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Relation Between Surface Rhythm and Rhythmic Modes in Turkish Makam Music

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Abstract

Sounds in a piece of music form rhythmic patterns on the surface of a music signal, and in a metered piece these patterns stand in some relation to the underlying rhythmic mode or meter. In this paper, we investigate how the surface rhythm is related to the *usul*, which are the rhythmic modes in compositions of Turkish makam music. On a large corpus of notations of vocal pieces in short *usul* we observe the ways notes are distributed in relation to the *usul*. We observe differences in these distributions between Turkish makam and Eurogenetic music, which imply a less accentuated stratification of meter in Turkish makam music. We observe changes in rhythmic style between two composers who represent two different historical periods in Turkish makam music, a result that adds to previous observations on changes in style of Turkish makam music throughout the centuries. We demonstrate that rhythmic aspects in Turkish makam music can be considered as the outcome of a generative model, and conduct style comparisons in a Bayesian statistical framework.

Keywords: Makam music, musical meter, rhythm analysis, style change, Turkish music

1 Introduction

The interplay between rhythm as a phenomenon inherent in music, and meter as a mental construct that helps listeners to organise and memorise the temporal structure of music has been discussed throughout the decades by various scholars. For instance, Kolinski (1973) described rhythm as organised durations, while meter serves as organised pulsation functioning as a framework for rhythmic design. Ligeti, who throughout his life explored ways to shape time in novel and perceptually intriguing ways, defined rhythm as "every temporal sequence of notes, sounds and musical *Gestalten*", while he referred to meter as "a more or less regular structuring of temporal development" (Ligeti, 2007). It seems

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fair to say that the common point in descriptions of rhythm and meter is the description of rhythm as a sort of perceived pattern, while meter serves in cognitive processes as an organising force with a regular and periodic structure. In the context of Eurogenetic¹ classical and folk music, Temperley (2007) examined several approaches to model note sequences observed in a piece, and concludes that a statistical model that considers duration and metrical position yields the best fit between metrical model and corpus. Palmer and Krumhansl (1990) explored how note locations within a bar support the music-theoretic predictions of event placements in the context of Eurogenetic classical music. They conclude that composers reinforce the meter by manipulating the frequency of events at each metrical level. Furthermore, they conduct two series of listening tests, which give evidence for the importance of implicit knowledge of meter in the perception of tonal sequences, and that this knowledge is stratified into several hierarchical levels. The support by note onsets for a stratified metrical hierarchy was shown to exist even for European vocal pieces of the 16th century (Veltman, 2006), which implies that a hierarchical stratification of meter is a characteristic formed throughout many centuries and encountered in a diversity of styles in Eurogenetic music. Change in rhythmic style was observed *e.g.* by Huron and Ommen (2006), who evaluated how syncopation developed between 1890 and 1939 in a corpus of American popular music.

The above mentioned studies concentrate on styles of Eurogenetic music. So far, few studies have been conducted that attempt to investigate the stratification of meter, the relations between meter and surface rhythm, and aspects of stylistic change in different periods in other cultural contexts. In the context of African music, Agawu (2003) describes *topos* or time line (Nketia, 1974) as a rhythmic figure of modest duration that is audible throughout a performance, often played by bells or other percussive instruments with little dynamic and timbral range. The time line is a point of reference for the phrase structure of a performance that is based on an enabling structure in the background. While meter in Eurogenetic music tends to be counted, African cultures seem to prefer syllabic memorisation of rhythmic patterns instead (Stone, 2005). While the studies mentioned provide valuable information on African music theories, there are several aspects that impede corpus studies on rhythmic aspects. Firstly, the term African music is misleading, as it implies that it could be approached as a unified whole entity, which represents an ethnocentric reduction of the vast diversity of musical styles in the continent. Secondly, while corpus studies in Eurogenetic music can profit from the written form in which music is notated, African cultures, at least in their majority, can be considered oral cultures and no consistent written notation exists. Finally, a corpus study of rhythm in African music would involve the risk of enforcing the focus on rhythmic aspects in African music, to which African music is often reduced in music discourse.

¹We introduce this term because we want to avoid the misleading dichotomy of Western and non-Western music. We use the word “genetic” rather with its connotation as “pertaining to origins”, coined in 1831 by Carlyle from Greek *genetikos* “genitive”, from *genesis* “origin”, and not in its biological sense as first applied by Darwin in 1859 (<http://www.etymonline.com>). The term was proposed by Prof. Robert Reigle (MIAM, Istanbul) in personal communication.

Two music cultures that attracted many studies both from the fields of ethnomusicology and engineering are the Hindustani and Carnatic traditions of India. Rhythmic aspects of Hindustani were at the focus of the inspiring book by Clayton (2000), which gives a detailed insight into how the underlying rhythmic modes interact with the performance of melodic and percussive instruments. In the context of Carnatic music, a prominent example for studies of rhythmic aspects can be found in the work of Richard Widdess, for instance in (Widdess, 1980). Hence, based on the vast amount of literature on Indian music, one can obtain detailed insight into the stratification of meter in Indian music, relations between surface rhythm and rhythmical modes, as well as historical developments in style. The main difficulty for a larger corpus study consists in the oral nature of the Indian traditions, which renders a representative study of notations impossible.

For Turkish makam music, Wright (1988) has studied the increase of note density in notations over the centuries, concluding that this increase was caused by a decrease of performance tempo. While various forms of notation have existed throughout the history of Turkish makam music (Feldman, 1996), and a large corpus of notations is available (K. Karaosmanoğlu, 2012), a study of the rhythmic properties of this corpus has not yet been approached. Such a study can shed light on the following questions; to what extent a stratification of meter can be observed in this music; how the compositions relate to the underlying rhythmic modes; and how these aspects might have changed throughout history. The notational form further enables us to draw comparisons with Eurogenetic music, providing insights into shared concepts and differences between musical cultures. The present study represents, to the best of our knowledge, the first attempt to explore the rhythmic structure in compositions of Turkish makam music.

This work focuses on processing of machine-readable notations due to several difficulties involved in accurate rhythmic analysis of audio signals, which would demand highly accurate onset detection (Bello et al., 2005) and metrical inference (Holzapfel, Davies, Zapata, Oliveira, & Gouyon, 2012). The choice of notations enables us to have immediate knowledge of the note onset instants. The disadvantage is that no insight can be obtained into aspects of playing style, such as ornamentations or rubato. In our study we are going to investigate how the Turkish compositions relate to their underlying rhythmic modes and how they support the inference of a metrical grid. Especially we will investigate, what insights towards this end can be provided by the way note events are distributed in the compositions. As will be explained in more detail in Section 2, the rhythmic elaboration of this music is based on a set of rhythmic patterns: the *usul*. We want to investigate how these *usul* are related to the note events in a composition, and what can be inferred from these results regarding meter as a latent mental construct. The use of statistical models for rhythm analysis was proposed previously by Temperley (2007), and we show on a large music corpus that the application of similar models can provide insight into rhythmic structure of Turkish music. Our results imply a less emphasized stratification into metrical layers, and a less clear emphasis on the downbeat, when comparing

our corpus with results available on Eurogenetic music. Furthermore, we are able to provide evidence that rhythmic style of Turkish composers has changed throughout centuries, with more recent compositions emphasizing aspects of rhythmic style that could be termed Eurogenetic.

In our paper we will start by describing the rhythmic framework of Turkish music in Section 2, where we also discuss some fundamental differences with Eurogenetic music. Section 3 describes the analyzed music collection and the methodology that is applied in order to analyze the data in the subsequent sections. In Section 4, we perform discrimination between rhythmic modes using either patterns learnt from data or patterns similar to stroke patterns of the *usul*. We observe the superiority of a Maximum Likelihood approach over measuring correlations between patterns in this discrimination task. Then, in Section 5, we examine how note onsets and durations are related to the underlying rhythmic modes. This comparison is performed using Bayesian model comparison, which is a generalization of the Maximum Likelihood model as applied in our discrimination experiment. Furthermore, we present a comparison with previous results obtained on corpora of Eurogenetic music. Section 6 is the final experimental section, in which we examine the change in rhythmic style between two popular composers that represent the earliest and the latest periods of Turkish music that are sufficiently represented in our corpus. We observe a clear change in rhythmic style that seems to emphasise the beginning of a rhythmic cycle in a clearer fashion for the later period. Finally, in Section 7 we summarise our results, put them in a wider context, and discuss their importance for future research.

2 Background

Melodic progression and scales in Turkish makam music are governed by the modal framework of the *makam*, and the rhythm of non-improvised pieces is guided by rhythmic modes (Marcus, 2001) called *usul*, which are rhythmic patterns that define a sequence of strokes with varying intensity. An example of such a pattern is shown in Figure 1, using the notation commonly applied in Turkish music practice: the *usul Aksak* has a length of nine beats, which is obtained by adding up the note durations of the strokes. The notes on the upper line labelled *düm* have the highest intensity, while the notes on the low line denote weaker intensity. These patterns are memorised by the musicians, and awareness of the *usul* patterns is commonly assumed to increase the ability of players to place proper accentuation in their performances. As discussed by Clayton (2000), one characteristic of musical time is its cyclic nature, which is shaped by the repetition of the *usul* in the case of Turkish music. One instance of this repetition will be referred to as an *usul* cycle, or as a bar throughout the text. We will refer to the beginning of an *usul* cycle as the downbeat.

The form depicted in Figure 1 represents the simple, or basic form of the *usul*. Throughout the history of Ottoman music, patterns with additional strokes became common, the so-called *velveleli* pattern. According to Feldman (Feldman,

1996) this addition of strokes coincided with a decrease in performance tempo towards the end of the 17-th century. There is a wide variety of *usul*, ranging from a length of 2 to a length of more than 100. However, it is commonly assumed that there is a group of short *usul* with a maximum length of 15, and the long *usul* with a length greater than that (Hakkı Özkan, 2001).

Figure 1: Symbolic description of the *usul Aksak*. The upper line denotes right-hand strokes, while the lower line denotes left-hand strokes. The strokes with largest emphasis are labelled “düm”.

In this paper we want to investigate how surface rhythm created by the note positions within a bar relates to the underlying *usul*. For short *usul*, a large variety of compositions is available for analysis, and an analysis of long *usul* raises the additional question of how the long cycles are subdivided into shorter structures. For these reasons, we focus in this initial study on compositions with short *usul*. A vast majority of the pieces in our corpus were composed after the 17th century, which impedes an investigation of changes between simple *usul* and *velveleli* form and their relation to the composition. For that reason, and in order to reduce the representation complexity, we focus on the simple *usul* patterns throughout the paper.

Metrical structure in music is usually assumed to be hierarchical, with the strong accents on top of the hierarchy (Lerdahl & Jackendoff, 1983). A common representation for this hierarchy is given in Figure 2, showing the example of a Eurogenetic 4/4 meter; the strongest accent lies on the beginning of the depicted pattern (*i.e.* on the downbeat). The next strongest accent is on the half note

Figure 2: Accent pattern for Eurogenetic 4/4 meter

level, and this results in an amplitude of 3 in the middle of the pattern. Then the accents on 2 and 4 follow, with an amplitude again reduced by one relative to the accent on 3. Similar to Palmer and Krumhansl (1990), in this paper the lowest metrical level is chosen to be the 16th note, which results in a histogram-like representation with 16 bins for the 4/4 meter. We will refer to such a representation as *accent pattern* in this paper. The regularity of the structure depicted in Figure 2 is caused by the fact that each metrical level can be obtained from its ancestor in the hierarchy by doubling the tempo of its pulsation.

When we map the rhythmic patterns of the usul to such a representation, the differences to an accent pattern of *e.g.* the Eurogenetic 4/4 meter are apparent. In order to obtain accent patterns from usul we apply weights for each stroke following the educational software *mus2okur* (M. K. Karaosmanoğlu et al., 2008), which applies weight 3 for the *düm* strokes and 1 for the weakest strokes in an usul. The accent patterns for six of the most frequently used usul are shown in Figure 3. For instance, the accent pattern of Aksak is depicted in Figure 3a, and it can be seen that this pattern of length 18 cannot be equally subdivided *e.g.* into three patterns of length 6. Therefore, Aksak compositions are usually counted in asymmetric groups of $(2+2+2+3)/8$ and can be considered as related to an additive meter. However, if the magnitudes of the strokes used for graphical representation stand in close relation to the surface rhythm in compositions, and how notes are placed at accents without any usul strokes remains to be examined. It is one important aim of this study to obtain insights into a more complete metrical structure that might be shared by compositions of a specific usul. The usul of Turkish music do not exactly define the meter in all its aspects, and how compositions actually interact with the mode, and how they might evoke a musical meter are questions so far not examined in detail.

3 Methodology

We are going to examine the rhythmic properties of a corpus of Turkish makam music compositions, which is a subset of the collection presented by Karaosmanoğlu (2012). All compositions are available in MIDI form, and the chosen subset consists exclusively of vocal pieces of either *şarkı* or *türkü* form. All MIDI was obtained by synthesizing the scores of the pieces, and not from human performances, which makes the data absolutely precise in timing, and on the other hand completely inexpressive in terms of dynamics. The position of each note within the usul cycle is known, because a simple percussive accompaniment in a separate MIDI channel marks the usul strokes. The usul strokes contained in the percussion channel are excluded from the analysis; only the MIDI channel containing the main melody is used. The songs were chosen from the six usul classes that are depicted in Figure 3. The distribution of songs among the six rhythmic modes and the number of notes (N_{Notes}) and bars (N_{Cycles}) in each class are given in Table 1, columns 2 to 4. The columns denoted as Beats and *Mertebe* define the time signature in which the usul is usually notated, *e.g.* 4/4 for *Sofyan*. Using the *miditoolbox* (Eerola & Toivainen, 2004) the onset times

Figure 3: Accent patterns according to theory for the six usul in the dataset

in beats of the notes contained in the melody are derived.

CLASS	N_{Songs}	N_{Cycles}	N_{Notes}	Beats	$Mertebe$
AKSAK	249	11665	105427	9	8
CURCUNA	123	6718	50120	10	8
DÜYEK	172	7527	55994	8	8
SEMAI	72	6362	18734	3	4
SOFYAN	244	8979	73766	4	4
TÜRK AKSAĞI	53	3528	19870	5	8

Table 1: Some properties of the corpus used for the analysis

In order to determine how the note onsets in a composition relate to the strokes of the usul, we sample all pieces on a 16th-note grid. This choice is influenced by the fact that shorter notes are usually related to grace-notes, which are indicators for possible ornamentations. Then we determine the onset positions relative to the usul cycle of the piece. We give an illustration of that process in Figure 4, where Figure 4a displays six bars from a composition in the usul Düyek. Düyek, with its underlying usul pattern depicted in Figure 3c, is usually notated as 8/8, and therefore one bar will be discretized into 16 accent positions. The notes of the six bars shown in Figure 4a are assigned to the 16 the accent positions as depicted in the note matrix on the top of Figure 4b.

Figure 4: Illustration of note onset positions in a score, and the derivation of the event probability vector

Such a note matrix is the basic material all our analysis in this paper will be based upon.

For a group of compositions with the same underlying usul, we can calculate the probability of observing an onset for each accent position. As depicted in the lower part of Figure 4b, we get these probabilities by determining the percentage of all observed bars in a set of songs that have an onset at the particular position. The resulting vector Π contains probability values, with the length of the vector equal to the length of the usul accent pattern, and we will refer to this vector as event probability vector. Each element in an event probability vector takes on probability values between 0 and 1, while the whole vector usually does not add up to 1. We attribute each note to the temporal bin where it starts and neglect annotated durations of the notes and rests in our analysis.

The event probability vectors obtained from onset frequencies completely disregard the importance of note durations. As has been observed *e.g.* in (Lerdahl & Jackendoff, 1983), in Eurogenetic music long note durations tend to occur more often at high metrical levels. In order to investigate the relation

between rhythmic mode and note duration for Turkish music, we determine the mean duration of the notes events assigned to the bins of the event probability vector. The average duration is given in multiples of sixteenth notes. For instance, for the third accent position of our Dyek example in Figure 4b we obtain the value 3, since $(4 \times 1/4 + 2 \times 1/16)/6 = 3/16$. These vectors will be referred to as event duration vectors, and have the same length as the accent patterns of the usul they are related to.

In the next Section we will shed light on the question of how far the note onset locations contain sufficient information for a discrimination between classes related to the usul. To this end, we apply a Maximum Likelihood (ML) based comparison which we will explain now, again using our Dyek example in Figure 4. Let us consider the event probability vector depicted in Figure 4b as an accurate model, M_D , of how onsets are distributed in this usul. This model is described by the event probability vector $\mathbf{\Pi}_D$, and we wish to calculate the likelihood $p(\mathbf{y}|\mathbf{\Pi}_D)$ of some note sequence $\mathbf{y}$ being produced by this model. For instance, let the notes in the first bar be denoted as $\mathbf{y}_a$, then, assuming independence between the accents, its likelihood given model M_D is obtained by computing

$$p(\mathbf{y}_a|\mathbf{\Pi}_D) = \prod_i \pi_D(i)^{\mathbf{y}_a(i)} (1 - \pi_D(i))^{1-\mathbf{y}_a(i)} \quad (1)$$

where $\mathbf{y}_a$ is assumed to contain one at accents with onsets, and zero otherwise, which results in a likelihood of 0.0457 in our example. In practice we apply this scheme to much larger amounts of data, and perform the computations using log-likelihoods in order to avoid computational problems caused by the multiplication of small numbers. In order to assign a composition to one of n classes, we compute all n log-likelihoods $\log p(\mathbf{y}|M_n)$ and assign the composition to the class with the highest log-likelihood. Note that a composition can be compared to a model obtained for a class with different event probability vector length. This is done simply by reading the notes of the composition into a note matrix with number of accent positions equal to the event probability vector length of the model to be compared with. In our Dyek example in Figure 4a, for instance, we used black dots above the staff to imply the groups of notes that would be written to separate rows of the note matrix when we want to compute the log-likelihood of the song given a Semai model (3/4). The proposed ML classification is equivalent to the cross entropy computation in the context of the fine-grained position model, which Temperley (Temperley, 2010) demonstrated to be an accurate model for note onsets in a large study of European folk songs and a set of classical string quartets.

After the initial experiment using Maximum Likelihood in Section 4, we will address the question of how strong the observed event probabilities are related to the accent patterns depicted in Figure 3. We will approach this question using Bayesian model selection (Bishop, 2006). While ML approaches provide insight into how much a certain parameter setting makes a model to fit observed data, Bayesian model selection addresses the question how well a model is capable of capturing the structure in the data in general, without assuming certain model

parameter values. To this end, $p(\mathbf{y}|M_n)$ is interpreted as marginal likelihood that can be obtained by integration over all possible model parameters π_n

$$p(\mathbf{y}|M_n) = \int p(\mathbf{y}|\pi_n, M_n)p(\pi_n|M_n) \quad (2)$$

which, in our context, enables us to ask the general question how the theoretical usual patterns relate to individual compositions. Note that by solving integrals like the one in 2, the parameters of the model (here π_n) are integrated out, which means that for Bayesian model comparison no specific values for the parameters need to be assumed. We will derive the basic principle of Bayesian model selection in the contexts of event probabilities and durations. A detailed explanation of Bayesian model selection cannot be provided at this place, and the reader is referred to (Bishop, 2006).

For usual accent patterns, we assume the model to have four different parameters. Three parameters, $\pi_1 \dots \pi_3$, are related to the three different stroke intensities in the patterns depicted in Figure 3, and one more, π_0 to the areas without any strokes. Then, assuming statistical independence, we can factorize the marginal likelihood for usual n into

$$p(\mathbf{y}|M_n) = \prod_{i=0}^3 \int d\pi_i p(\mathbf{y}_i|\pi_i)p(\pi_i|M_n) \quad (3)$$

where $\mathbf{y}_i$ denotes the partition of the data sample that is related to usual stroke intensity i . For instance, in the Dyek usual, $\mathbf{y}_3$ would refer to all data at accent positions 3 and 9, where for this usual the maximum intensity strokes occur. We assume data in $\mathbf{y}_i$ to follow a Bernoulli distribution with parameter π_i :

$$p(\mathbf{y}_i|\pi_i) = \prod_{j=1}^{N_i} p(\mathbf{y}_{i,j}|\pi_i), \text{ where } p(\mathbf{y}_{i,j}|\pi_i) = \pi_i^{\mathbf{y}_{i,j}}(1 - \pi_i)^{1-\mathbf{y}_{i,j}} \quad (4)$$

where j indexes the individual datapoints in $\mathbf{y}_i$, and N_i is the amount of datapoints in $\mathbf{y}_i$. For the parameter prior distribution $p(\pi_i|M_n)$ we assume a Beta distribution, since this distribution is the conjugate prior to the Bernoulli distribution (Bishop, 2006, p. 117). This enables us to solve the integral in (3) analytically:

$$p(\pi_i|M_n) = \mathcal{B}(\pi_i; a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \pi_i^{a-1} (1 - \pi_i)^{b-1} \quad (5)$$

Substituting (4) and (5) into (3) we obtain

$$p(\mathbf{y}|M_n) = \left(\frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \right)^4 \prod_{i=0}^3 \frac{\Gamma(a+S_i)\Gamma(b+N_i-S_i)}{\Gamma(a+b+N_i)} \quad (6)$$

where S_i is the number of notes coinciding with strokes of intensity i . In Section 5, we will use this type of model selection to examine the relation between the accent pattern defined by theory and the observed onsets in the data.

For the comparison between the accent patterns and event duration vectors, we have to adapt the type of distribution assumed for the data. While the onsets are described by a binary variable $\mathbf{y}$, the durations can take on values that are multiples of $1/16$. Therefore, we apply a Poisson distribution with parameter λ to the event durations $\mathbf{d}$:

$$p(\mathbf{d}_i|\lambda_i) = \prod_{j=1}^{N_i} p(\mathbf{d}_{i,j}|\lambda_i), \text{ where } p(\mathbf{d}_{i,j}|\lambda_i) = \frac{\lambda_i^{\mathbf{d}_{i,j}} e^{-\lambda_i}}{\mathbf{d}_{i,j}} \quad (7)$$

where $\mathbf{d}_i$ denotes the event durations related to partitions of the data sample aligned with usul strokes of intensity i . We apply a Gamma distribution, the conjugate prior for the Poisson distribution, over the λ_i :

$$p(\lambda_i|M_n) = \frac{1}{\Gamma(\alpha)} \beta^\alpha \lambda_i^{(\alpha-1)} e^{-\beta\lambda_i} \quad (8)$$

which enables for a simple solution of the integral in presence of a Poisson distribution. The marginal likelihood for the duration variables can be then expressed as

$$\begin{aligned} p(\mathbf{d}|M_n) &= \prod_{i=0}^3 \int d\lambda_i p(\mathbf{d}_i|\lambda_i) p(\lambda_i|M_n) \\ &= \left(\frac{\beta^\alpha}{\Gamma(\alpha)} \right)^4 \prod_{i=0}^3 (\beta + 1)^{-(\alpha + \sum_j \mathbf{d}_{i,j})} \frac{\Gamma(\alpha + \sum_j \mathbf{d}_{i,j})}{\prod_j (\mathbf{d}_{i,j}!)} \end{aligned} \quad (9)$$

Both marginal likelihood computations in (6) and (9) will be performed in the logarithmic domain for reasons of numerical stability. We can conclude that onset locations in a song is more likely to be produced by model M_n than model M_m if the difference $\log p(\mathbf{y}|M_n) - \log p(\mathbf{y}|M_m)$ is positive; for the durations we compute the according term $\log p(\mathbf{d}|M_n) - \log p(\mathbf{d}|M_m)$. These difference terms are the criteria we will apply in our subsequent experiments that involve Bayesian model comparison in Sections 5 and 6. This difference is the logarithm of what is usually referred to as the Bayes factor in literature (Bishop, 2006).

4 Discrimination

In this Section we evaluate how to discriminate between various usul using the information of note onset positions. In a first experiment we will use correlation as a measure for a baseline classification, since it has been applied by Palmer and Krumhansl (1990) to determine relations between event probabilities and accent patterns for Eurogenetic music. In order to test the hypothesis that a song is based on one specific usul, we first compute an event probability vector given the length of the usul to be tested for. For instance, if testing an Aksak song on Curcuna, we compute an event probability vector of length 20 (*i.e.* length of Curcuna in $1/16$ -notes). Then we determine the correlation coefficient

between class pattern and the event probability vector. Finally we assign the song to that class which is related to the maximum correlation coefficient.

In a second experiment, we apply the ML approach, as described in Section 3. For this we calculate the likelihood of a song being produced by the event probability vector of an usul, and assign the song to that usul that achieves the highest likelihood value.

In both experiments we apply the theoretical accent patterns shown in Figure 3 as well as event probabilities learnt from data as reference for classification. When trying to classify a song we learn the reference probability vector from all samples of the same usul except of the sample to be classified, *i.e.* we do not use the test songs for training the model. In order to be able to apply the accent patterns in Figure 3 in the ML approach, we assign the measured event probability values to each of the accent that coincide with an usul stroke, while setting all other accents to a low probability value (*e.g.* $\pi = 0.2$). We evaluated the statistical significance of the differences between accuracies using a binomial test (Salzberg, 1997).

In Table 2 we depict the classification accuracies obtained when using the correlation method with the theoretical accent patterns (Corr:Theory) or the event probabilities learnt from the data as reference for a class (Corr:Learnt). Both results are significantly better than a random classification, which would achieve an expected accuracy of 16.67%, but the difference between Corr:Theory and Corr:learnt was found to be not significant. Therefore, both the stroke patterns and the learnt metrical weights seem to have similar discriminative power when applied in this context. However, in the ML approach, the achieved accuracies are significantly higher than for classification using correlation. Furthermore, for the ML approach, concentrating the description of the usul to the stroke positions in ML:Theory lead to a significant improvement over applying the full event probability vector as a generative model.

Experiment	Corr:Theory	Corr:Learnt	ML:Theory	ML:Learnt
Accuracy (%)	54.1	49.6	83.57	72.4

Table 2: Mean classification accuracies for correlation and maximum likelihood experiments

It is informative to compare the confusion matrices obtained from the Corr:Theory experiment (Table 3) with those obtained from the ML:Theory experiment (Table 4). For the Corr:Learnt experiment, higher confusion between rhythmic cycles with unequal length can be observed, where for instance 10.5% of the Aksak pieces (cycle length 18/16) were classified as Sofyan usul (length 16/16). Such misclassification makes little sense musically, and is likely to be caused by applying an inadequate similarity measure on an over-simplified description. However, as soon as we interpret the probability vector as a generative model which produces the note onsets, most instances of confusion between usul of unrelated length disappear. The main source of confusion is the misclassifications

between Düyek and Sofyan (both of length 16/16). Furthermore, Türk Aksağı being classified as Curcuna for 13.5% of the pieces can be explained by their cycle lengths being related by a factor 2.

		Classified usul					
True usul		Ak.	Cu.	Dü.	Se.	So.	Tü.
	Ak.	<u>76.3</u>	3.6	5.6	1.2	10.5	2.8
	Cu.	0.8	<u>37.4</u>	0.8	0	0	61.0
	Dü.	9.9	3.5	<u>45.3</u>	2.9	34.9	3.5
	Se.	1.4	0	0	<u>8.3</u>	88.9	1.4
	So.	9.0	2.0	12.3	13.1	<u>56.6</u>	7.0
	Tü.	5.7	7.5	1.9	1.9	15.1	<u>67.9</u>

Table 3: Classification using frequency count histograms (Corr:Theory): Mean accuracy 54.1%. Underlined values denote correct classification per class, bold numbers denote highest confusion per class.

		Classified usul					
True usul		Ak.	Cu.	Dü.	Se.	So.	Tü.
	Ak.	<u>97.6</u>	0	1.2	0.4	0.8	0
	Cu.	0	<u>95.9</u>	0	0	1.6	2.5
	Dü.	1.2	0.6	<u>60.5</u>	2.9	34.9	0
	Se.	2.8	0	1.4	<u>88.9</u>	6.9	0
	So.	5.7	0.4	11.1	3.7	<u>78.7</u>	0.4
	Tü.	1.9	13.2	0	0	5.7	<u>79.2</u>

Table 4: Classification when using frequency counts in the ML:Theory experiment: Mean accuracy 83.6%. Underlined values denote correct classification per class, bold numbers denote highest confusion per class.

Concluding this experiment, we can state that a Maximum Likelihood approach that focuses on the positions of the usul strokes lead to a superior discrimination between the usul. In the following Section, we shall therefore have a closer look at the obtained event probabilities and their relations with the usul strokes.

5 Note location and duration

In Figures 5a to 5f we depict the event probability vectors for the six chosen usul, measured using the data described in Table 1. We can observe that at those bins which coincide with usul strokes (grey bars), high peaks in the probability vectors of the usul appear. This indicates that at the instances of strokes in the

Figure 5: Event probability vectors for the six usul, which denote the probability to observe a note onset at a specific position in an usul cycle. Accents that coincide with an usul stroke are gray shaded.

usul pattern notes are very likely to occur in a composition. However, observations and theory are not as strongly related as for Eurogenetic music Palmer and Krumhansl (1990). We observed that in most cases the metrical positions different from the strongest stroke in the accent pattern obtain higher probability than would be expected, *i.e.* note probabilities do not decrease consistently from high intensity to low intensity stroke positions. This can be seen *e.g.* for *Sofyan* in Figure 5e, where the peaks at 9 and 13 are higher than those in the related accent pattern (Figure 3e), while the peak at 1 is lower than would be expected from the accent pattern. For the three usul Curcuna, Düyek and Sofyan, the first bins of the vectors do not have the largest probabilities of observing an onset, a phenomenon that is strongest for the Düyek usul. This implies that for these three usul note onsets are more likely to be encountered on accents in the middle of the usul cycle than on the downbeat.

We applied Bayesian model selection as described in Section 3, in order to address the question how strongly the data summarized by the event probabilities in Figure 5 are actually related to the underlying accent patterns depicted in Figure 3. Or, stated another way, we want to answer the question of how far the theoretical usul patterns represent an unambiguous description of the way notes are distributed in a composition. We evaluated the log-Bayes factor $\Delta_k = \log p(\mathbf{y}|M_{true}) - \log p(\mathbf{y}|M_k)$ between the true model M_{true} and all models M_k , $k = 1 \dots 6$, for the usul, including the true usul. We then determined for each song in the collection the value k that leads to a minimum log-Bayes factor Δ_k , which gives the most likely model for the song. We obtained a best-model matrix as depicted in Table 5, in which the percentage of songs of the class specified in the rows assigned to the models listed in the columns is listed. Firstly, by looking at the underlined values on the diagonal of the matrix, it

becomes apparent that all models M_1 to M_6 described by the theoretical accent patterns of the usul seem to be very strongly related to the compositions, since the values on the diagonals are consistently the largest in each row. For Sofyan, however, an interesting modification had to be performed in order to achieve this: the simple usul pattern depicted in Figure 3e had to be replaced by the *velveleli* pattern, that is equal to the Aksak pattern depicted in Figure 3a when omitting the last two accents. This pattern contains more strokes than the simple usul pattern, and these patterns are more frequently applied in slow pieces. A *velveleli* pattern did not achieve an improvement of the acceptance rate for the correct model for any of the other usul. The most likely models apart from the true model in each row are depicted using bold numbers. Large numbers can be interpreted to indicate a similarity of the usul patterns in the light of the available data. These similarities nicely resemble confusion in the discrimination task of Section 4. The most similar models are Sofyan and Dyek, which are identical regarding the length of their accent patterns. However, the numbers still indicate a differentiation between both models. The pair of Curcuna and Trk Aksaı is also similar to some extent, which is reflected in the relation of their cycle lengths by a factor of 2. Interestingly, the identity mentioned between the Sofyan and the first 16 accents of the Aksak pattern does not lead to any confusion. While the models share a similar stroke pattern, the differing lengths overshadow this aspect. Generally, the results of this model comparison confirm that the patterns applied in the ML:Theory experiment in Section 4 represent a well-performing choice of parameters for the model that was examined in this model comparison.

	$M_1(9/8)$	$M_2(10/8)$	$M_3(8/8)$	$M_4(3/4)$	$M_5(4/4)$	$M_6(5/8)$
Ak.(9/8)	<u>94.4</u>	0.8	0.8032	0.8	2.0	1.2
Cu.(10/8)	0	<u>88.6</u>	0.8	0	0	10.6
D��.(8/8)	1.2	0	<u>61.6</u>	0	36.6	0.6
Se.(3/4)	2.8	0	0	<u>90.3</u>	6.9	0
So.(4/4)	3.7	0	13.9	2.0	<u>79.9</u>	0.4
T��.(5/8)	1.9	11.3	0	0	5.7	<u>81.1</u>

Table 5: Model comparison: percentages of the most likely models M_k for songs of the classes given in the rows of the matrix. The diagonal denotes the true model for the class (underlined). The highest confusion value is printed in bold numbers.

In order to obtain more insight into relations with meter in Eurogenetic music, it is interesting to compare the two usul which can be counted as a 4/4 meter with event probabilities obtained by Temperley (Temperley, 2010) for the Essen collection of European folk songs. This comparison is illustrated by Figure 6, where we reduced the temporal resolution from the 1/16 to the 1/8 level in order to be able to compare with Temperley’s results. It is apparent that the only accent with a clearly higher event probability for the Essen collection

is the downbeat (*i.e.* the first accent of the cycle). Compared to European 4/4 meter, the Turkish songs place much more events on places in a rhythmic cycle which could be expected as having a low accent (*bins 2,4,6 and 8*), both using the accent pattern of the 4/4 meter or the related *usul* patterns as a referent. This indicates a difference between the repertoires, which is characterised by fewer events on the downbeat, and more events in other locations of the cycle for Turkish makam music than for European folk music. In order to further illustrate the difference of the event probabilities depicted in Figure 6, we evaluated how many of the 416 Düyek and Sofyan examples in our corpus would obtain a higher likelihood for the event probabilities of the Essen corpus than for its own *usul* event probability. The result is that only for 16 files (3.85%) the Essen corpus event probabilities achieve a higher likelihood than the Turkish event probabilities, which further underlines the significance of the differences observed in Figure 6. Similar conclusions can be drawn when comparing with frequency counts that Palmer and Krumhansl obtained (Figure 1 in Palmer and Krumhansl (1990)) from a corpus of Eurogenetic classical music. On this corpus, similar to the Essen corpus, the downbeat is clearly emphasised by event probabilities, while locations that receive low accent in the 4/4-meter receive very few note events. This supports the existence of a difference between the underlying metrical framework of Turkish makam music, and Eurogenetic metrical frameworks of equal length. This difference consists mainly in note onsets forming a stronger emphasis of the downbeat, and a stronger stratification of accents for Eurogenetic music.

Furthermore, many note onsets appear where there is no accent specified by the *usul* pattern. This is not surprising as the *usul* are more sparse than *e.g.* the accents given for a complete metrical description as given in Figure 2. The sparseness of the theoretical description, however, does not necessarily imply that note onsets are less frequent in the absence of an *usul* stroke. It appears more reasonable to interpret the *usul* patterns as guidelines to which metrical positions high stress should be given, since we saw in our discrimination experiment that focusing attention on the notes coinciding with *usul* strokes helps in differentiating between *usul*. On the other hand, measured event probabilities might be interpreted as a possibility to define metrical accent on all possible locations in the bar.

In order to investigate the relation between note durations and accent pattern we computed the event duration vectors depicted in Figure 7. The relation between duration and *usul* is very strong in Turkish songs, as can be seen by comparing the duration vectors in Figure 7 with the related accent patterns in Figure 3. For convenience, again the *usul* stroke accents are shaded grey in Figure 3. The depicted duration vectors show the mean note duration encountered at every location of the underlying *usul*-pattern. Especially the beginning of a rhythmic cycle seems to be more strongly related to longer durations than to a high event probability, because in all but one case the durations on the first accent are the largest in the *usul* cycle. We applied the Bayesian model selection to evaluate how much the measured durations are related to the structure defined by the *usul* strokes. The results shown in Table 6 resemble those in

Figure 6: Comparison of the event probabilities for the usul Düyek and Sofyan with the probabilities as documented by Temperley (2010) for the Essen folk song collection.

Table 5 in structure, with the confusion between the models generally slightly higher for the durations. This confirms, in the context of Turkish music, the finding by Temperley (Temperley, 2010) that duration is an important aspect to include into metrical models.

	$M_1(9/8)$	$M_2(10/8)$	$M_3(8/8)$	$M_4(3/4)$	$M_5(4/4)$	$M_6(5/8)$
Ak.(9/8)	<u>94.4</u>	1.2	1.2	1.6	0.8	0.8
Cu.(10/8)	0	<u>91.9</u>	0.8	0	0.8	6.5
Dü.(8/8)	0.6	0	<u>59.9</u>	8.7	30.8	0
Se.(3/4)	2.8	0	0	<u>88.8</u>	6.9	1.4
So.(4/4)	0	0.4	32.8	10.2	<u>56.2</u>	0.4
Tü.(5/8)	0	13.2	5.7	1.9	3.8	<u>75.5</u>

Table 6: Model comparison for durations: percentages of the most likely models M_k for songs of the classes given in the rows of the matrix. The diagonal denotes the true model for the class (underlined). The highest confusion value is printed in bold numbers.

6 Style change

The previous sections provided insight into the distribution of note events in Turkish makam music, by using the whole size of a corpus which consists of compositions from mainly the last three centuries. We will now examine if the way events are placed and the durations of the events have changed throughout time in Turkish makam music. Significant change regarding the melodic density was observed by Wright (1988), which he argued was caused by a reduction of

Figure 7: Event duration vectors that depict the average note durations at the various accents in an usul. Accents that coincide with an usul stroke are gray shaded.

speed in performance through the centuries. In this section, we complement these findings with an analysis of aspects of change in rhythmic style. To this end, we collected the compositions by two composers who can be considered as having influenced the compositional style to a great extent in their periods. In order to address the question if observed changes are a matter of personal style, or rather a phenomenon shared with other composers, we also compiled two sets of compositions by other composers who lived in the same periods as the two influential composers.

6.1 Biographies

The first composer, Hamamizade Ismail Dede Efendi (1778-1846), is considered the most influential composer of his time. He served as a master musician, instructor and composer in the Ottoman palace most of his life and had been supported by all the Sultans of the time with great admiration (III.Selim, IV. Mustafa, II. Mahmut and Abdülmecit). His works are considered to be the most representative (yet creative) examples of the Turkish makam music tradition. He composed in both religious and secular traditional forms including pieces in 39 distinct usuls, 67 distinct makams and 17 distinct forms, a total of about five hundred pieces, only half of which are accessible today. He is considered to be the master of combined use of rhythmic, melodic and poetic aspects in great harmony. He lived during a period of important reforms with an increasing influence by the Western culture over time. As he grew older, he had the chance to listen to Western musical instruments, orchestras, and works of Italian composers that were becoming increasingly popular in the palace. Detailed biographical notes can be found in Kılınçarslan (2006) and Salgar (2004).

The second composer, Sadettin Kaynak (1895-1961), lived in a period of

emphatic Westernisation in all dimensions of the culture, especially after the foundation the new republic. After the closure of Darüelhan in 1927, no governmental body for Turkish makam music education was available until the 1970s. There have been periods when Turkish makam music was banned on the radio, and when religious lodges - which served continuation of traditional music to a great extent - were closed. Sadettin Kaynak had a religious education and served as an officer of religion (imam of the Sultan Selim mosque) and at the same time gave concerts in Europe, composed many popular pieces for the large audiences in various forms including şarkı, movie scores, folk songs (türkü), children songs, valse, tango and new forms like fantasy, recorded with Columbia, Odeon and Pathe records. He is considered one of the most important composers of Turkish makam music in the 20th century, famous for his freer style in using makams, usuls and forms. He has more than six hundred compositions in 16 forms, 58 makams and 20 usuls (he also applied novel ways of using usuls in combination which lead to 42 new combinations) (Özdemir, 2009). Many of his works are still amongst the most popular today.

While both composers are famous for their highly creative style in their periods, we can consider Ismail Dede Efendi as a composer of traditional forms and Sadettin Kaynak as composer of popular pieces with a freer style in makam and usul use. Kaynak was definitely more subject to Western influences, and he even composed a few pieces in Western forms.

6.2 Change in note event location and duration

For both composers, there are two usul for which a sufficient number of compositions are in our corpus: Aksak and Düyek. Therefore we computed the event probability vectors and the duration vectors for both composers for the compositions in these two usul. The results regarding the note event probabilities are depicted in Figure 8, focusing on the metric accents which coincide with usul strokes. We observe for both usul that accents in the middle of the usul cycle obtain decreased event probabilities for the compositions by Sadettin Kaynak, while the downbeats (*i.e.* the beginning of the cycle) obtain similar numbers of onsets. In order to evaluate these changes for significance, Bayesian model selection was applied. We tested the hypothesis of the onsets at a specific metrical accent coming either from one unified model (*i.e.* compositional style), or being generated by two different statistical models, each describing the event probabilities for the specific composer. Those accents which were found to have significantly different characteristics are highlighted using a grey background in Figure 8. It is apparent that the decrease of onset probabilities in the middle of the cycles is a significant change. This can be interpreted as the downbeat having obtained a relatively higher importance within the rhythmic cycle by the decreased emphasis on other metrical accents. This emphasis is further enhanced by a change in the average note durations between the composers. Generally, we observed an increase of note durations of 14% and 23% for Aksak and Düyek, respectively. However, the downbeats are characterised by the largest increases of 29% and 34% in duration for the more recent compositions

by Kaynak, as depicted in Figure 9. The increases on the downbeats were larger than increases on all other accents in the usuls. Again, these changes were found significant based on Bayesian model selection, this time using a Poisson distributions for the note durations instead of binomial distributions as for the onset events (see Section 3). These two findings fit together to form the conclusion that Sadettin Kaynak tends to put increased emphasis on the downbeat in a bar, by placing relatively more note events of longer duration than Dede Efendi.

It could be argued that the differences described regarding rhythmic elaboration are rather aspects of personal style than style change between two periods. In order to test for this possibility we collected compositions in our corpus by composers related to the periods of Dede Efendi and Kaynak. We obtained a set of 74 Aksak and 97 Düyek compositions that do not include the compositions by Dede Efendi or Kaynak. We observed changes that are highly consistent with the changes depicted in Figures 8 for the two composers. Specifically, we were able to confirm all significant changes in event probabilities using the same Bayesian model comparison applied to the larger data set. Regarding durations, only a statistically significant increase in duration for Düyek could be confirmed (from 2.17/16 to 2.48/16), while for Aksak no significant change in duration on the downbeat was encountered. Therefore, the differences between the two composers, at least in terms of note positioning, are unlikely to be simply aspects of personal style.

6.3 Example melodies

We illustrate the way these changes are reflected in individual compositions using two examples in usul Aksak. Figure 10a shows the first two lines of the Evic Şarkı “Sevdim Bir Gonca-i Bânâ” composed by Dede Efendi, and Figure 10b depicts the first two lines of the Hüzzam Şarkı “Gönlüm Seher Yeli Gibi” by Sadettin Kaynak. Comparing the two short examples it can be seen that for the composition by Kaynak in all bars a syllable starts on a downbeat with a note equal or longer than a quarter note. On the other hand, the example by Dede Efendi is characterised by three bars where the first syllable of the lyrics appears on the third accent of the 1/8 metrical level, therefore decreasing the note lengths on the downbeat in comparison with the Kaynak composition, and putting a stronger emphasis on locations different than the downbeat. Interestingly, this finding could be confirmed by our co-operations with musicians, who helped us annotate melodic phrase boundaries in Turkish compositions; while for Aksak compositions by both Dede Efendi and Sadettin Kaynak melodic phrases, according to the annotations, are most likely to start on the downbeat, in compositions by Dede Efendi many phrases start on the third accent as observed in the example. This indicates that the observed change in rhythmic style is closely related to a different melodic phrasing, which seems to be more aligned with the downbeat for Sadettin Kaynak.

(a) Aksak Event Prob.

(b) Düyek Event Prob.

Figure 8: Change in event probabilities for two usul. Onsets are more frequent in the middle of the usul cycle for old pieces. Differences that are significant according to a Bayesian model comparison are highlighted.

6.4 Usul preferences and form

Related to the observed changes in rhythm it is interesting to consider which usul the composers in the periods preferred for their compositions. From the information available in (Kılınçarslan, 2006; Özdemir, 2009) we compiled the pie charts depicted in Figure 11 for the two composers. The first difference that can be observed is the wider variety of usul used by Dede Efendi. The second difference is that Sadettin Kaynak composed a majority of his pieces in short cycles having a length equal to a power of two (*i.e.* 2/4, 4/4, 8/4, 8/8), with 61% of the pieces listed in (Özdemir, 2009) belonging to such types of rhythmic modes. For Dede Efendi, only 24% of the listed pieces belong to such an “even” rhythmic mode, while much more pieces are in some ternary rhythmic mode (*i.e.* 3/4, 6/4) or in usul longer than 15 strokes. These differences are related to a change in preference regarding compositional form, away from forms such as the instrumental *peşrev* or the vocal form *beste*, which were used less often

Figure 9: Amount of increase in duration on the downbeats. Sadettin Kaynak's compositions have significantly longer note values on the start of a rhythmic cycle, related to an increase of 29% and 34% in average for Aksak and Düyek, respectively.

(Ah) Sev dim bir gon ca i râ nâ
Ga la ta da To do ra ki

Ger da nı el mas tan â lâ SAZ
Be yağ lun da Va si lâ ki

(a) Dede Efendi composition

Gönlüm se her ye li gi bi SAZ
Dal dan da la es sem di yor SAZ

(b) Sadettin Kaynak composition

Figure 10: Two excerpts from Aksak compositions that depict the changes in note distribution and duration.

in more recent periods. Instead, Sadettin Kaynak tended to compose in the popular şarkı vocal form using mostly Aksak usul or usul of lengths equal to powers of 2. A similar shift in usul preferences was observed when considering

Figure 11: Choice of usul in the work of the individual composers

pieces by composers who were contemporaries of either Dede Efendi or Kaynak.

Therefore, we can conclude that the preferences regarding the used usul have changed throughout the periods, as well as the way compositions interact with the specific usul. The change in usul preferences is partly related to a change in chosen compositional form as well, towards a preference of secular short songs. Taking into account the historical context of these periods, it is evident to relate these changes to a general change towards European style norms after the foundation of the Turkish republic. Political guidelines regarding Westernisation had their impact on education in general, but also on the musical education. We provided support for the hypothesis that these general changes in the Turkish society also affected the way rhythm is shaped in compositions.

7 Conclusions

In a classification task, we found that focusing models on the onset events coinciding with the usul strokes leads to an improved recognition of the usul of a piece. This implies that the usul patterns in Turkish music indicate which accents in the meter are significant for the recognition of a specific usul. We showed that our methodology can identify differences between Eurogenetic and Turkish music, as well as differences related to processes of change in musical style throughout the periods in Turkish makam music. Important changes took place regarding the compositional forms, as well as regarding melodic phrasing and rhythmic style. All this represents a complex of stylistic change that is consistent with the dramatic historic and social changes towards the dawn of the Turkish republic, which can be considered as a point in history of massive Westernisation in all cultural aspects. Using our methods, we were able to observe the changes in rhythmic style and their correlation with the change in melodic phrasing is a challenging aspect of future investigation.

Using a large corpus of compositions of Turkish makam music we investigated the way the surface rhythm relates to the underlying usul. We saw that the way

note events are distributed within a bar is highly related with the rhythmic mode at least for the short *usul*, which were the object of investigation in this study. Meter models in the form of event probability and duration vectors were obtained from our corpus, and we showed that the strokes in the patterns describing the rhythmic modes coincide with accents that have many long note events. Both event location and duration contribute to the impression of meter in this music, an aspect that Turkish music shares with Eurogenetic music. Interesting differences towards Eurogenetic music are a less stratified meter, as event probabilities for Turkish music take very high values for several accents different from the downbeat.

Since the present study used notations as a basis for the analysis, we were able to compare our findings with similar studies for Eurogenetic music. A systematic comparison with oral music cultures can only be based on information obtained from the audio signals of performances, if possible supported by information from the practising musicians. While such a comparison was not in the focus of this work, the study of Turkish rhythms reveals interesting similarities and differences with other cultures. To mention only one aspect, it is interesting to observe that rhythms in Turkey, just as in other parts of the world, are rather described in a syllabic way than counted. This might imply that the Eurogenetic model of a metrical hierarchy, which is strongly related to the idea of counting rhythm, might not capture rhythmic concepts of other cultures well. In fact, African time lines are rather flat in nature, and the thought of a metrical hierarchy seems less important in African musics. For Turkish music, rhythms we encounter seem to provide a more emphasized hierarchy, but with a less clear stratification than Eurogenetic music.

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