AN EFFICIENT APPROACH FOR GENRE CLASSIFICATION

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ABSTRACT

In this submission, audio features that approximate timbre, rhythm and tempo are used for genre classification and music similarity estimation. This abstract describes the feature set, distance computation method, and classifier model used for the submitted algorithms.

1. INTRODUCTION

In our system, audio data are modeled as long-term accumulative distribution of frame-based spectral features. This is also known as the "bag-of-frames" (BOF) approach wherein audio data are treated as a global distribution of frame occurrences. This approach is widely used in MIREX submissions. For MIREX 2010 genre classification and audio similarity estimation task, the BOF approach was used for some of the top performing systems[1][2] .

The features that are extracted from audio files are approximations of timbre, rhythm and tempo. The feature extraction, distance computation and classification algorithms are implemented in MATLAB®.

2. FEATURE EXTRACTION

This section describes the processes involved in feature extraction. More detailed explanation can be found on the cited references.

2.1 Audio Preprocessing

The input signal is assumed to be sampled at 22050 Hz, as specified in MIREX wiki[1]. The audio signal is normalized and preprocessed to remove inaudible parts. The signal is then cut into frames with a window size 512 samples (~23 msec.) and hop size 512 samples.

2.2 Timbre Component

The timbre component is represented by the Mel-Frequency Cepstral Coefficients (coefficients 2:20) [3]. We then model the distribution of the MFCCs for the audio file using a Gaussian mixture model (GMM). In this work, we use a single Gaussian represented by its mean μ and covariance matrix Σ. This feature is complemented by appending its time derivative.

2.3 Rhythm Component

The rhythm component based on the Fluctuation Patterns [4] (FPs) of the audio signal. Fluctuation patterns describe the amplitude modulation of the loudness per frequency band.

For each frame, the fluctuation pattern is represented by a 12x30 matrix. The rows correspond to reduced Mel-frequency bin while the columns correspond to modulating frequency bands. To summarize the FPs, the median of the matrices is computed. Additional features derived are FP mean and FP standard deviation.

2.4 Tempo Component

The tempo component is derived from a technique using onset autocorrelation [5]. The tempo is computed by taking the first-order difference along time of a Mel-frequency spectrogram then summing across frequency. A high-pass filter is used to remove slowly-varying offsets. The global tempo is estimated by autocorrelating the onset strength and choosing the period with the highest windowed peak.

3. GENRE CLASSIFICATION

The timbre, rhythm, and tempo distances are calculated separately. Before they are combined, each distance component is normalized by removing the mean and dividing by the standard deviation of all the distances. Symmetry is obtained by summing up the distances in both directions for each pair of tracks [6].

To accelerate audio similarity estimation, the MFCC and time derivative vectors are mapped to *k*-dimensional Euclidean space using a modified FastMap algorithm[7]. The number of dimensions is arbitrary, with higher values leading to a more accurate mapping. The number of dimensions is set to 60 for this submission.

Distances between timbres are computed by simply computing the Euclidean distance between the mapped vectors. This is much faster than computing a full linear scan with Kullback-Leibler divergence. The Euclidean distance is used to compute distance between rhythms. For tempo distances, a simple absolute distance is computed.

The genre classification starts by filtering the training set to return a number of possible nearest neighbours to

[1] http://www.music-ir.org/mirex/wiki/2011:Audio_Music_Similarity_and_Retrieval

an untagged track. This is done by computing the squared Euclidean distances on the mapped vectors. This process is much faster, even with high values of *k*, than performing a linear scan over the training set using SKL. The result is refined by computing the transformed SKL on the candidate subset. Two distance values are produced (from MFCCs and ΔMFCCs) then combined to return the *true* nearest neighbours. Finally, the genre of the nearest track based on weighted distances of the features is used to label the untagged track (1-NN).

4. RESULTS

This submission is an updated version of the algorithm submitted to MIREX 2011 Train/Test task. From the MIREX 2011 data, the classification accuracy obtained was 58.51%. For comparison, the best performing system [8] in MIREX 2011 had a classification accuracy of 80%.

5. ACKNOWLEDGMENTS

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6. REFERENCES

[1] K. Seyerlehner, M. Schedl, T. Pohle, and P. Knees, "Using Block-Level Features for Genre Classification , Tag Classification and Music Similarity Estimation," in *Submission to Audio Music Similarity and Retrieval Task of MIREX 2010*, 2010.

[2] K. Seyerlehner, G. Widmer, M. Schedl, and P. Knees, "Automatic Music Tag Classification Based on Block-Level," in *Proceedings of Sound and Music Computing 2010*, 2010.

[3] B. Logan and A. Salomon, *A music similarity function based on signal analysis*. IEEE, 2001, pp. 745-748.

[4] E. Pampalk, "Computational Models of Music Similarity and their Application in Music Information Retrieval," Vienna University of Technology, 2006.

[5] D. P. W. Ellis and G. E. Poliner, "Identifying `Cover Songs' with Chroma Features and Dynamic Programming Beat Tracking," in *2007 IEEE International Conference on Acoustics, Speech and Signal Processing - ICASSP '07*, 2007, p. IV-1429-IV-1432.

[6] E. Pampalk, "Audio-Based Music Similarity and Retrieval : Combining a Spectral Similarity Model with Information Extracted from Fluctuation Patterns," in *Submission to MIREX 2006*, 2006.

[7] D. Schnitzer, A. Flexer, and G. Widmer, "A Filter-and-Refine Method for Fast Similarity Search in Millions of Tracks," in *ISMIR 2009*, 2009, no. April, pp. 537-542.

[8] P. Hamel, "Pooled Features Classification MIREX 2011 Submission," in *Submission to Audio Train/Test Task of MIREX 2011*, 2011.