Technical Report

Universidad del País Vasco Euskal Herriko Unibertsitatea

UNIVERSITY OF THE BASQUE COUNTRY
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July, 2015

San Sebastian, Spain
www.ehu.eus/ccia-kzaa
hdl.handle.net/10810/4562

BERTSO TRANSFORMATION WITH PATTERN-BASED SAMPLING

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ABSTRACT

This paper presents a method to generate new melodies, based on conserving the semiotic structure of a template piece. A pattern discovery algorithm is applied to a template piece to extract significant segments: those that are repeated and those that are transposed in the piece. Two strategies are combined to describe the semiotic coherence structure of the template piece: inter-segment coherence and intra-segment coherence. Once the structure is described it is used as a template for new musical content that is generated using a statistical model created from a corpus of bertso melodies and iteratively improved using a stochastic optimization method. Results show that the method presented here effectively describes a coherence structure of a piece by discovering repetition and transposition relations between segments, and also by representing the relations among notes within the segments. For bertso generation the method correctly conserves all intra and inter-segment coherence of the template, and the optimization method produces coherent generated melodies.

1. INTRODUCTION

Since the creation of the first computer in 1840 by Lovelace and Babbage people have speculate about automatic music composition being possible [11]. There have been many invented instruments in the twentieth century that automatically produced sounds according to formal systems, aleatoric procedures or natural physical phenomena. Among the first automatically generated composition instances are those of Lejaren Hiller and Leonard Isaacson from 1955-56 [13], and since then researchers have developed many different approaches to the idea of automatic music composition, using grammars, evolutionary methods, knowledge-based systems or statistical models [6].

Statistical models of symbolic music representation have been used in computational modelling of several musical styles, and the main advantage they offer is that they can capture some musical features that make it possible to generate new musical sequences that reflect an explicit musical style, and that they can be learned from a corpus of music [6, 12]. This is especially useful when transforming a melody while retaining its musical style. Especially for folk music generation several computational approaches have been developed [20–22].

All methods for music generation from statistical models face the *intra-opus coherence problem*: ensuring that pieces contain material that repeats or recalls in a more abstract sense material presented earlier in the piece. One way to handle this problem is by deriving the coherence structure from a template piece, constraining the statistical model to generate into this structure. This approach to music generation can be referred to as *generation by transformation*.

In this work a *bertso* melody is used for transformation. Bertsos are improvised Basque songs (as discussed in Section 2) that respect various melodic and rhyming patterns and which have fixed rhythmic structures. People who sing bertsos (bertsolaris) improvise lyrics using a known melody. Since rhythmic structure is so important in bertsos, in this paper will be conserved, and only melody will be transformed, so that it can be used with lyrics created for the original melody.

Musical cohesion is analysed in [1], where music is compared to linguistic discourse. In that work the author concludes music is composed by segments semantically related, that support the coherence of the piece. Coherence can be described using semiotic labels assigned to musical material at different structural levels [3]. In earlier work [15] we presented an approach to generate a bertso melody using note coherence, where notes selected according to a melodic reduction method were given semiotic labels. In this paper we extend this approach to consider coherence at a higher structure level. The approach still retains coherence within segments (*intra-segment*) but also considers *inter-segment* coherence in a unique way, by employing a segmentation using pattern discovery applied to the template piece. The basis of the approach of this paper is to use strong constraints on semiotic structure, generating into this with a simple statistical model of abstract viewpoints, which can be trained on a small dataset but still retains accurate statistics of local transitions. Intra-segment coherence is important on sampling when the statistical model that is used is created from a small corpus and it is not strong enough. These statistical models can give high probabilities to unwanted sequences of notes, like long repetitions of the same note. Using intra-segment coherence ensures that sampled segments will have a note variety.

To describe the coherence in a piece for the purpose of semiotic labelling a segmentation of the original piece, manual or automatic, must be used to identify the segments that are repeated through the piece and that are similar to one another. In order to segment a musical piece, similar patterns must be identified, to do so, many pattern discovery algorithms have been developed to extract patterns from both within a piece (*intra-opus*) and in a corpus (*inter-opus*) [4, 7, 9, 16, 18]. In this paper a pattern discovery algorithm is used to extract significant patterns from a bertso melody, and a pattern based sampling strategy is developed to transform the original piece, using a statistical model build from a small bertso melody corpus. Section 2 explains bertsolaritza and bertso melodies, and the features they have, and Section 3 describes the methods used in this paper, pattern discovery, semiotic labelling, sampling and rendering. Section 4 and Sections 5 explain the results obtained in this work and some conclusions and areas for future research.

2. BERTSOLARITZA

Bertsolaritza or bertsolarism is the art of singing improvised songs in Basque (bertsos), respecting various melodic and rhyming patterns. It is defined as a sung, rhymed and metered discourse by the book *The Art of Bertsolaritza: Improvised Basque Verse Singing*, written by Garzia et al. [14]. There is evidence of bertso singing and written bertso poem samples since the 15th century, and it is a very popular art nowadays in the Basque Country.

Bertsos are sung in many different occasions, like informal lunches with friends, homage ceremonies or competitions and any topic can occur in a bertso. Many bertsolari competitions take place every year in the Basque Country, and every four years the national championship final is held, with around 15000 people in attendance.

The melody, rhyme and meter are technical aspects of the bertso. Bertsolaris (bertso singers) are the only improvisers known in the world that perform without the help of any musical instrument. The melodies they use can be classified into three categories:

- Traditional folk melodies (the great majority);
- New airs that coincide with the traditional metre;
- Melodies that are specifically composed.

Experts say the chosen melody for singing a bertso and the manner in which it is sung can be the key for the communicative success of the bertsolari, since the chosen melody must be able to combine with the created lyrics to transmit what the bertsolari wants to express with the bertso. These melodies are usually short and they have phrases that are repeated through the piece or that are similar to each other.

2.1 Bertso doinutegia

Bertso Doinutegia is a collection of 3059 bertso melodies, created by Joanito Oiartzabal and published for the first time on 1995. It is updated every year by Xenpelar Dokumentazio Zentroa with new melodies that are used on competitions or bertso exhibitions. Entries in the collection have a melody name, the name or type of the strophe, type of the melody (genre), creator, bertsolari who has used it, name and location of the person who has collected the melody and year of the collection. Melodies are classified into 17 different types or genres, and this classification is done based only on melodic content. Some of the melodies in the collection have links to recordings of exhibitions or competitions where those melodies were used.

3. METHODS

It is a fact that almost all forms of music involve repetition [17], either of sequences of pitch of notes or at some higher levels of structural grouping, and that repetition imparts a sense of meaning to music [19]. It is also known that what allows us to identify a piece of music is the relation between notes (the intervals), not the absolute pitch of the notes.

As explained earlier, in music generation by transformation the repetition structure of the original piece is an important feature to analyse and conserve. This is even more important when transforming bertso melodies, since the phrase structure and strophic aspects of the melodic repetition in these melodies is an important feature.

The idea of using patterns, combined with statistical models of events, for music generation was discussed by Conklin [6]. Patterns can represent concrete sequences or, as applied in this paper, a more abstract coherence structure of the events. This approach permits the abstract representation of *where* motives are repeated rather than exactly *what* are those motives. That is, the coherence structure describes abstract *relations* between events and motives.

To describe the coherence structure of a piece the segments that form the piece have to be identified. This task is currently a scientific challenge, and several approaches have been developed, like the description of acoustic structure, functional structure or semiotic structure. Semiotic structure is defined as a representation of similar segments in a piece by a limited set of arbitrary symbols, where each symbol represents an equivalence class of segments [3]. Types of semiotic structure to describe a melodic style and compose new material according to that style have been developed, like the generation method of Collins [5]. In his work the author looks for geometric patterns that can identify repetitions and transpositions in polyphonic textures. In this paper we use viewpoints, which can capture more abstract features of events in melodic sequences.

Once different segments have been identified, the coherence within the segments is described, using a semiotic labelling which assigns different labels to notes with different pitch number. This way, inter-segment and intra-segment coherence are both described.

3.1 Pattern discovery

In this work segments that are repeated or appear transposed in different places in a piece are identified using a pattern discovery algorithm. Pattern discovery methods identify segments that are repeated through a symbolic representation of a musical piece or a corpus. Patterns are defined as sequences of event features, and a piece instantiates a pattern if the pattern occurs (one or multiple times) in the sequence: if the components of the pattern are instantiated by successive events in the sequence [9]. In this work a pattern discovery algorithm named SPAM [2] has been used to identify similarities between and within segments. This is an algorithm that finds all the frequent sequential patterns (patterns that occur more times than a given threshold) in a transactional database, specially efficient with large databases. Candidates are created with a depth-first search strategy and various pruning mechanisms reduce the search space.

$$\begin{array}{lllllllll}
(1) & s_1 & s_2 & s_3 & s_4 & s_5 & s_6 & s_7 & s_8 \\
(2) & & s_2 & s_3 & s_4 & s_5 & s_6 & s_7 & s_8 \\
(3) & & & s_3 & s_4 & s_5 & s_6 & s_7 & s_8 \\
(4) & & & & s_4 & s_5 & s_6 & s_7 & s_8 \\
(5) & & & & & s_5 & s_6 & s_7 & s_8 \\
(6) & & & & & & s_6 & s_7 & s_8 \\
(7) & & & & & & & s_7 & s_8 \\
(8) & & & & & & & & s_8
\end{array}$$

Figure 1. Suffix-based database for an eight event sequence.

In this work we are interested in *feature set patterns* [7], patterns of the form

$$\left[\begin{pmatrix} \mathsf{inter} : x \\ \mathsf{pitch} : y \end{pmatrix} \begin{pmatrix} \mathsf{pitch} : z \end{pmatrix} \right]$$

This pattern represents a two contiguous event pattern, where the first event has pitch y and interval x, and second event has pitch z.

For a symbolic representation of the bertso melody a *multiple viewpoint* approach has been chosen [10]. For representing the notes, pitch and interval (measured in scale steps) viewpoints have been chosen, because in this work segments with melodic repetition and transposed segments both have to be identified. The method is capable in theory of working with any viewpoints, including ones that could describe abstract melodic contour patterns, but for this study just the two essential (absolute and relative repetition) viewpoints were used.

To discover feature set patterns, two modifications of the SPAM algorithm are necessary. First, the SPAM method is designed for multiple sequences, returning support counts for the number of sequences matching the pattern. In this work, we wish to count the total number of occurrences in a single sequence. Second, SPAM allows discontiguous patterns and at this stage of our work we wish to focus on contiguous patterns, to restrict our pattern representation to feature set patterns, and maintain some simplicity of the pattern-based transformation algorithm. To achieve both modifications we first compute a suffix-based database from the multiple viewpoint representation of the piece, as seen in Figure 1, where an eight event sequence is transformed into an eight entry database. Each s_i is the set of all viewpoint values of event e_i. This technique allows us to effectively use SPAM looking for patterns only in the beginning of each database entry. The algorithm has also

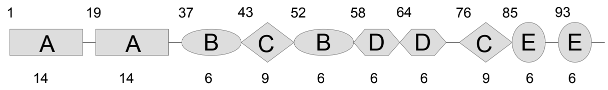

Figure 2. Schema of a discovered pattern structure of the bertso melody.

been modified to only look for contiguous patterns in the transformed suffix set.

The SPAM algorithm produces all the patterns that appear more times than a given threshold and it does not have a more sophisticated method to rank discovered patterns. This could be done by measuring the distinctiveness of each pattern as in [7], but in this work the priority is not to find patterns that are over-represented in a piece with respect to an anticorpus. The priority is to find patterns that are significant in the piece, in terms of occurrence and length.

The melody that is being transformed in this work has only 100 notes, therefore we do not expect to find long patterns that appear many times, so we have put a threshold of patterns with length of six or more elements that appear two or more times. Five non overlapping patterns have been chosen and the piece has been segmented as seen in Figure 2, where different shape and labels correspond to different patterns. Below each pattern is the length of the pattern (number of notes that the pattern covers), and above is the position where the pattern starts. In Table 1 the description of the patterns of Figure 2 can be found according to the viewpoints that have been used in the pattern discovery algorithm. It can be noticed that there are short segments in the piece that are not part of any pattern: our algorithm does not require a complete tiling of the template piece with patterns.

Within the patterns that have been discovered, two types have been identified; patterns with pitch information and patterns with interval information only. Patterns with pitch information represent segments with melodic repetition, and patterns with only interval information represent segments with possible transpositions.

Segments of notes that are not covered by any pattern have been treated as if they were contained within unique segments covering the gapped region (see Figure 2) this way we have a piece completely tiled by patterns, making the sampling easier.

3.2 Semiotic labelling

For intra-segment coherence semiotic labelling is used, assigning a different semiotic label to each different note in a segment. On sampling, this label structure is taken as a constraint, and all the notes with the same label in a segment must have the same pitch value, as represented in Figure 3 (original stave), which shows a pattern labelled A with its intra-segment semiotic labels. It can be seen that the three score fragments have entirely different pitches but

Label	Pattern
A	(pitch:60) (pitch:65) (pitch:67) (pitch:69) (pitch:65) (pitch:70) (pitch:70) (pitch:72) (pitch:69) (pitch:65) (pitch:70) (pitch:70) (pitch:72) (pitch:69)
B	(inter:+1) (inter:+1) (inter:+1) (inter:0) (inter:-1)
C	(pitch:67) (pitch:69) (pitch:70) (pitch:70) (pitch:64) (pitch:65) (pitch:67) (pitch:69) (pitch:65)
D	(pitch:69) (pitch:67) (pitch:69) (pitch:72) (pitch:72) (pitch:70)
E	(pitch:65) (pitch:67) (pitch:69) (pitch:70) (pitch:69) (pitch:67)

Table 1. Specification of patterns represented in Figure 2. Each row represents a segment label, where the segments are delineated by the pattern discovery algorithm.

Figure 3. Example fragment of a transformation, showing a template segment (first phrase of the bertso melody *Abiatu da bere bidean*) with its first segment A (see Table 1) and note semiotic labels from a to f (*original* stave). A random fragment with intra-segment pitch coherence (*random* stave) with cross-entropy of 3.77 bits/note, a transformation example with no intra-segment coherence and two transformations with low cross-entropy of 2.36 bits/note (*trans. 1*) and 2.22 bits/note (*trans. 2*).

all respect the semiotic structure.

Intra-segment labelling makes it possible to have musical meaning when sampling into long segments, since it guarantees that there will not be inappropriate note repetition within the segments, even if these repetitions have high probability according to the statistical model. To illustrate this point, an example of a transformation with no intra-segment labelling can be seen in Figure 3, where many unison intervals can be found due to the high probability of unison transitions in the five-point contour model, and which is not of high quality.

3.3 Pattern-based sampling

Statistical models of music have been used productively for classification, prediction, and generation. Given some event space ξ, which describes the set of possible events, a statistical model assigns probabilities to entire event sequences. On trained and validated models, sequences having high probability are assumed to retain more aspects of the music style under consideration than sequences with low probability. The process of *sampling* is concerned with drawing high probability sequences from statistical models.

Since in bertsos meter is a very important feature, in this work the rhythmic structure of the original piece is conserved, and a new melody line is created. A statistical model is used to extract some contour features of a 50 piece corpus, which are part of the melody corpus described in Section 2.1. To build the statistical model a five-point melodic contour (leap down, step down, repetition, step up, leap up) viewpoint is computed, steps involving a contour motion of one or two semitones and leaps a motion greater than two semitones. The statistical model chosen is intentionally simple, and alone will over-generate (by generating many more unacceptable melodies than acceptable ones). In the context of intra-segment semiotic labelling, however, the statistical model is naturally constrained to generate only those melodies respecting the semiotic labels.

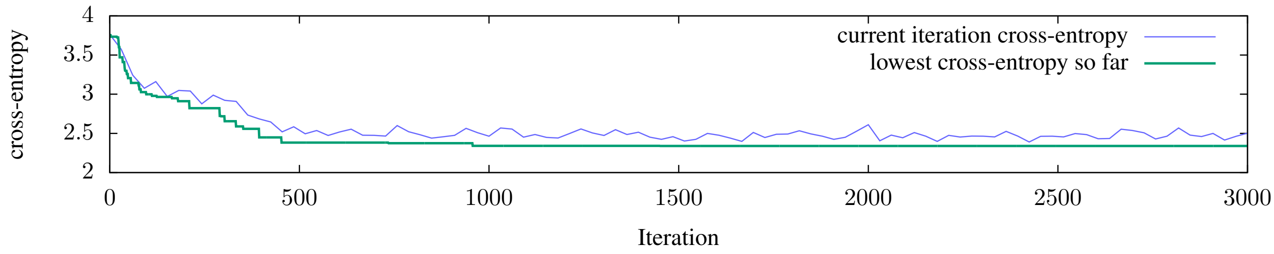

Figure 4. Cross-entropy of the piece through the iterations and the lowest cross-entropy reached.

A *stochastic hill climbing* method is used for sampling and it is iterated 10^4 times. This method iteratively modifies a piece $\mathbf{e} = e_1, \ldots, e_i, \ldots, e_\ell$: in each iteration of the process a random location i in the piece is chosen. A random element $e_i \in \xi$ is substituted into that position, producing a new piece $\mathbf{e}$ with an updated probability. In the bertso melody transformed in this work a nine element vocabulary is used, with F major diatonic pitches $\xi = [\text{C4}, \ldots, \text{E5}]$.

The probability of the piece is computed using the single viewpoint model described in [8] presented in the equations below. Letting $v_i = \tau(e_i|e_{i-1})$ be the contour feature of event e_i in the context of its preceding event e_{i-1} defined by the statistical model, the probability of the piece $\mathbf{e}$ is computed as:

$$P(\mathbf{e}) = \prod_{i=1}^{\ell} P(v_i) \times P(e_i|v_i, e_{i-1})$$

$$P(e_i|v_i, e_{i-1}) = |\{x \in \xi : \tau(x|e_{i-1}) = v_i\}|^{-1}$$

The probability is used to measure the *cross-entropy* of the piece, that measures the mean negative log probability of an event in the piece $\mathbf{e}$, defined by $-\log_2 P(\mathbf{e})/\ell$. If the new cross-entropy is lower than the last saved one, it is saved and next iteration is executed on the new piece.

Since in this work a pattern based structure is used to conserve the repetitions and transpositions of the piece, the piece that is created as the first step of the method must keep the pattern structure of the original piece. To achieve this events are sampled from a uniform distribution over the pitch range, and every time an event is sampled all the occurrences of the patterns containing the event must also be sampled.

Patterns extracted in the pattern discovery process are used to create the inter-segment coherence structure of the initial piece. Four out of the five discovered patterns are repetition patterns (they have pitch information). This means positions in the piece that are covered with a pattern with the same label must have the same notes.

During the iterative modification of the piece, the new note must be put in all the positions in the pattern that have the same semiotic label, in all the occurrences of that pattern. If the chosen note is not part of the vocabulary (it is out of the range or is not on the tonality), the cross-entropy of the piece increases, this way we ensure that the transformation will conserve the note-range and the tonality of the template melody.

Pattern B is a transposition pattern (see Table 1), since it only has interval information, and segments that instantiate this pattern can be transposed versions of one another. To control these transpositions, every time a position that belongs to a transposition pattern is sampled, the interval sequence of the pattern is computed, and it is reproduced in every other position that pattern is instantiated.

4. RESULTS

An example of a transformation made in this work can be seen in Figure 5, where all the patterns are delimited by rectangles and pattern labels are annotated. All the patterns except pattern B are repetition patterns. It can be seen that the coherence of the original piece is conserved using the pattern-based method described in this paper, and both repetition and transposition patterns are maintained. Further, though not completely tiled by patterns, most of the notes are covered by a segmental pattern.

A small segment of that transformation can also be seen in Figure 3, (trans. 1). In the original segment, the segmental pattern A can be seen, with the labels of each note of the pattern. Different labels are assigned to different notes in the pattern. The small part that is out of the pattern is also labeled as explained in Section 3.2. Another example segment of a transformation can also be seen in Figure 3 (trans. 2).

In the initial starting segment (Figure 3, random), it can be seen that the intra-segment coherence (given by the note semiotic labels) is maintained but the melody contains an inappropriate number of leaps and would be difficult to sing. In the first low cross-entropy solution (Figure 3, trans. 1) the melodic motion is much smoother, and the phrase cadences in F major: though this is not specified in the semiotic labelling, some types of harmonic movement will naturally be filtered by the semiotic labels.

Turning to a full generated melody (Figure 5), it can be seen that the pattern B (the interval pattern) correctly coheres within the piece. Interestingly this pattern in the template piece spans two phrases in the second occurrence: in the pattern discovery no attempt was made to remove such patterns, though this could easily be done in future work.

The graph in Figure 4 shows the evolution of the cross-entropy of the piece through the iteration of the stochastic hill climbing method. The blue line shows the cross-entropy of the stochastic modification of the piece at each

Figure 5. Example of a transformed piece, with the regions covered by discovered patterns (see Table 1) delimited by rectangles. Cross-entropy of the piece is 2.36 bits/note.

iteration. It has been approximated using splines, so that the direction of the cross-entropy can be seen even if it is computed using probabilities of 3000 iterations. The lowest cross-entropy is reached before iteration 1500, in green. The stochastic hill climbing method cannot guarantee that the optimal piece is going to be found, but it does improve the initial piece. Even if the statistical model is simple, combined with inter- and intra-segment coherence constraint we have obtained good results on melody generation by transformation.

5. CONCLUSIONS AND FUTURE WORK

In this paper a method to transform bertso melodies using pattern-based sampling is presented. The basis of the method is the use of a simple statistical model combined with patterns that represent the coherence structure of a template piece. Pattern discovery is done using a modified version of SPAM that extracts non-overlapping patterns of the template piece, which can be repetition or transposition patterns. Intra-pattern coherence is also described using semiotic labelling on notes. New musical content is created taking into account the inter- and intra-segment coherence structure and using a statistical model for sampling which iteratively changes notes in random positions to improve the final piece. In contrast to other existing methods to sample on repetition and transposition patterns [5, 6], this work implements an optimization of an initial coherent piece that improves the piece by increasing its probability.

The method presented herein has created acceptable transformed melodies using the coherence structure of a template piece, even if it has been tried using basic viewpoints and a simple statistical model. As future work we plan to apply the method using more complex and abstract viewpoints, such as contour viewpoint, using a larger corpus and higher-order statistical models. An optimization method for pattern ranking and tiling could be developed to choose the most appropriate, in terms of length and coverage, patterns discovered by SPAM. Different method to specify intra-segment coherence should be tried, using contour reduction algorithms to unlabel some notes (citation omitted for anonymous review). Though stochastic hill climbing is effective at optimizing the transformation, other methods such as simulated annealing, variable neighbourhood search, Gibbs sampling and genetic algorithms could be explored.

Finally it is planned to evaluate the generated melodies by giving them to some bertsolaris and asking them to improvise using these melodies. They will do the evaluation depending on how natural it is to improvise using the new melodies and how effective they are to transmit the intended message of the bertsolari.

6. ACKNOWLEDGEMENTS

This research is supported by the project Lrn2Cre8 which is funded by the Future and Emerging Technologies (FET) programme within the Seventh Framework Programme for Research of the European Commission, under FET grant number 610859. This research was also supported by the Basque Government Research Team Grant (IT313-10).

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