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Application of the CICC to the Detection of Non-Music Components

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Introduction

The Tonic and Carnatic Interval Cepstral Coefficients were retrieved and employed by the Raga model to identify the Raga, as explained in Chapter 5. In this chapter, we'll look at how to utilize these characteristics to extract non-music data from a music signal, such as Singer, Instrument, Emotion, and Genre. Extracting Spectrum characteristics like the spectral flux, spectral centroid, autocorrelation, and Cepstral features like the MFCC, and OFCC, and developing a GMM, HMM, or SVM utilizing these feature values, as stated in Chapter 2, identified the Singer, Instrument, Genre, and Emotion (Kim and Whitman 2002, Nwe and Li 2007, Panagakis et al 2008, Li and Ogihara 2004, Yang et al 2006).

Identification Of The Singer

Researchers have presented the challenge of automated Singer recognition for Western music. Voice coding elements were employed for Singer identification in one of the approaches (Kim and Whitman 2002). They constructed the Gaussian Mixture Model (GMM) and the Support Vector Machine (SVM) using acoustic characteristics generated from LP coefficients and formant frequency, and compared the results of their performance. When the input featured a voice or a mix of voice and non-voice, the SVM performed better for Singer identification.

The GMM, on the other hand, only worked well when the input was a monophonic speech stream.

Another method of Singer identification is to utilize the Singer's vibrato features, which are basically periodic changes in pitch (Nwe and Li 2007). The vibrato features of a singing voice are dominating, and this is reflected in the derived coefficients. Maddage et al. suggested the Octave Frequency Cepstral coefficients (OSCC/OFCC), which were employed by the authors (2004). As previously stated, the OSCC / OFCC are based on the keyboard's Octave scale, with each filter bank's cut-off frequency determined by the frequency allocated to the keys of an octave. The authors retrieved 9 coefficients and utilized them to build a Hidden Markov Model (HMM), which is used to identify Singers.

The developers of another Singer identification approach (Mesaros et al 2007, Levy 1982) employed the MFCC in conjunction with a novel distance measure to conduct Singer identification.

In general, the MFCC and OSCC features were used to determine the qualities transmitted in the Singer identification procedure for Western music.

Because of the basic differences in the music characteristics of the two systems, as stated in Chapter 1, the methodologies presented for Western music Singer identification based on the OSCC cannot be directly applied to Carnatic music Singer identification (Sambamurthy 1983).

Furthermore, the Octave Frequency Cepstral coefficients procedures are based on the major scale frequency band of Western music and cannot be directly applied to Carnatic music. The MFCC were designed for speech processing, hence their use to music signal processing is unjustified. Cepstral Coefficients, on the other hand, communicate timbral properties and are hence excellent for Singer identification. As a result, we employ our specifically constructed Carnatic Interval Cepstral Coefficients (CICC) in this study to identify the Singer by developing the GMM as the foundation for Singer identification. The LDA principle, which we described before, has also been used to identify the Singer.

Instrument Identification

After identifying the Singer from the voice-only component of the input, the non-voice component is used for determining the Instrument present in the input signal. Martin and Kim (1998) concluded that identifying cue phrases in musical signals could result in better Instrument identification.

As discussed in Chapter 2, Instrument recognition was also carried out by isolating monophonic musical Instrument sounds using six features, namely, Cepstral coefficients, constant *Q* transform frequency spectra, multidimensional scaling analysis trajectories, RMS amplitude envelopes, spectral centroid and vibrato. Kitahara et al (2003) exploited the pitch dependency on Timbre characteristics to improve the instrument recognition accuracy by 75%. This motivated us to try our Carnatic Interval Cepstral coefficients, which incorporated the tonic for Instrument Identification.

Emotion Identification

Emotion is yet another important component that is conveyed by a given musical piece, and can be deciphered even by a person who does not have musical knowledge.

Many of the algorithms that are available for recognizing Emotion in music have been derived from speech processing systems. These algorithms, when applied to music, try to look for speech specific characteristics rather than music characteristics. Researchers in Western music scenario have explored Emotion identification in music, by incorporating music characteristics like rhythm, tempo etc. In our work, we have adapted the algorithms used for speech and for Western music and incorporated some features of Carnatic music like Raga and tonic, for the process of Emotion identification. The basis of using Raga and tonic for Emotion detection is derived from the fact, that Carnatic music literature outlines the use of specific Ragas to convey specific Emotions.

As discussed in Chapter 2, using the features like the fundamental frequency, the mean, standard deviation of the signal, minimum and maximum peak frequency, speaking rate and up and down slopes of the frequency, and articulatory features (Dellaert et al 1996) Emotion is recognized from speech. In addition to this, other features like the MFCC are used for constructing GMM to identify the Emotion from speech (Tang et al 2009).

Although the characteristics of music are different from those of speech, the MFCC was used to identify the Emotion from music (Li and Ogihara 2004). Yang et al (2006) have done work on identifying and classifying the Emotion of Western music, are based on Thayer's 2D model (1989).

Genre Identification

Genre refers to the style of music. In Western music some typical Genres include Rock, Jazz, Beat, Blues, Rap, etc. In the Indian music context, many such Genres of music exist, like Thalattu, Oppari, Vayalorapattu, Ghana, Therukoothu, Melody, Romance, Keli, etc. In this thesis we propose to identify the typical Genres of music that are specific to the South Indian context.

As already discussed, the typical Genres of Tamil music, namely, Ghana (music that has a simple repeated melody which is typically used in places to necessitate ease of singing), Keli(the song symbolizes teasing), Themmangu (referring to the king of folk music), Thalattu (music used for putting some one to sleep), Vayalorapattu (music that is rendered during farming to ease out the tiredness), melody (music indicating feeling of comfort), oppari(music used to mourn the death of someone to convey sorrow), and therukoothu (typical road side music).

Based on the discussion on Chapter 2 on Genre identification and the survey carried out by Scaringella et al (2006), in this work, we wanted to explore the capability of the CICC features for Genre identification. From the conclusion that can be arrived at based on the work on Genre identification and the use of Cepstral features for the same, we wanted to explore the use of the CICC features for the Genre identification of South Indian music. The use of the CICC is justified, as it incorporates the Cepstral features representing the timbral characteristics and pitch information in the form of Tonic. Hence, we explored Genre identification of Tamil music using this CICC feature and additional information in terms of the swara pattern.

We explored two approaches, one using the simple concept of tracking the pitch envelope and the CICC, to construct the GMM to identify the Genre. The other approach used the HMM based on the CICC features for determining the Genre.

Conclusion

To determine the Tala of the input music, the segmentation algorithm may be improved further. Attempts might be made to extract musical material from any part of the input song, not only the beginning. The tonic identification method is based on template matching and might be tweaked to include signal characteristics. The octave interval is assumed to be 22 in our newly developed CICC coefficient. Other Octave intervals (24, 48, 96, 32, 57) might be used to determine the CICC. Only a few Raga lakshana properties were included in our method for Raga identification utilizing the Raga model. Other Raga lakshana features like as Tara, Alpatva, Bahutva, Apanyasa, and Vinayasa may be used to enhance the performance of the Raga model. Furthermore, the idea of Gamaka, in which there are various variants of pitch inflexion, is a significant feature that has been overlooked in the work. New Vakra Ragas might be handled in the future employing additional Raga lakshana features and Gamakas.

Other aspects of the music signal, such as genre, emotion, instrument, and so on, may be used as index keys in the MIR scenario. In addition, the Multi-key indexing approach may be used to index various components of other multi-media material.

REFERENCES

1. Manoj A. and Kahar "Phenotype frequencies of blood group systems (Rh, Kell, Kidd,Duffy, MNS, P, Lewis, and Lutheran) in blood donors of south Gujarat, India" AsianJournal of Transfusion Science - Vol 8, Issue 1, January - June 2014.
2. Shamsian BS, Arzanian MT, Shamshiri AR, et al. Frequency of red cell alloimmunization in patients with β-major thalassemia in an Iranian referral hospital.Iran J Pediatr. 2008; 18:149-153.
3. Singer ST, Wu V, Mignacca R, et al. Alloimmunization and erythrocyte autoimmunization in transfusion-dependent thalassemia patients of predominantly Asian descent. Blood. 2000; 96:3369-3373.
4. Rabeya Yousuf et al. Incidence of Red Cell Alloantibody among the Transfusion Recipients of University Kebangsaan Malaysia Medical Centre. (Indian J Hematol Blood Transfus (Apr-June 2013) 29(2):65–70).
5. Salama MA, Sadek NA, Hassab HM, et al. Erythrocyte autoantibodies and expressionof CD59 on the surface of red blood cells of polytransfused patients with beta- thalassaemia major. Br J Biomed Sci. 2004; 61:88-92.
6. Hari Krishan Dhawan et al., Alloimmunization and autoimmunization in transfusiondependent thalassemia major patients in Pgimer, Chandigarh 160012 India.2014.
7. Al Joudi F et al. Prevalence and specificities of red cell alloantibodies among blood recipients in the Malaysian state of Kelantan. (Asian J Transfus Sci 2011;5:4245).
8. Spanos TH, Karageorga M, Ladis V, et al. Red cell alloantibodies in patients with thalassemia. Vox Sang. 1990; 58:50-55.
9. Ameen R, Al-Shemmari S, Al-Humood S, et al. RBC alloimmunization and autoimmunization among transfusion-dependent Arab thalassemia patients. Transfusion. 2003; 43:1604-1610.
10. Madeeha Rehan et al. Red Cell Alloantibodies in Multi - Transfused Patients of Beta Thalassaemia Major. Journal of Rawalpindi Medical College (JRMC); 2015; 19(2):152-154.
11. Davari K, Soltanpour MS. Study of alloimmunization and autoimmunization in Iranian βthalassemia major patients. (Asian J Transfus Sci 2016;10:8892).