Scientific Journal of Impact Factor (SJIF): 4.72

e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 4, Issue 3, March -2017

Music Classification Based On Mood Recognition

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Abstract- Music emotion is a vital component in the field of multimedia database recovery and computational musicology. The online musical datasets are major challenges for searching, retrieving, and organizing the music content. Therefore, there is a require for robust automatic music emotion classifier system for organizing variety music pieces into different classes according to the specific viable information. Basic components are to be considered for music emotion classification audio feature origin and classifier design. In user propose diverse audio features to precisely characterize the music substance. The feature sets belong to groups dynamic, rhythmic, spectral, and harmonic. Four statistical parameters are considered as representatives, including the fourth-order central moments of each feature as well as covariance part. Number of unimportant parameters is forced by minimum unemployment maximum relevance(MRMR)algorithm and principal component analysis(PCA). Support Vector Machine(SVM) is used as a classifiers to classify the music mood recognition.

Keywords- *Music emotion recognition, Feature extraction, Two level classification, Music mood classification.*

I. INTRODUCTION

The automatic music emotion classification has gained increasing attention in the field of music information retrieval. The user activities in this field are not only extremely diversified, but also consistently growing. The diversity comes from the fact that emotions classification set up certain relationships between music and its effect in human emotional state like happy, anger, sad, tender, etc. In addition, the growth is inevitable to increase the accessibility to music databases. As the quantity of music satisfy continues to disprove, the searching time is unexpectedly increasing. The solution of widespread music collection under different emotions could lead to a decrease in the information retrieval search time on the online system.

Music Classification is application which provides important functionalities for music retrieval. Music classification has received much notice from MIR researches in resent year. In this thesis focuses on music mood classification. Automatic music mood classification has some different tasks. The user proposed approach for automatic music mood classification is show in Figure 1. In Feature Extraction according Feature set will be use. Energy, Temporal, Harmony and Rhythm. Using SVM detect mood of emotion classification classis. After this task again use SVM and classify emotion subclass.

Some of the major difficulties in MER are related to the fact that the reading of emotions evoked by the song is inherently personal: different listeners often receive clear emotions while listening the same song. Besides, even when listeners agree in the observe emotion, there is calm much ambiguity regarding its description. Additional more, it is not yet well-understood how and why music elements create specific emotional response in listeners [1]. In general, there are two models to describe emotions i.e. a categorical approach and dimensional one [2]. The categorical model focuses on the characteristics that differentiate emotions from one another. The essentiality of this model is the ideas of basic emotions, such as happiness, sadness, anger, fear, disgust, and surprise. On the other hand, the dimensional model focuses on identifying emotions based on their arrangement in a incessant dimensional emotion area with a small number of axes. In the emotion gap, each bipolar axis usually has its own meaning i.e. valance and stimulate.

The music mood classification with decrease feature sets using support vector machine (SVM) classifier is shown in the Fig. 1. It represents the impression of proposed method of mood classification. Basically, there are particular problems require to be addressed in music mood classification i.e. audio feature origin and classifier design. Besides these, feature analysis also plays a important role in mood classification. The feature analysis means finding out the most discriminative feature or set of features from feature pool. In this scheme, minimum redundancy maximum relevance (MRMR) [3] and PCA [4] approaches implement for feature reduction. MRMR gives the Music Classification is application which provides important functionalities for music retrieval. Music classification has received much notice from MIR tool researches in resent year. In this thesis focuses on music mood classification. Automatic music mood classification has some different tasks. The proposed approach for automatic music mood classification is show in Figure 1. In Feature Extraction according Feature set will be use. Energy, Temporal, Harmony and Rhythm. Using SVM detect mood of emotion classis. After this task again use SVM and classify emotion subclass of music classified output.

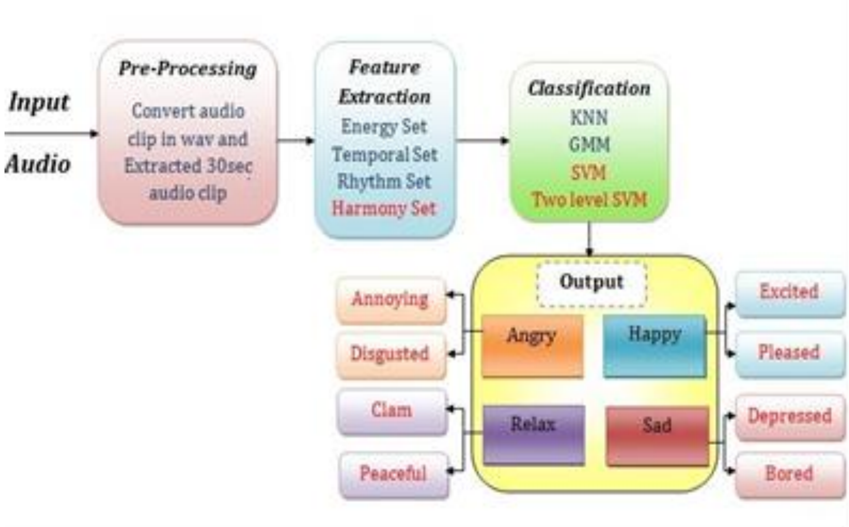

Figure 1: Block diagram of proposed Method.

1.1)Pre-processing

To begin with, we selected 550 songs for each mood based on the survey conducted among different people and based on the results of Vallabha Hampiholi[8].We wanted to assert the mood of a particular song based on the generalized perspective of human mind. The survey was conducted among 100 people and the result was tabularized so as to set the range of threshold for each mood.

1.2) Feature Extraction

Audio was used for the feature extraction process. Each clip is divided into 0.5 overlie 32ms-long frames. The extort features reduction into four categories: timbre, intensity, rhythm. The first three sets can express mood information to some degree and are very important for mood detection.

1.2.1) Temporal features

Happy songs usually sound bright and vibrant, while grief ones sound pensive and gloomy. Timbre features can be used to give your opinion whether the emotion is negative or positive. The timbre features we used are listed as follows: Centroid, Roll off Point, Fluctuation, Zero Crossing, Strongest Frequency Via Zero Crossing, Strongest Frequency Via Spectral Centroid, Strongest Frequency Via FFT Maximum, Compactness, MFCC, LPC, Peak based Spectral Smoothness. user, Calculated the mean and standard deviation over all structure.

1.2.2) Energy features

Intensity features can used to judge whether the emotion is very strong or not. For example, if songs fast a positive emotion, then using strength features we can get whether it is enthusiastic or lively. In this paper, the intensity features are RMS and Fraction of Low Energy Windows. By calculating the average and normal, we got 4 intensity features.

1.2.3) Rhythm feature

Through rhythm features, we also can get some information about whether the music emotion is positive or negative. Fast songs have a tendency to be happier than slow down ones. We extracted rhythm features including Beat Sum, Strongest Beat and Strength of Strongest Beat. Also by calculating the mean and standard, led to 6 rhythm features. The features are take out and combine for each music piece in a standard file format so as to make it easy for mining the relations between these features w.r.t. the corresponding mood of the audio files.

1.3 Feature Selection

There are certain features which give similar values for audio of any mood. Hence such features can hold back the accuracy of the system. After conducting review and feature origin process, Information Gain algorithm was used to select the defined features and remove the superfluous ones. Information gain helps to determine which attribute in a given set of training feature vectors is most useful for discriminating between the classes to be learned [17]. When a particular classification model has multiple features, there is higher probability that many (if not most) of the features are low information. These are the features that are common across all classes and therefore contribute meagre information to the classification process. Individually they are innocuous, but in aggregate, low information features can decrease performance. Eliminating low information features gives your model clarity by removing noisy data. When the higher information features are used, performance is increased and the size of the model is decreased, which results in less memory usage along with faster training and classification.

CONCLUSIONS

In this paper, diverse audio feature such as dynamics, rhythm, spectral, and harmony are selected for music emotion classification. In the next stage, these features are integrated using lower (mean and standard deviation) and higher order moments (skewness and kurtosis). Similarly, covariance components are also calculated to improve the classification.

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