On Operationalizing the Musicological Concept of Tune Family for Computational Modeling

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Abstract

We present a computational investigation of melodic similarity among a large collection of Dutch folk song melodies, hosted at the Meertens Institute (Amsterdam). The primary aim is to develop a similarity measure for melodies that corresponds to the way musicological experts would evaluate the similarity between folk song melodies. Therefore, we aim to relate our computational solutions to existing knowledge from ethnomusicological studies on Western folk song melodies. The most important concept from the musical domain is the concept of tune family. It appears that the existing algorithm for sequence alignment (Needleman-Wunsch) with appropriate musicological knowledge incorporated is adequate to retrieve members of the same tune family from the full collection of melodies. Based on the automatic similarity assessments, the musicological collection specialists of the institute reconsidered the classification of several melodies. Furthermore, they could classify several melodies they were not able to recognize before.

1. Introduction

One of the elementary activities of ethnomusicologists has been the gathering of field recordings of musical performance. This has resulted in many audio archives containing ethnic music. To digitally explore and unlock such an audio archive, adequate models of the musical contents are needed. It is one of the primary tasks of computational (ethno)musicology to design such models. In this paper we present an approach to unlock the collection of recordings of Dutch folk songs that is hosted at the Meertens Institute (Amsterdam). This research was performed in the context of the WITCHCRAFT-project (Wiering, 2009).[1]

The research on melodies from oral tradition already has an extensive history in the humanities domain. It is our strong aim to adhere as much as possible to this humanities tradition in our computational modelling of musical contents. This interdisciplinary approach will result in musically informed computational models that are relevant in the humanities domain. In our case, the relevant research tradition is the area of folk song research, which focuses on the study of Western folk music.

2. Some Notes on Methodology

In order to maximally benefit from both the musicological domain, and the computer science domain, we take the following research cycle as a point of departure:

1. understanding the musical problem, which involves studying relevant musicological literature, especially the specific discourse concerning the research question at hand;
2. designing musically meaningful data-structures and algorithms: the computational model as hypothesis;
3. interpreting the algorithmic output;
4. revising the model in case of failure;
5. integrating the results in the musicological discourse.

Within Computer Science, many *abstract* algorithms and data-structures have been developed during the last decades. An algorithm consists of a series of operations on formalized data. Many of these algorithms have potential for application to music. In steps 2, 3 and 4 of our cycle, the main challenge is to formulate the musical problem at hand in terms of algorithms and corresponding data structures. Examples of such data structures are a sequence of symbols, a vector of feature values, a graph, a point set in a geometric space, and so on. Examples of algorithmic tasks are sorting, aligning, clustering, classification, etc. The extent to which direct relations exist between data-structures and algorithms on the one hand, and properties of the music on the other hand, is an important success factor for a computational study of music. Therefore, one of the basic principles of our approach is to design computational measures of similarity that are adequate from a musical point of view. The required musicological background is provided by the research tradition of musicology. Therefore, the first step in the cycle is to study the relevant musicological discourse.

Steps 3 and 4 need to be performed iteratively. Failure of the algorithm indicates an opportunity for improvement and knowledge-gain (cf. McCarty, 2005). A major question is how to determine whether an algorithm fails or succeeds. A common approach is to prepare a set of known results (a so-called 'ground-truth', or reference set) and to compare the algorithmic output with it. The better the algorithm is able to reproduce the ground-truth, the more successful it is. A major problem with this approach is that in most humanities discussions no well known,

[1] The acronym stands for: What Is Topical in Cultural Heritage: Content-based Retrieval Among Folksong Tunes

definitive, right results exist that can serve as ground-truth. In many cases, there is rather discussion and difference in opinion. Therefore, it is necessary to compare the outcome of algorithms in other ways with domain data. The exact way of doing this is different for each concrete research project.
In the fifth step in our cycle newly gained musicological insights are published in musicological forums (journals, conferences, etc.), thus making the results accessible, and debatable, for the musicological community.

3. The Musicological Concept of Tune Family

The musicological concept that is all-important for our specific research question is the concept of *tune family.* It was introduced in the 1950s by Samuel Bayard (1950) to denote a group of melodies that is supposed to have a common 'ancestor' in oral transmission. Since the variation that occurs to the melodies in the process of oral transmission can be considerable, the members of a tune family may show major differences of various kinds. In folk song research there have been investigations into the kinds of differences that occur. Important contributors to this line of research are, among others, Ilmari Krohn (1903), Béla Bartók and Zoltán Kodály (see e.g. Suchoff, 1981), Walter Wiora (1941), Bertrand Bronson (1950), Ernst Klusen et al. (1978) Wolfram Steinbeck (1982), James Cowdery (1984), Barbara Jesser (1991), and Zoltan Juhasz (2010). None of these studies, however, resulted in a precise model of the concept of tune family, which is needed when this concept is used to digitally unlock a folk song archive. Therefore, it is our aim to understand this concept by both performing an in-depth analysis of the similarity relations between melodies that form a tune family and a computational approach to evaluate the similarity between melodies.

4. The Annotated Corpus

The Meertens Institute in Amsterdam hosts a collection of over 7000 audio recordings of Dutch folk songs, called *Onder de groene linde* (Grijp, 2008). These recordings were made from the 1950s till the 1980s, mainly by the field-workers Will Scheepers and Ate Doornbosch. They visited many people across the country with their tape recorders. Since most of the recorded songs were sung from memory, considerable variation can occur between variants of the same tune. In a previous project many of these recordings were transcribed into musical notation. In the course of the WITCHCRAFT project, around 2500 of these song transcriptions, along with more than 3000 songs from written sources have been digitized and are thus available for computational processing. Because of its size, composition and quality of metadata, *Onder de groene linde* is in fact a unique resource for studying the mechanism of oral transmission of melody. And, because of the amount of melodies, it would be essential to search and order these automatically, not just using the metadata, but especially the musical content.
The melodies in the collection have been classified by musicological experts at the Meertens Institute into tune families such that each tune family is considered to consist of melodies that have a common historic origin. Since the actual historic relation between the melodies is not known from documentary evidence, the classification is based on similarity assessments. If the similarity between two melodies is high enough to assume a plausible genetic relation between them, the two melodies are classified into the same tune family.
As an example, Figure 1 shows the beginnings of four members of the tune family "Soldaat kwam uit de oorlog".

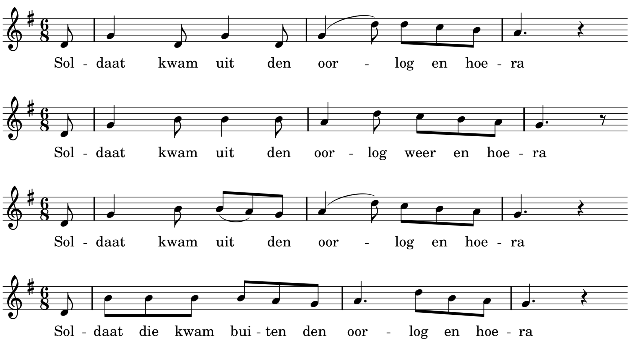

Figure 1: Incipits of four members of the tune family "Soldaat kwam uit de oorlog"

The domain experts base their similarity assessment in most cases on an intuitive, holistic decision. In case of doubts, single features of the melodies are examined to achieve a decision on the classification of the song. Furthermore, in the human process of classifying into tune families some melodies receive the status of a prototypical melody of their tune family as the most typical representative, to which new candidate tune family members are compared. Therefore such a melody can be considered a reference melody for the tune family.
To achieve better understanding of the concept of tune family, as it is operational at the Meertens Institute, we designed an annotation experiment. For 360 melodies from 26 tune families, the domain specialists annotated the degree of similarity between pairs of melodies for different features: contour, rhythm, motifs, and lyrics. We refer to this corpus as 'the Annotated Corpus'. These 360 songs have been carefully selected to form a relatively small subset that is representative for the collection as a whole concerning the various similarity relations between the songs. An additional constraint was that considerable variation has to occur among the melodies that belong to the same tune family. 'Easy' tune families have not been selected. Thus, the results of studying this subset are expected to be indicative for the results that would be obtained when studying the entire corpus. For each tune family, one melody has been selected as reference melody by one of the domain experts. Next, the similarity relations of the reference melody to each of the other members have been annotated. For each of the features contour, rhythm, motifs and lyrics, the experts rated the degree of similarity between the reference melody and a member melody on a three-valued scale: 0 for dissimilarity, 1 for somewhat similar melodies, and 2 for obvious similarity. For each of the features we established precise criteria for the ratings (see for the details: Volk et al. 2008 and Van Kranenburg, 2010, Ch. 3).
The resulting annotations answer the question why the human experts classified the song under consideration into a certain tune family. The annotations show that the – already mentioned – melodic features of contour, rhythm

and recurring melodic fragments (motifs) are important for human assessment of melodic similarity. An important conclusion is that the relative importance of these features varies from case to case between and within tune families. In general, however, the occurrence of characteristic melodic motifs appeared the most important reason for grouping melodies into the same tune family. From this we conclude that a computational model of the concept of tune family needs to be based on various aspects of melody (contour, rhythm, motifs); specifically, such a model should incorporate the notion of shared melodic motifs. This finding seems related to the contribution of James Cowdery (1984) to the discussion on the concept of tune family. Based on observations in Irish folk music, Cowdery extended the definition of Bayard with the notion that melodies that are composed from material from the same 'pool of motives' also have to be considered a tune family. In his view, the conception of tune family in which all melodies go back to one 'ancestor' tune is too limited.

Our set of 360 melodies, together with their similarity annotations, offer a rich resource for testing models of melodic similarity and for testing Music Information Retrieval systems for melodies.

5. An Alignment-Based Similarity Measure for Melodies

An important device for folk song researchers to examine the similarity of two melodies is the construction of an alignment. By notating the melodies below each other such that the corresponding parts are aligned, the differences and similarities between the melodies are easier to inspect visually. As an example, Figure 2 shows an alignment that was constructed by Walter Wiora (1941). As all the alignments in his article, which are many, it was 'hand-crafted'. The availability of a method to *automatically* find an adequate alignment of two melodies would enable the employment of this device on a large scale.

Figure 2: Example of an alignment of two folk song melodies by Wiora (1941).

In computer science, an algorithm has been developed for the alignment of sequences of symbols (Needleman and Wunsch, 1970). Although the intended field of application was Biology, this algorithm solves the problem to find an optimal alignment of two sequences of symbols *at an abstract level*. Therefore, it is applicable in other domains as well.

In the approach of Needleman and Wunsch, the quality of an alignment is measured by the alignment score, which is the sum of the alignment scores of the individual symbols. If we consider two sequences of symbols $\boldsymbol{x}$: $x_1,\ldots,x_i,\ldots,x_n$, and $\boldsymbol{y}$: $y_1,\ldots,y_j,\ldots,y_m$, then symbol x_i can either be aligned with a symbol from sequence $\boldsymbol{y}$ or with a gap. Both operations have a score, respectively the substitution score and the gap score. The gap score is mostly expressed as penalty, i.e. a negative score. The optimal alignment and its score are found by filling a matrix D recursively according to:

$$D(i,j) = \max \begin{cases} D(i-1,j-1) + S(x_i, y_j) \\ D(i-1,j) - \gamma \\ D(i,j-1) - \gamma \end{cases},$$

in which $S(x_i,y_j)$ is a similarity function for symbols, which is the substitution score, and γ is the gap penalty, $D(0,0) = 0$, $D(i,0) = -i\gamma$, and $D(0,j) = -j\gamma$. $D(i,j)$ contains the score of the optimal alignment up to x_i and y_j and, therefore, $D(m,n)$ contains the score of the optimal alignment of the complete sequences. We can obtain the alignment itself by tracing back from $D(m,n)$ to $D(0,0)$. The standard dynamic programming algorithm has both time and space complexity $O(nm)$. In our modeling, we use an extension of the algorithm proposed by Gotoh (1982), which employs an affine gap penalty function without loss of efficiency. In this approach, the extension of a gap gets a lower penalty than its opening.

The abstract terms of the algorithm are the symbols, the similarity function $S(x,y)$ for symbols, and the gap penalty function. The crucial step to design an adequate musical application of this algorithm is to define both the symbols and the similarity measure in terms from the musical domain. This is one of the core aspects of the interdisciplinarity in our approach.

Pitch:	a^1	b^1	c^2	d^2	e^2	f^2	e^2	d^2
Duration:	1/4	1/8	1/8	1/4	1/4	1/8	1/8	1/4
Scoretime:	0	1/4	3/8	2/4	3/4	4/4	9/8	5/4
BarTime:	0	1/4	3/8	0	1/4	0	1/8	1/4
Onset:	0	2	3	4	6	8	9	10
Bar:	0	0	0	1	1	2	2	2
Phrase:	0	0	0	0	0	0	0	0
Upbeat:	false	false	false	false	false	false	false	false
Meter:	2/4	2/4	2/4	2/4	2/4	2/4	2/4	2/4
Free meter:	false	false	false	false	false	false	false	false
Accented:	true	false	false	true	false	true	false	false
IOI ratio:	[1]	0.5	1	2	1	0.5	1	2
Metr.weight:	1	0.853	0.382	0.853	1	0.853	0.382	0.853
Phrasepos:	0	0.2	0.3	0.4	0.6	0.8	0.9	1

Figure 3: Example of a melody as sequence of symbols with attributes.

Since we have the melodies available as sequence of notes, we take the notes as the symbols. Each note has a number of attributes that can be used in computing the similarity between two notes. In our studies, we used the following attributes: pitch (in base-40 encoding, see Hewlett, 1992), duration (rational number), score time (rational number), time in bar (rational number), onset (integer), current bar number (integer), current phrase number (integer), upbeat (boolean), current meter (rational number), free meter (boolean), accented (boolean), inter-onset-interval ratio (rational number), normalized metrical weight (real number in [0, 1]) and the time position within phrase (real number in [0, 1]). The metrical weight is computed according to the Inner Metric Analysis (IMA) as described in Volk, 2008. The time position of the note in the phrase is a value between 0 and 1, where 0 corresponds to the onset time of the first note of the phrase, and 1 corresponds to the onset time of the last note in the phrase. Figure 3 shows an example with the attributes we use in our approach.

In an extensive study, we evaluated numerous similarity measures for the symbols (Van Kranenburg 2010, Ch.6). The best performing similarity measure in terms of retrieval results is based on the pitch, the metric weight (IMA) and the time-position of the note in its phrase. The more similar two notes x_i and y_j are with respect to these parameters, the higher the similarity score. The exact equations are as follows.

$$S_{pitchband}(x_i, y_j) = \begin{cases} 1 - \dfrac{\mathrm{int}(x_i, y_j)}{23} & \text{if } \mathrm{int}(x_i, y_j) \leq 23 \\ -1 & \text{otherwise} \end{cases},$$

where $\mathrm{int}(x, y) = |p(x) - p(y)| \bmod 40$, in which $p(x)$ is the pitch of note x. A perfect fifth has value 23 in base-40 encoding. Thus, all intervals up to a perfect fifth get a positive substitution score and all larger intervals are considered a bad match.

$$S_{ima}(x_i, y_j) = 1 - 2|w(x_i) - w(y_j)|,$$

in which $w(x)$ is the metric weight of note x.

$$S_{phraseposition}(x_i, y_j) = 1 - 2|phr(x_i) - phr(y_j)|,$$

in which $phr(x)$ is the time-position of note x in its phrase. Each of these similarity functions returns a value between -1 and 1. The final similarity score that is used in the alignment algorithm is obtained by scaling each of $S_{pitchband}$, S_{ima}, and $S_{phraseposition}$ into the interval [0,1], multiplying the resulting values, and scaling the result of that back into the interval [-1,1]. For the gap penalties, we take 0.8 for a gap opening and 0.2 for a gap extension. Thus, a gap opening is slightly 'cheaper' than a bad match, and we stimulate a lower amount of long gaps rather than a larger amount of short gaps. An example of an alignment according to this configuration is shown in Figure 2.

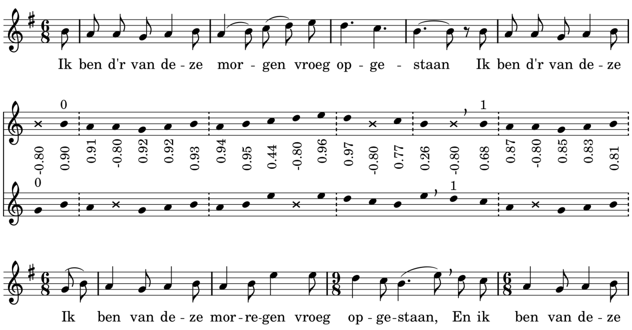

Figure 2: Example of an alignment. The similarity scores for the aligned notes are shown between the middle staves.

6. Evaluation of the Similarity Measure

We evaluated our alignment configuration by measuring its retrieval performance on the Annotated Corpus. Each melody from the Annotated Corpus is taken once as query and the other melodies are sorted according to the normalized score of the alignment with the query melody, using the similarity measure for symbols that was presented in the previous section. To get a better indication of the performance for the whole collection, we included 4470 melodies from other tune families in the data set, as well. For each annotated melody, this results in a ranked list of 4830 melodies, among which the other melodies from the same tune family. From these ranked lists we compute several standard information retrieval performance measures. At each rank we compute average recall and average precision over all ranking lists. These values are plotted in a diagram. Furthermore, we compute the mean average precision (MAP) by averaging the precision of all relevant items for all queries, and we compute the recognition rate, which is the percentage of queries that has a relevant item on the first rank. The criterion for relevance is the membership of the same tune family as determined by the musicological experts.

The resulting values for our alignment-based similarity measure are the following. We find a MAP of 0.68, and a recognition rate of 92%. Figure 5 shows the resulting precision-recall diagram. The relatively high recognition rate indicates that this similarity measure is useful for identifying melodies. In the vast majority of the cases a relevant item is at the top of the ranked list. It appears that for 98% of the queries at least one relevant item can be found among the first 10 items on the ranked list. For ranked lists of size 4830 and tune families of typical size between 10 and 20 melodies, these are good figures.

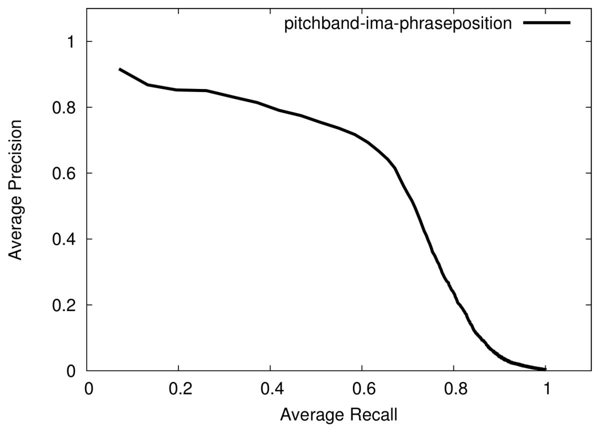

Figure 5: Average Precision vs. Average Recall for the retrieval based on the alignment algorithm.

7. False negatives

At this point, we could stop our investigation. We have a similarity measure that delivers good retrieval results, and, thus, can be used in a melody search engine for our collection. From a musicological perspective, however, it is interesting to examine the false negatives.

We identified false negatives by taking the reference melodies as queries and by checking which related melodies are low on the ranked list. Melodies that are on average lower than two times the size of the tune family for a large number of alignment configurations are taken as false negatives. Table 1 shows these songs. The song ID is the record number in the Dutch Song Database. The median rank is the median of the ranks the melody has on various ranked lists, and the average similarity rating is an average of the similarity ratings that were manually assigned by the domain experts during our annotation experiment.

Except for 76271_01 and 73277_01, the average manual similarity rating of these songs is the lowest for any of the songs in the respective tune families. This explains why these songs have low ranking when querying with the reference melodies. It indicates that these low rankings are not just a failure of the algorithm; the songs are really problematic. They were assigned to the tune family, but at the same time judged not to be very similar to the reference melody by the domain experts.

ID	Tune Family	Median rank	Average similarity rating
15569_01	Maagdje	49.5	1.208
70078_01	Stavoren	755	1.08
71666_01	Maagdje	331	1.417
71957_03	Ruiter 1	4157	0.733
72253_01	Halewijn 4	849	0.867
72851_01	Ruiter 1	3672.5	0.55
72851_02	Ruiter 1	3433	0.8
73277_01	Boom	1249	1.267
73929_01	Jonkheer	599.5	0.917
74603_01	Halewijn 4	984.5	0
75525_01	Stil	1518.5	1.033
76271_01	Vrouwtje	72.5	1.625
76495_01	Femmes	867.5	1.333

Table 1. Ranking and annotations for the false negatives.

It is possible that two songs of the same tune family are more similar to each other than to the reference melody. In that case, the reference melody is not sufficiently representative for all melodies in the tune family. It turns out, that six of the false negative songs do have relevant items high on their ranking lists, when taken as query. In these cases, the reference melodies are not sufficiently representative for the tune family.

We asked the domain expert at the Meertens Institute to re-evaluate the seven remaining songs, resulting in the following decisions. 75525_01 is considered quite dissimilar indeed because only the first two phrases have some melodic similarity with the other songs. Therefore a new tune family has been defined for this song. 74603_01 is reassigned to tune family *Halewijn 2* instead of *Halewijn 4*. This song has four other songs from *Halewijn 2* among the first 10 ranks, indeed. One of them even on the top rank. 72851_01, 72851_02 and 71957_03 are strongly interrelated. They were originally assigned to the tune family *Ruiter 1* mainly because of lyrical resemblance, but are considered melodically dissimilar by the domain expert. Therefore, their tune family membership is considered questionable.
The two songs that remain, 73929_01 and 73277_01, are the only songs that are really hard to recognize automatically. They have no other songs from their respective tune families at the top of the rankings lists, and upon re-examination, their tune family membership is confirmed. The phrase endings in 73929_01 are inconsistent with the other songs in the tune family, which causes low similarity scores for related notes. Furthermore, this song is the only one in 4/4 meter, while all other songs in the tune family are in 6/8 meter. Originally, the main reason for 73277_01 to be classified into tune family *Boom* is the occurrence of a melodic motif that is very characteristic for that tune family. Indeed, in the manual annotations, 73277_01 has rating 2 for motifs and rating 1 for contour. For both cases, the global alignment approach we take in this study seems inappropriate.

8. Hard to Classify Melodies

In the past few years, the musicological experts at the Meertens Institute were able to classify many songs from oral tradition 'by hand' with help of the text incipits. There are, however, 111 songs that have been left unclassified, because the experts could not find appropriate tune families to assign them to. As a test of the practical usability of the alignment-based retrieval, we used each of these 111 songs as query and present the musicologists the ranking lists according to three well performing configurations, and asked them whether the songs can be classified with help of these ranking lists. The result is that 42 songs have been classified. For 32 songs, a relation with one or more tune families has been found, but the relation is not strong enough to assign the song to the tune family. For the remaining 37 songs, no related melodies have been found at all. Another result is that two tune families have been merged into one. These two tune families were established based on the lyrics. Using the melodic ranking, it now turns out that these two lyrics are sung with the same melody.
Considering that these 111 songs were the 'hard' cases, this is a good result.

9. Conclusions and Future Research

One of the bases for our research has been the design of musically meaningful computational methods. The musicological potential of methods from Computer Science is related to the extent in which the musical problem at hand can be formulated in terms of the data structures and algorithms. The further the computational setup moves away from musical concepts and musical relations, the less relevant the results are from a musicological point of view. The better the terms and traits of an algorithm are interpretable from a musicological point of view, the more the results contribute to musical knowledge. Therefore, collaboration between music scholars and computer scientists is crucial for the success of Computational Musicology. Obviously, this can be extrapolated to Computational Humanities in general. Computational techniques should not 'blindly' be applied to problems from humanities. Instead, computational models should be based on theories and insights from humanities.
We consider it a success that the musicological domain specialists were able to improve the classification of several melodies using the results of the alignment algorithm. This is a desirable kind of interaction between computational modeling and human understanding of the data. By evaluating the meaning of the algorithmic results for the ground-truth data, the research gets a more interdisciplinary character, resulting in new knowledge for both the computational and the musical aspects of the research.
To fully account for the importance of the recurrence of melodic motifs, as was discovered in our annotation experiment, the next step of our research is to focus on

methods to define and discover melodic motifs in large corpora of folk song melodies and to investigate how these motifs contribute to similarity relations between the melodies. This research will be performed in the context of the Tunes & Tales project in the computational humanities research program of the Royal Netherlands Academy of Arts and Sciences. Moreover, similarity based on motifs as found to be crucial for tune families, is a general principle in music to establish relations both between and within musical works, termed the variation principle. Researching this principle will allow to model the similarity of musical works between different styles of music. This research will be performed in the VIDI-project "Modelling musical similarity over time through the variation principle" at Utrecht University. In this project we will study the effects of folk tune families on other musical styles as suggested, for instance, by Middleton (1990), who has proposed that structural patterns found in folk tune families could be found in tunes of popular music.

The alignment method described above has already been integrated into the infrastructure of the Dutch Song Database. In the NWO-sponsored COGITCH project, interoperability with other collections, specifically the sound recordings of the Dutch Institute of Sound and Vision, will be realized.

Acknowledgements

This work was supported by the Netherlands Organization for Scientific Research within the WITCHCRAFT project NWO 640-003-501, which is part of the Continuous Access to Cultural Heritage (CATCH) program. We thank musicologists Ellen van der Grijn, Mariet Kaptein and Marieke Klein for their contribution to the annotation method and for creating the annotations.

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