Feature Extraction Using Pitch Class Profile Information Entropy

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Abstract. Computer aided musical analysis has led a research stream to explore the description of an entire musical piece by a single value. Combinations of such values, often called global features, have been used for several identification tasks on pieces with symbolic music representation. In this work we extend some ideas that estimate information entropy of sections of musical pieces, to utilize the Pitch Class Profile information entropy for global feature extraction. Two approaches are proposed and tested, the first approach considers musical sections as overlapping sliding onset windows, while the second one as non-overlapping fixed-length time windows.

Keywords: Pitch Class Profile, Information Entropy, Global Features, Composer Identification.

1 Introduction

Pitch Class Profile has previously been used for exploring information entropy of sections of musical pieces [1]. In the paper at hand, we utilize these ideas to produce global features from musical pieces. A *global feature* is a numerical descriptors that "encapsulates information about a whole piece into a single value" [2]. In this work we investigate whether the *tonal information entropy* contained in subdivisions of musical pieces is suitable as a feature for composer identification.

2 The Proposed Approaches

Overlapping sliding onset windows: A musical piece can be considered as a set of temporally ordered note events, $\{e_1, e_2, \ldots, e_n\}$. Each note event, e_i, is characterized by an onset value, i.e. its relative time position in the piece. A note event can be either *monophonic* or *polyphonic* depending respectively on whether a single note or multiple notes are sounded simultaneously.

An onset window of length l is a musical section $\{e_i, e_{i+1}, \ldots, e_{i+l}\}$. We can compute the PCP[1] of this section of length l which is referred as $\mathrm{PCP}^l_{\mathrm{onset}}(i)$. If

[1] The PCP of a section of a musical piece, is the distribution vector of the 12 pitch classes within this section. The interested reader can find more information in [3].

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we slide this window by a single onset, we obtain a new window $\{e_{i+1}, \ldots, e_{i+l+1}\}$ and its PCP is denoted by $\mathrm{PCP}^{l}_{\mathrm{onset}}(i+1)$. If a musical piece is constituted by n onsets, we can obtain $n - l$ overlapping sliding onset windows as well as their respective PCPs. Since every PCP is a distribution over the discrete variable of the 12 pitch classes, we can compute its Shannon information entropy. Thus, for the PCP of the i-th onset window, $\mathrm{PCP}^{l}_{\mathrm{onset}}(i)$, we can compute the value of the Shannon information entropy, $S^{l}_{\mathrm{onset}}(i)$. Two global features can be extracted for every piece by the aforementioned information entropies, the mean value μ_{onset} and the standard deviation σ_{onset}. Intuitively, the mean value indicates the overall *tonal uncertainty* of this piece, while the standard deviation indicates whether there exist sections of tonal stability as well as how steeply they are interchanged with unstable ones.

Non-overlapping, fixed-length time windows: The above approach does not consider the temporal structure of a musical piece, since a window is forwarded to the next onset regardless of its time distance. This constitutes a drawback, as distant time events are less influential to the memory of tonal structure. To overcome this problem, we consider pitch information in a number of bars of the musical piece, thus in fixed-length time windows. We denote as $\mathrm{PCP}^{m}_{\mathrm{bar}}(i)$ the PCP of the i-th musical segment of length m bars. Let $C^{m}_{\mathrm{bar}(i)}$ denote the Shannon information entropy of the aforementioned *current* segment's PCP. Additionally, we consider the *movement information entropy* between the $(i-1)$-th and the i-th segments. This is the Shannon entropy of the absolute difference vector of the PCPs of the respective segments, i.e. $|\mathrm{PCP}^{m}_{\mathrm{bar}}(i-1) - \mathrm{PCP}^{m}_{\mathrm{bar}}(i)|$. We denote this entropy as $M^{m}_{\mathrm{bar}}(i)$. For every musical piece, four global features can be extracted by *current* and *movement* information entropies. Those are, the mean value and standard deviation of current ($\mu^{\mathrm{curr}}_{\mathrm{bar}}$, $\sigma^{\mathrm{curr}}_{\mathrm{bar}}$) and movement ($\mu^{\mathrm{move}}_{\mathrm{bar}}$, $\sigma^{\mathrm{move}}_{\mathrm{bar}}$) entropies.

3 Results

We employ the kth Nearest Neighbor (kNN) supervised classifier on a data set that consists of 50 pieces by J.S. Bach (Ba), and 50 movements of string quartets by each of the composers Haydn (H), Mozart (M) and Beethoven (Be), thus a total of 200 pieces. Composer identification simulations are performed in pairs and with a leave one out strategy, as suggested in previous works in data sets of similar size [4,5].

Overlapping sliding onset windows: In this approach, each musical piece is represented by two global features described in Sect. 2, the mean value (μ_{onset}) and the standard deviation (σ_{onset}). In Fig. 1(a–c), we observe that smaller window sizes exhibit better results for separating pieces of J.S. Bach from the string quartets. Similar results are obtained by a range of k values below 40. Identification success decreases with the increase of window size. This reveals that transition information from onset to onset is crucially different between those pieces. On the other hand, as we observe in Fig. 1(d–f) identification success increases with the increase of window size for the separation of the string quartets.

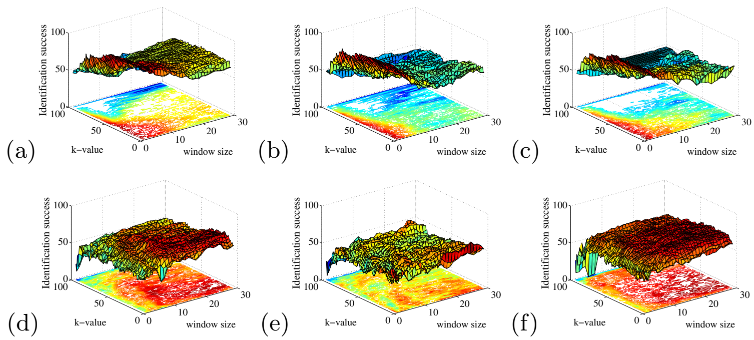

Fig. 1. Identification success between all composers for different overlapping sliding onset windows and different k values. Identification simulations: (a) Ba – Be, (b) Ba – H, (c) Ba – M, (d) Be – H, (e) H – M and (f) M – Be

Non-overlapping fixed-length time windows: In this approach, each piece is represented by four global features, the mean values and standard deviations of *current* ($\mu_{\text{bar}}^{\text{curr}}$, $\sigma_{\text{bar}}^{\text{curr}}$) and *movement* ($\mu_{\text{bar}}^{\text{move}}$, $\sigma_{\text{bar}}^{\text{move}}$) information entropies within different consecutive time windows. In Fig. 2(a–c) we observe that identification success between pieces of J.S. Bach and the string quartets presents relatively stable behavior for windows of multiple bars. This indicates that information entropy within a time frame of less bars does not reveal differences between composers.

The latter comment does not come into contradiction with the respective results presented in Fig. 1(a–c) but as complementary to them. Fig. 1(a–c) presents that 2 to 4 consecutive onsets are ideal for separating those composers. Identification success drops dramatically for windows of 10 onsets, which is near the expected number of onsets per bar. Thus Fig. 1(a–c) and Fig. 2(d–f) indicate that differences in information entropy between the pieces of J.S. Bach and the

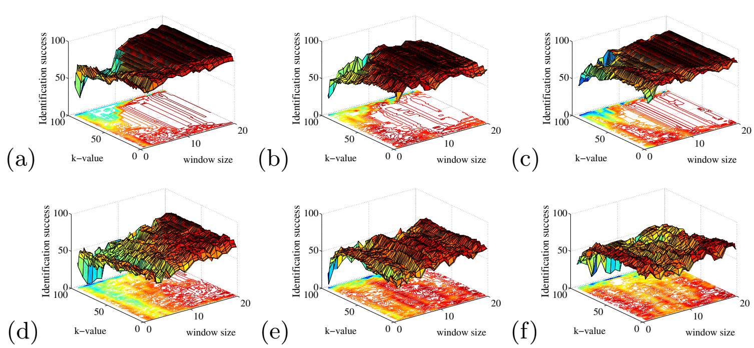

Fig. 2. Identification success between all composers for different non-overlapping fixed-length time windows and different k values. Identification simulations: (a) Ba – Be, (b) Ba – H, (c) Ba – M, (d) Be – H, (e) H – M and (f) M – B

string quartets, are obvious either in a very small or a very large scale. It should also be noted that the maximum achieved identification success for the string quartets of Haydn and Mozart, 72%, is comparable or better than results of previous works, where more global features have been used [4,5]. String quartets of Haydn and Mozart have also been modelled as Markov Chains and their variations [4,6,7], with identification successes ranging between 65% to 80%.

4 Concluding Remarks

For the data set used in this work, both models exhibited better results for the separation of J.S. Bach's pieces by the string quartets. This exhibits that epoch or genre classification could be performed more safely by these features. Even though the separation of the string quartets did not yield impressive results, they were comparable to results obtained by previous works. The features proposed in this study could be combined with other features proposed in literature and hopefully improve music classification.

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