats, which are missed by the baseline.

Experiment 2: Full model

To assure computational efficiency, we did an efficient implementation of the joint state space[3]. The average f-measure of detected beats for the different metrical cycles can be seen in Table 5.1. The beat tracking accuracy for the Turkish usuls is on par with the results reported in Holzapfel et al. [2014, Table 1.a-c, R=1]. The results reported are only with the simple weighting scheme for the vocal note onset transition model. Table 5.1 shows a reasonable improvement of vocal onset detection accuracy for both usuls.

For simple weighting, adding the automatic beat tracking results in improvement over the baseline, whereas this was not the case with manual beats. This suggests that the concurrent tracking of beats and vocal onsets is a flexible strategy and can accommodate some off-beat vocal onsets. We observed also that the vocal onset accuracy is on average almost the same as that with manual beat annotations (done with the time-redistribution weighting).

[3]We extended the python toolbox for beat tracking https://github.com/CPJKU/madmom/

5.4 Onset-aware lyrics-to-audio alignment

In the previous section we investigated the relation of metrical accents to the positions of vocal onsets in a melodic phrase. We proposed a method for automatic vocal onset detection in a way aware of metrical accents.

Using as input the detected vocal onsets, in this chapter we propose a strategy to improve LAA by representing the interaction of vocal onsets to syllable transitions. In this way the influence of metrical events on syllable transitions is represented implicitly through its influence on vocal note events, which are in turn influenced by metrical events. The note onset is the initial segment of the three temporal segments of a vocal note: onset, sustain and release. The other vocal events - sustain and release (offset) also have undoubtedly impact on the transition of phonemes. However, due to the time limitation of this study, we considered only the impact of vocal note onsets. The reason to focus on note onsets among the three vocal note events is that onsets have arguably the more evident influence on syllable transitions.

As we saw in the previous chapter, automatically determining the time positions of transitions between sung syllables can be greatly assisted by information from the music score. Similarly, by relying on music score, one can infer automatically the timestamps of vocal note onsets. Such timestamps are estimated reasonably well by a recent study on automatic score-to–audio alignment Şentürk [2016, chapter 6]. In contrast, with the help of automatic singing voice transcription, vocal note onsets can be derived without the need of music score. Since we intend that the proposed methodologies can be applicable for material with no music scores available, we preferred to apply automatic vocal onset detection instead of score-to-audio alignment. Detecting vocal onsets in any setting is arguably one of the hardest MIR problems. Still for the study of onset-aware phoneme transitions, it is important that onsets timestamps are as correct as possible. To assure correctly detected onset timestamps, experiments in this section are conducted on a cappella material from OTMM.

A general overview of the proposed approach is presented in Figure 5.2. As in all approaches presented in this thesis, first an audio recording is manually divided into segments according to the coarse level complementary context - the sections of the composition. The boundaries of vocal section (one of zemin, nakarat, meyan) are taken from manual annotations. An audio recording and its corresponding lyrics are input. The vocal note onsets (automatically detected or manually annotated) together with phoneme transition rules are fed as input to the transition model. The phonetic recognizer, guided by the

phoneme transition rules, returns start and end timestamps of aligned words.

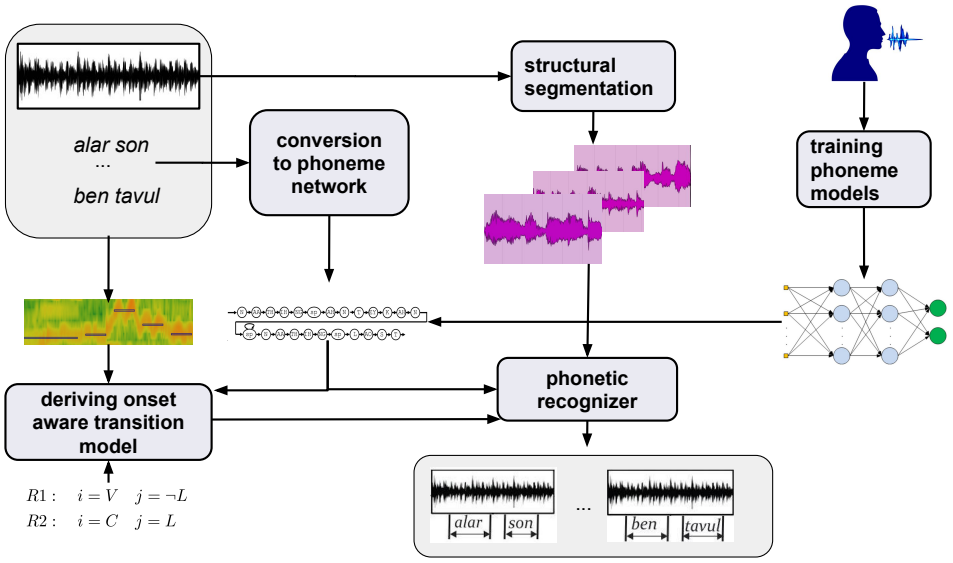


Figure 5.2: Overview of the modules of the proposed approach. The transition model is derived from phoneme transition rules and onset positions from the singing voice transcription. Then it input to the phonetic recognizer, together with the phonemes network and the features, extracted from audio segments.

5.4.1 Phoneme transition rules

The transition to a consecutive lyrics syllable implies a concurrent transition to a new note. The onset of the new note occurs usually at the start of the first voiced sound in the syllable. If we look at this reversely, the occurrence of note attack in a sung melody can signal a phonetic transition. The transition depends on the phoneme types, since, for example, a new note cannot start at unvoiced consonants. Taking advantage of that fact, we formulate rules that guide the transition between consecutive phonemes when a note onset is present. In general, we consider note onsets (attack) events as a comple-

mentary context of phonetic timbre. Similar phoneme transitions rules have been used successfully to enhance the naturalness of synthesized singing voice [Sundberg, 2006]. The onset aware phoneme transitions rules, we designed, have been presented in Dzhambazov et al. [2016a].

We formalize transition rules described in this Section for Turkish language, in which each syllable has exactly one vowel. In this sense, the rules could be transferred to another language with single-vowel syllables. [4].

Let V denote a vowel, C denote a consonant and L denote a vowel, liquid (LL, M, NN) or the semivowel Y. Rules $R1$ and $R2$ represent inter-syllable transition, e.g. phoneme i is followed by phoneme j from the following syllable:

$$\begin{aligned} R1: &\quad i = V \quad j = \neg L \\ R2: &\quad i = C \quad j = L \end{aligned} \tag{5.10}$$

For example, for rule $R2$ if a syllable ends in a consonant, a note onset imposes with high probability that a transition to the following syllable is done, provided that it starts with a vowel. Same rule applies if it starts with a liquid, according to the observation that pitch change takes place during a liquid preceding the vowel Sundberg [2006, timing of pitch change]. Rule R2 is valid also for intra-syllabic phoneme patterns, together with rule R3:

$$R3: \quad i = V \quad j = C \tag{5.11}$$

Essentially, if the current phoneme is vocal and the next is non-voiced (e.g. $R1$, $R3$) the transition no next phoneme is discouraged. An example of the intra-syllable $R2$ can be seen for the syllable KK-AA in Figure 5.3 where the note onset triggers the change to the vowel AA. Unlike that, an onset for example, to the syllable Y to onset at Y for the syllable Y-E-T.

5.4.2 Transition model

The phoneme transitions are dependent on the current note state. When a note is in its onset phrase, the transition between phonemes is different

[4] Among single-vowel syllabic languages are also Japanese and to some extent Italian

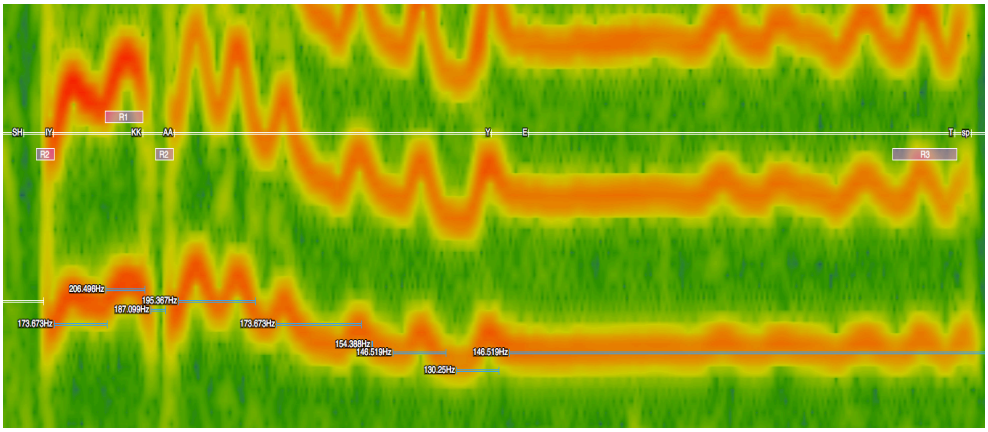


Figure 5.3: Ground truth annotation of syllables (in orange/top), phonemes (in red/middle) and notes (with blue/changing position). Audio excerpt corresponding to word şikayet with syllables SH-IY, KK-AA and Y-E-T.

compared to when a note is in a non-onset phase. This dependence can be represented in a DBN in Figure 5.4.

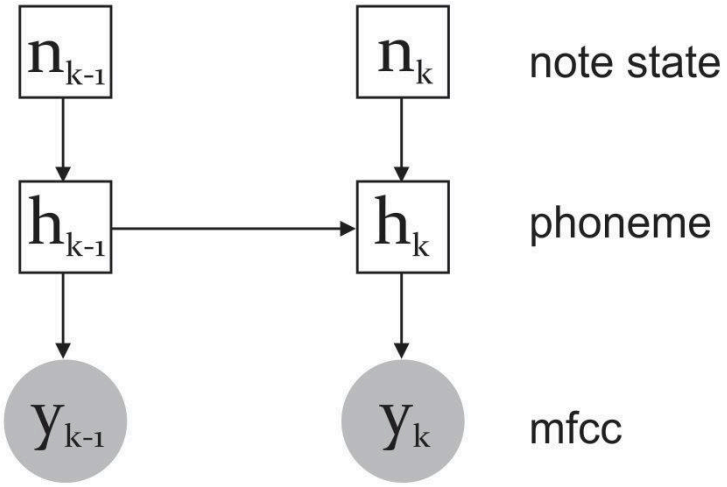


Figure 5.4: A DBN for the simultaneous musical note and phoneme states. A phoneme transition is conditoined on the vocal note state. If a note onset is present the likelihood of transition is modifies according to what the current h_{k-1} and its following h_k phoneme are.

For particular states, transitions are modified depending on the presence of time-adjacent note onset. Let k' be the timestamp of the onset $\Delta n_{k'} = 1$, which is closest to given time k. Now the transition probability can be rewritten as

$$a_{ij}(k) = \begin{cases} a_{ij} - g(k,k')q, & R1 \text{ or } R3 \\ a_{ij} + g(k,k')q, & R2 \end{cases} \tag{5.12}$$

$R1$ to $R3$ stand the phoneme transition rules, which are applied in the phonemes network by picking the states i and j for two consecutive phonemes. The term q is a constant whereas $g(k,k')$ is a weighting factor sampled from a normal distribution with its peak (mean) at k':

$$g(k,k') = \begin{cases} f(k;k',\sigma^2) \sim \mathcal{N}(k',\sigma^2), & |k-k'| \leq \sigma \\ 0 & else \end{cases} \tag{5.13}$$

Since singing voice onsets are regions in time, they span over multiple consecutive frames. To reflect that fact, $g(k, k')$ serves to smooth in time the influence of the discrete detected Δn_k, where σ has been selected to be 0.075 seconds. In this way an onset influences a region of 0.15 seconds - a value we found empirically to be most optimal. Furthermore, this allows to handle slight timestamp inaccuracies of the estimated note onsets.

5.4.3 Inference

The most likely state sequence is found by means of a forced alignment Viterbi decoding. Similarly to the inference for metrical-accent aware detection of vocal onsets (see Section 5.3.6) we apply a variable-time HMM decoding. The standard transition probabilities in the Viterbi maximization step are substituted for the onset aware transitions $a_{ij}(k)$ from Eq. 5.12:

$$\delta_k(j) = \max_{i \in (j, j-1)} \delta_{k-1}(i)\, a_{ij}(k)\, b_j(O_k) \tag{5.14}$$

5.4.4 With automatically detected onsets

We employed the note onset detection methodology developed for flamenco singing [**Kroher and Gómez, 2016**]. However, this algorithm does not allow to be integrated in a HMM. Therefore note onset segmentation is performed as preprocessing step to the actual decoding of the phoneme sequence.

To obtain reliable estimate of singing note onsets, we adapt the automatic singing transcription method, developed for polyphonic flamenco recordings Kroher and Gómez [2016]. It has been designed to handle singing with high degree of vocal pitch ornamentation. We expect that this makes it suitable for material from OTMM singing having heavily vibrato and melismas, too. We replace the original first stage predominant vocal extraction method with the vocal pitch detection method of Atlı et al. [2014], which we described in Section 3.3.2.

The algorithm of Kroher and Gómez [2016] considers two cases of onsets: interval onsets and steady pitch onsets. A Gaussian derivative filter detects interval onsets as long-term change of the pitch contour, whereas steady-pitch

onsets are inferred from pitch discontinuities. As in the current work phoneme transitions are modified only when onsets are present, we opt for increasing recall at the cost of losing precision. This is achieved by reducing the value of the parameter cF: the minimum output of the Gaussian filter. The extracted note onsets are converted, as in the case of manually annotated onsets, to a binary onset activation at each frame $\Delta n_t = (0, 1)$.

5.4.5 Experiments

With manually annotated onsets

The above presented DBN has the drawback that the integrity of phoneme transitions depends largely on the accuracy of the detected note onsets. Unfortunately, as we saw in Section 5.2 note onsets could not be estimated from polyphonic recordings with high accuracy. To assure reasonable accuracy, we utilized manually annotated note onsets. This is done to test the general feasibility of the proposed model, unbiased from errors in the note segmentation algorithm, and to set a glass-ceiling alignment accuracy.

Firstly, lyrics-to-audio alignment is run on 6 recordings with manually annotated MIDI notes, which serve as an oracle for note onsets. We have tested with different values of q from Eq. 5.12 achieving best accuracy of 83.5% at $q = 0.23$, which is used on all further reported experiments.

With automatically detected onsets

As a baseline we conduct alignment of the test dataset with unaffected phoneme transition probabilities, e.g. setting all $\Delta n_t = 0$, which resulted in alignment accuracy of 70.2%. Further, we measured the impact of the note segmentation approach of Kroher and Gómez [2016] (introduced in Section 5.2), varying onset detection recall by changing the minimum output of the Gaussian filter (controlled by the parameter cF). Table 5.2 summarizes the alignment accuracy with VTHMM depending on recall. On a cappella best improvement over the baseline is achieved at recall of 72.3% (at $cF = 3.5$). This is somewhat lower than the best recall of 81-84% achieved for flamenco Kroher and Gómez [2016]. Setting recall higher than that degraded performance because there are too many false alarms, resulting in forcing false transitions.

Figure 5.5 allows a glance at the level of detected phonemes: the baseline HMM switches to the following phoneme after some amount of time, similar

	cF	5	4.5	4.0	3.5	3.0
a cappella	**OR**	57.2	59.7	66.8	72.3	73.2
	AA	71.1	73.3	74.5	**75.7**	72.0
polyphonic	**OR**	52.8	58.2	65.9	66.2	68.4
	AA	61.2	63.3	**64.8**	64.6	60.3

Table 5.2: VTHMM performance on a cappella and polyphonic audio, depending on onset detection recall (OR). Alignment accuracy (AA) is reported as a total for all the recordings.

for all phonemes. One reason for this might be that the waiting time in a state in HMMs with a fixed transition matrix cannot be randomly long Yu [2010]. In contrast, for VTHMM the presence of note onsets at vowels activates rules $R1$ or $R3$, which allows waiting in the same state longer, as there are more onsets (for example AA from the word SH-IY-KK-AA-Y-E-T has five associated onsets). We chose to modify *cF* because setting it to lower values increases the recall of *interval onsets*: Often in our dataset several consecutive notes with different pitch correspond to the same vowel. In fact, it is characteristic of Turkish classical music that a single syllable may have a complex melodic progression spanning many notes (up to 12 in our dataset) [Ederer, 2011]. However, for cases of vowels held long on same pitch, conceptually VTHMM is not capable of bringing any benefit. This is illustrated in Figure 5.5 by the prematurely detected end boundary of E from the word SH-IY-KK-AA-Y-E-T.

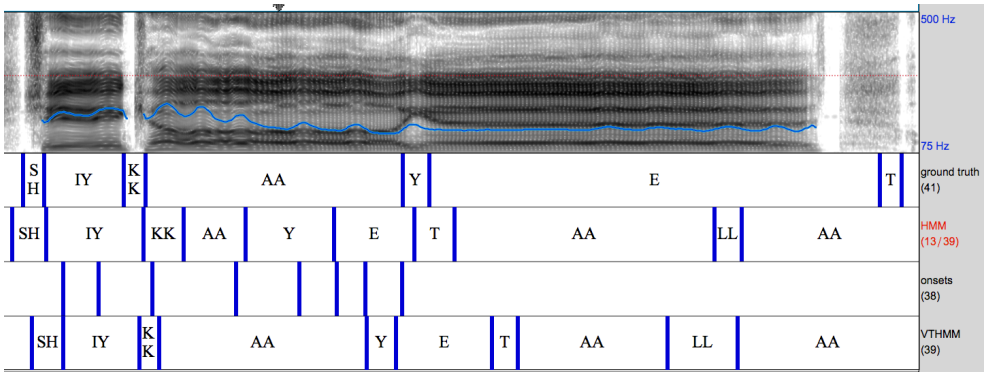


Figure 5.5: Example of boundaries of phonemes for the word şikayet (SH-IY-KK-AA-Y-E-T): *on top*: spectrum and pitch; *then from top to bottom*: ground truth boundaries, phonemes detected with HMM, detected onsets, phonemes detected with VTHMM; (excerpt from the recording 'Kimseye etmem şikayet' by Bekir Unluater).

5.5 Summary

In this chapter we assessed the contribution of explicitly representing metrical accents (fine-level complementary context) for improving the tracking of sung lyrics. We studied the relation of metrical accents to lyrics in two steps: how metrical accents interact with vocal onsets and how the latter, in turn, interact with phoneme transitions. In this way, the influence of metrical events on syllable transitions is represented implicitly through its influence on note onsets, which are in turn influenced by metrical events. Therefore, we presented two separate probabilistic models for two separate tasks: metrical-accent aware vocal onset detection and onset aware lyrics-to-audio alignment. We carry out an evaluation on material from OTMM.

Metrical-accent aware vocal onset detection We strived to improve the automatic vocal note onset detection by incorporating information about their position in a metrical cycle (i.e. metrical accents). To this end we proposed a DBN for the simultaneous tracking of metrical position and vocal onsets. The main contribution is that the approach integrates in one coherent model two existing state of the art probabilistic approaches for different tasks: beat tracking and singing voice transcription. We carried out an evaluation on a multi-instrument dataset from OTMM with two different usul types. Results confirmed that the proposed model reasonably improves vocal note onset detection accuracy compared to a baseline model that does not take the metrical position into account.

Detecting vocal onsets is polyphonic audio is arguably one of the hardest MIR problems. Although, not the goal of this thesis, the presented DBN can be used for full-fledged singing voice transcription.

Onset aware lyrics-to-audio alignment. We extended the phonetic recognizer approach by modeling the singing voice onsets, occurring simultaneously with phoneme transitions. We conceptualized onset-aware phoneme transition rules and proposed how to integrate them into the transition model of the phonetic recognizer. The method was tested on the a cappella OTMM dataset. The new model resulted in an improvement of absolute 5.5 percent over baseline unaware of singing voice onsets. In particular, due to rules discouraging premature transition, the states of sustained vowels were allowed to have longer durations. Results showed that the proposed model outperforms a baseline approach unaware of onset transition rules. This is, to our knowl-

edge, the first attempt to model explicitly onsets from the vocal melody in the LAA decoding process itself.

Chapter 6

Conclusions

Broadly, this dissertation aimed to build culture-aware and domain-specific MIR approaches using probabilistic models for tracking lyrics in music audio signals. We proposed specific probabilistic models to represent how the transitions between consecutive sung phonemes are conditioned by different facets of music-domain knowledge. The models we build take into account some of these facets and consider them as 'temporal complementary context' that exists around lyrics.

In order to evaluate the potential of the proposed models, we built a complete methodology for the automatic alignment of lyrics to an audio recording (LAA) and evaluated its performance by the accuracy of the LAA. As a baseline we chose a phonetic recognizer based on hidden Markov models (HMM): a methodology applied in most of hitherto computational studies on lyrics tracking. We applied the proposed methodologies on compMusic datasets of OTMM and Beijing opera. These music traditions present a challenge to LAA because of their expressive singing style and its resulting high degree of temporal variability. The low accuracy of the baseline phonetic recognizer confirmed that.

We built two separate extensions of the phonetic recognizer: one for middle-level complementary context and a separate one one for fine-level context. As middle-level we modeled the influence of the structure of a melodic phrase on the phoneme transitions of lyrics. As to the fine-level context, modeled how phoneme transitions interact with the position of the accents in the metrical cycle.

6.1 Importance of complementary context

We represent events from complementary context as components in a DBN and their influence on the lyrics as a hierarchical dependence between the components. The presented solutions provide an alternative to the prevailing music-knowledge-uninformed MIR approach to modeling musical aspects, related to lyrics, in which the extracted acoustic features are agglomerated in a bottom-up fashion.

6.1.1 Middle-level context

We first proposed a phonetic recognizer that utilizes lyrics duration information as a cue, complementary to phonetic timbre. It is representing how the position of a lyrics syllable in a melodic phrase influences its duration. An advantage of the presented model is that it allows room for certain temporal flexibility to handle cases of significant deviation of sung vowels from the expected reference durations. Evaluation showed that syllable durations is the facet of complementary context with biggest contribution to improvement of LAA. For Jingju the relative improvement was somewhat bigger than for OTMM. One explanation is the very long durations of sung vowels in Jingju, which is a challenge to conventional HMMs.

6.1.2 Fine-level context

In this thesis we focused on one particular fine-level facet - the accents in the metric cycle. We studied the relation of metrical accents to lyrics in two steps: how metrical accents interact with vocal onsets and how the latter, in turn, interact with phoneme transitions. Therefore, we devised two separate probabilistic models for two separate tasks: vocal-onset aware lyrics-to-audio alignment and metrical-accent aware vocal onset detection. We tested the model on OTMM. Results confirmed that its well-grounded rhythmic framework provided an excellent piece of domain knowledge context.

For vocal-onset aware lyrics-to-audio alignment we conceptualized phoneme transition rules that consider in parallel the presence of note onsets. We integrated these into the transition model of the phonetic recognizer. Results showed that the improvement of alignment is not very big even with manually annotated onsets. However, the derived rules are an important contribution that can be easily transferred to other languages and singing styles.

A limitation of the duration aware model is the requirement for external source of syllable reference durations - usually the music scores. To reduce this lim-

itation, we built a separate methodology to extract vocal note onsets automatically. Based on evidence that in OTMM the position of note events in a melodic phrase is influenced by the position in a metrical cycle, we designed a model for simultaneously tracking vocal onsets and metrical accents. Vocal onset detection in multi-instrumental music is, in fact, one of the hardest MIR problems. It is even harder in OTMM because of the expressive singing phenomena: melodic onsets are often approached by slurs and melismas. The complementary metrical accent context proved to be an important 'stepping stone': the accuracy of vocal onset detection was increased reasonably for two different usul types. We believe that the biggest potential of the model lies in its generalisibility - applying it to singing material with different singing style and meter is as easy as tuning its parameters.

The most important advantage of the metric-accent models is that they do not necessarily depend on external sources of information such as music scores.

6.2 Summary of contributions

A summary of the specific contributions from the work presented in the dissertation are listed below.

6.2.1 Musicological contributions

We hope that the outcomes of this work will motivate researchers to use more often music context knowledge in future work. Some particular contributions are:

- We showed that a model of complementary context can be adapted to a different music tradition (the duration aware model has been applied to two different traditions). None of the facets of complementary context modeled are unique for a music tradition. This means that transferring the model to another music tradition is a matter of reducing the music knowledge context to an appropriate set of rules/patterns.
- We compiled several datasets of OTMM and Jingju with annotations of different music facets including lyrics, vocal sections, onsets of singing voice, beats.
- The most successful LAA approach developed, the syllable-duration aware LAA was integrated into Dunya-web. It can enable musicologists

to track not only the aligned lyrics, but also complementary musical facets and music-specific phenomena.

6.2.2 Technical and scientific contributions

- We conceptualized the interaction of phoneme transitions to other musical facets. These interactions were represented as hidden variables and their dependences in DBNs. DBNs are an elegant modeling tool (we presented illustrated the model dependencies in diagrams)
- Inference in DBNs is computationally demanding. Therefore, we proposed several implementation simplifications.
- All the methodologies presented in this thesis are implemented as modular and easy-to-extend software. A special focus has been put on making them reproducible. To our knowledge this is the first open source software for lyrics-to-audio alignment that is based on computational study.

Applying insights and methodologies from this culture-specific study can open up and make the existing computational methods more versatile. We hope that in the future researchers can apply and extend the outcomes of this work to improve and enrich existing MIR methodologies, thus fulfilling one of the ultimate goals of the CompMusic project [Serra et al., 2013].

Appendix A

Applications

Researcher of the CompMusic team have created a web application called Dunya-web[1] to showcase the technologies developed within the CompMusic project. Dunya-web is an application aimed at culture-aware music discovery. Dunya-web has a makam part, representing algorithms developed for the computational analysis of OTMM. Dunya-web stores all the audio recordings (including the OTMM datasets described in Section 3.2) and music scores, together with the lyrics.

The users can navigate the audio collection by searching or filtering by recordings, compositions, artists, makams, forms and/or usuls. Users can play the recordings and examine musical facets synchronous to the audio playback. Facets like pitch, the score, the tonic are visualized in a user-intuitive way.

The most successful lyrics-to-audio alignment (LAA) approach for OTMM, developed in this thesis, is the phonetic recognizer informed by phoneme durations. We integrated its python implementation into Dunya-web for a subset of the OTMM corpus available in Dunya-web (see Fig. A.1). This subset includes vocal recordings in the şarkı form with music scores and lyrics information available.

The ease of use of Dunya-web and intuitive interface allows expert users (e.g. music aficionados, musicologists and/or music students) to follow the aligned lyrics, while listening to the audio. Simultaneously, the acoustic features (inverse spectral representation of MFCCs) representing the timbral differences of phonemes are displayed.

[1] http://dunya.compmusic.upf.edu/makam

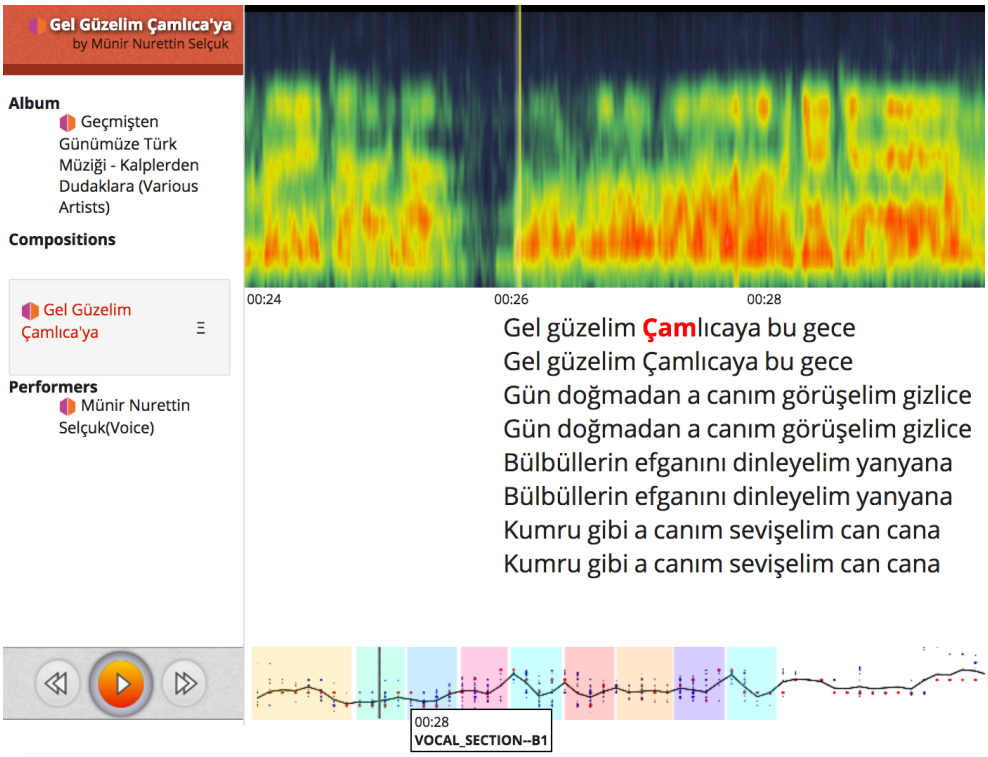


Figure A.1: Dunya-web: an interface for the dicovery of the music traditions of the world. The part on aligning automatically lyrics in vocal recordings of the OTMM şarkı form is presented.

List of publications

The following is a list of peer-reviewed conference publications of the author, organized by the relevance to the thesis. An up-to-date list of all publications can be found at:

https://www.researchgate.net/profile/Georgi_Dzhambazov2

Publications in the context of the thesis and the CompMusic project

Georgi Dzhambazov and Xavier Serra. Modeling of phoneme durations for alignment between polyphonic audio and lyrics. In *Sound and Music Computing Conference 2015*, Maynooth, Ireland, 2015. URL http://mtg.upf.edu/node/3266.

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