Affective Analysis of Musical Chords

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***Abstract*—Music invokes emotions in humans and hence sentiment extraction in music has been researched for a long time. This paper focuses on 2 research goals (RGs):**

***RG1:* Identifying and analyzing emotions associated with different musical chords.**

***RG2:* Suggesting a technique to compute Evaluation, Potency and Activity (EPA) [31] values for musical chords.**

For RG1 a user study is conducted wherein 30 people are asked to name a song under two emotional categories - "Happiness" and "Sadness". Chord progression of each song is determined using the Chordify web service and the frequency of occurrence of the chords under the two emotional categories is calculated and the trends are analyzed.

For RG2, EPA values for chords are computed by utilizing the results of RG1 to calculate the probability of chord, given an emotion Pr(Chord|Emotion). This data is fed into the proposed formula to determine EPA values associated with different chords. Thereafter, application of these results to existing sentiment extraction models is suggested.

Keywords—Affective computing; Computer generated music; Sentiment analysis; Music information retrieval; Emotion recognition

I. INTRODUCTION

Music has long been considered an expression of emotions. Authors of [7] describe music as the "language of the emotions" and in [6] emotional expression has been rated as the most important attribute in determining the aesthetic value of music. In a survey study [10], 141 participants were asked what, if anything, music expresses. They were required to tick items from a list of options which were based on a thorough survey of the literature on expression in music. Results indicated that "emotions", unlike any of the other options, was selected by 100% of the participants.

Having said that, analyzing emotions in music faces several research problems. One of the major problems is defining and identifying emotions in context of music. One reason for this is that emotions in music are rather complex and different from everyday emotions. For example emotions such as fear and disgust are relatively unrelated to music. A lot of research has been done to identify emotions which are most relevant to music. For example, studies [10] [14] [15] show that emotions such as happiness, sadness, love and tenderness are amongst the top ten emotions expressed in music. These results were reflected across three different data sets containing musicians, students and countries.

Studies [16] [17] [18] confirmed that emotions of happiness, sadness and tenderness were accurately perceived by children, different cultures and brain-damaged patients respectively. Although these studies are convincing, it is hard to determine whether these emotions are perceived by the listeners or the music inherently represents and induces these emotions in the listener and what are the factors that shape the musical perception of an individual [8]. For instance, personal interpretation of music may lead to arousal of an emotion [9].

Due to this diversity in emotional perception of music, several theories of sentiment mapping have been devised. One view proposed in [11] is that listeners have the choice of interpreting music in infinite number of ways. This means that every emotion felt by the listener is a representation of the emotions expressed by the music. Other research [12] maintains that there should be a minimum level of agreement among different listeners in order to accurately associate an emotion to a piece of music.

Another challenge is to devise a music centric model to conceptualize emotions in music. While several categorical and dimensional models exist, emotions expressed in music differ significantly from those experienced in day to day to life. Authors of [19] proposed a music specific model i.e. a model that specifically identifies the emotions perceived and felt by people while listening to music. They propose a *Geneva Emotional Music Scale* which identifies 9 major emotional categories in music.

In this paper, we try to associate sentiments with musical chords under two sentiments namely – "Happiness" and "Sadness". These two emotions are chosen since they consistently appear across various emotional models including the music-model mentioned in [19]. This study specifically analyzes musical chords, which is one of the components of music composition. A chord in music is a harmonic set of three or more notes that is heard as if sounding simultaneously [19]. A set of chord played in succession is called a chord progression. A chord in itself is based on a musical scale and chord progressions allow switching scales between these chords harmonically to produce different musical compositions. The paper proposes a methodology to calculate the EPA values for musical chords and discusses its application in existing sentiment mapping systems. EPA stands for Evaluation, Potency and Activity which are three most recurring attitudes used across various semantic differential scales which are used to identify connotative meanings and emotions towards various objects, situations and concepts.

The rest of this paper is organized as follows. In section II, previous work related to sentiment extraction in music is discussed. Section III discusses about the collection of data for analysis. Section IV talks about the methodology used to perform analysis of data obtained in section II. Section V sums up the findings of the study. In section VI, limitations of the proposed approach are discussed. Section VII concludes the study and section VIII talks about possible extensions of this idea for more accurate sentiment analysis of music.

II. RELATED WORK

The authors of [1] proposed a system to extract sentiments from music. Sentiments are conceived to be a combination of two features namely perception and cognition. Perception comes from the Latin word "percipio" which means to gain or to receive and involves identification, organization and interpretation of sensory information to make it comprehensible in order to represent and understand the environment [2]. Cognition is derived from the Latin verb "cognoscere" which means to learn. It involves analyzing the perceived information by focusing on how information is represented, processed, and transformed [3].

In this study, authors propose a model that extracts sentiments from music in three steps. First is the "Transcription" step in which the musical signal is converted into musical notes. This is done by creating a Time-Frequency map and histogram of the input sound (polyphonic) signal and identifying different attributes such as loudness, power, frequency maxima, beat length etc. to determine the note symbols and the attack positions of the notes. Second step involves identifying the musical primitives such as chord progression, rhythm, melody and tempo using the musical attributes obtained in the first step, coupled with some musical knowledge. The music knowledge represents a set of heuristic rules which when applied to the data yields different primitives. For example, authors consider a snapshot of data to be a “Melody” if it contains the sequence of the loudest and highest notes in the chord and the pitch difference between the adjacent notes is limited. Using similar heuristic rules, rhythm patterns, chords and key of the music input is identified.

In the third and the final step sentiments are extracted by using the musical primitives obtained in the second step and mapping them to sentiments under a set of rules. The rules used in this phase are devised by interviewing experienced musicians. For instance, the key F is reported to impart a "rural" feel by the interviewees. One limitation of this approach mentioned by the authors is that it takes into account personal opinion of specific group of individuals.

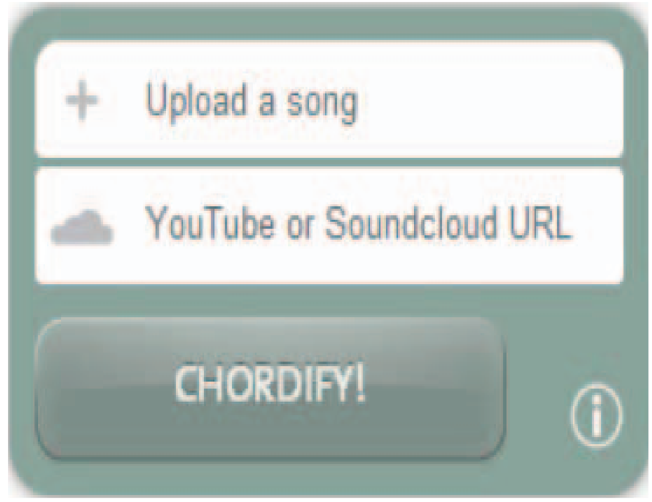

Fig.1. Musical source submission dialogue at Chordify.net

They suggest making this mapping universal by using semantic differential methods to measure the connotative meaning of musical primitives. We will discuss in the later sections about how the findings of this study can be incorporated in the sentiment mapping step of Katyose’s sentiment extraction model.

Authors of [4] present a method of representing music as a set of scalar descriptors based on human perception. In the proposed method, a large number of musical recordings are played to a group of people. This group then assigns a set of scalar values to each of the musical recordings. Examples of scalar values assigned are happiness tempo, “dancebility”, melodiousness and anger. In the next phase, each of these musical recordings is processed computationally to extract certain parameters. These parameters are chosen because they distinguish well between different sounds of all kinds and are mathematically distinctive and not parameters which are distinct based on human perception of music. This kind of mathematical computation of sound was proposed in [29] but it did not take into account the human perception in their analysis.

However, in addition to this, the authors of [4] use empirically generated algorithms to correlate the extracted parameters with the judgment based parameters on human perception obtained in the first phase. A model is then devised for each of the scalars for human perception which can be used in future to assign scalar values to music which has not been judged by a group of people previously.

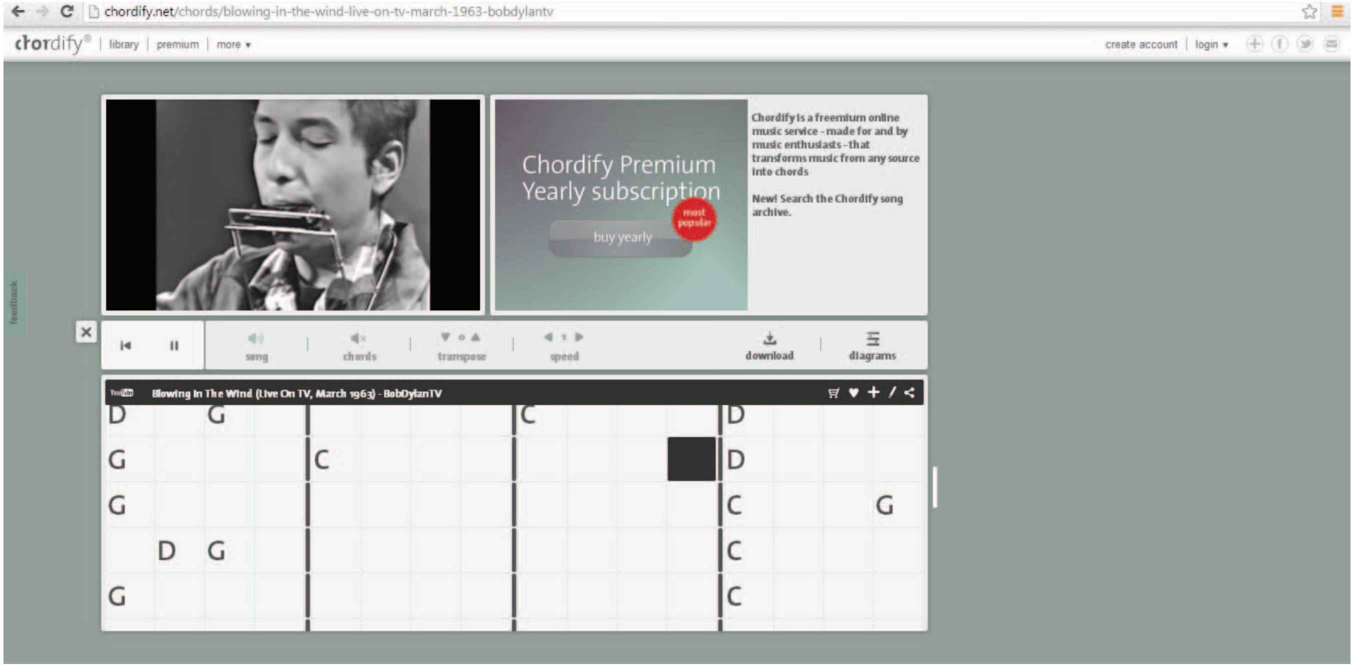

Fig.2. Screenshot of Chordify interface displaying the chords and YouTube video of the song blowing in the wind

In a nutshell, this method combines the computational feature extraction from music with the human perception of music. We propose a method which is in contrast to the method proposed in the aforementioned study in that, instead of playing large number of recordings to a group of people and analyzing their feedback we ask large number of people to provide a song under a pre-defined set of emotions. We will see in the later sections how this analysis can yield useful information about human perception towards music.

A. *Chordify*

In this study, as discussed in section III, Chordify web service is used to extract chords from the songs provided by the subjects. Chordify [24] [5] is a web-service that automatically transcribes the chord labels form an arbitrary audio source and displays them on screen. Figure 1 shows the musical source submission dialogue on the Chordify homepage.

It enables the users to provide Chordify with a song they wish to convert into chords. This song submission can be done in two ways – (i) by uploading the target sound file on Chordify web service or (ii) by directly inputting the Youtube [21], SoundCloud [22] or the Deezer [23] song URL. Once the song is uploaded or the song URL is pasted in the Chordify dialogue box, users can click the Chordify button to convert the audio source to labeled chords. Figure 2 shows the Chordify interface which appears when the chords are computed for the song. In this screenshot, the input audio is "Blowing in the wind" by Bob Dylan. The interface displays the audio source along with the music sheet with transcribed chord labels. As the song is played, the current beat position is highlighted telling the user which chord to play at which position in the song. This interface also allows the user to navigate to any portion of the song by clicking the relevant square on the music sheet. The music player will jump to the clicked position in the music sheet and start playing back from that position onwards. Users can also select specific sections in the music sheet, and put them in loop. The Chordify "diagrams" interface which is used in this study to determine the chords used in a song is shown in Figure 3. The interface provides the chord structures of all the chords used in the song. Choridify uses sonic annotator [26] and VAMP-plugin [25] for extraction of audio features which are then passed on to a Haskell program named HarmTrace [27, 28] which finds the beat positions where the beat of the input audio matches with a particular chord and then transcribed to the music sheet. In places where HarmTrace is uncertain about the chords, it automatically transcribes the chord label which satisfies the rules of tonal harmony the best. In sum Chordify is accurate in identifying chords in songs. A very good example can be seen in Figure 2 where Bob Dylan is playing "Blowing in the wind" live and changing the chords identified by Chordify at the predicted positions.

III. Data Collection

For data collection 30 people between the age group of 19-23 years were interviewed. They were required to name a song under two emotional categories: happiness and sadness. At the end of the interview phase a database of songs categorized according to the two emotions was obtained. The next step in data collection was identifying different notes and chords used in the songs.

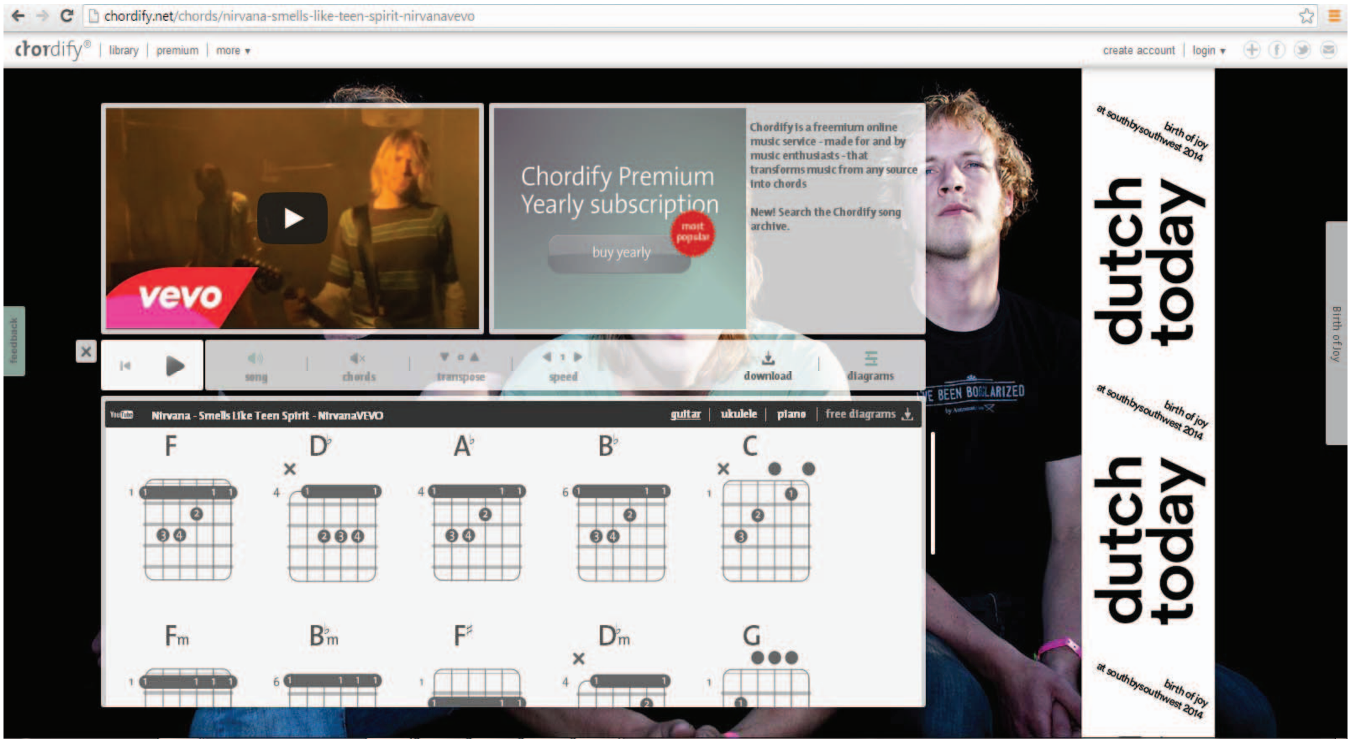

Fig.3. Screenshot of Chordify interface displaying the YouTube video and chords along with chord diagrams used in the song Smells like teen spirit (Never mind)

For this *Chordify.net* web service was used. Each song in the database was fed to Chordify via a YouTube URL of the song. The output of Chordify was a set of chords used in the song. These chords were manually inserted in the song database. The final output of this phase was a database containing the age and gender of subjects along with their choice of songs under the two emotional categories and corresponding set of chords for every song identified using Chordify. After obtaining the chord database, we determined the frequency of occurrence of different chords under each emotional category. Figure 4 and Figure 5 show the total number of occurrences of each chord under the happiness and sadness category respectively in descending order. There are several trends which can be observed. For example, all the "major" chords (A, B, C, D, E, F and G) appear with the highest frequencies in both the emotional categories. It is also observed that under the happiness category, chord B is the most frequently used chord whereas under the sadness category, chord A appears most frequently. Further, the Gm chord appears only 5 times under the happiness category as compared to 10 times under the sadness category. It is evident that even though all the chords appear throughout different emotional categories, their frequency of appearance changes significantly. Consequently, it is not possible to exclusively categorize a musical chord under one emotional category. Rather, a probabilistic association of chords to emotions is a better approach. This study proposes a method of probabilistic EPA calculation for musical chords.

IV. Methodology

In order to determine probabilistic EPA of different musical chords, the ratio of occurrence of a chord to the total number of occurrences of all the chords in each emotional category is determined. This ratio helps us to evaluate the probability of a chord to appear under a particular emotional category. Figure 6 shows the aforementioned ratio for all the chords in the happy and sad categories respectively.

We name the ratios obtained for the two emotional categories as R_{happy} and R_{sad}. The next step is to identify the EPA value of the parent emotion. In this study we use Interact.jar [30] to determine the EPA values for the happy and sad emotions. EPA value for the two emotions is used under the setting Indiana 2002-04 and the gender is male. We define probabilistic EPA as following:

$$EPA_{prob\ of}\ chord = \Sigma\ EPA_{Parent\text{-}emotion} * R_{Parent\text{-}emotion}$$

Here $EPA_{prob\ is}$ the probabilistic EPA of the chord which we intend to find. $EPA_{Parent\text{-}emotion}$ is the EPA profile of the parent emotion. For instance, in this case happiness and sadness are parent emotions. Hence their EPA profile would be considered. $R_{Parent\text{-}emotion\ is}$ the ratio of occurrence of a chord to total number of occurrences of all chords for the “parent-emotion” category. Since we are considering only two emotions in this study, we will calculate the value of R_{happy} and R_{sad} .

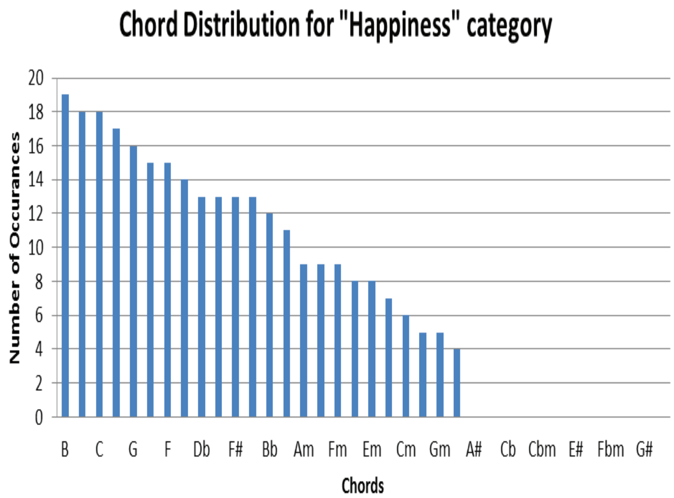

Fig.4. Distribution of chords in happiness category

Next, to get the EPA profile of a chord under one category we multiply $R_{\text{Parent-emotion}}$ and $EPA_{\text{Parent-emotion}}$. For instance, to get EPA profile of a chord under happiness category we will multiply R_{happy} and EPA_{happy}. Once the EPA profile of a chord is obtained under all the emotional categories (in this case 2), we add all these EPA values to determine EPA_{prob} which is the probabilistic EPA of the chord. Figure 6 shows the calculation of R_{happy}, R_{sad} and EPA_{prob} for all the chords appearing in the songs database.

V. RESULTS

We observe that EPA values of happiness are positive and that of sadness is negative. The purpose of summation in the formula is to measure the net offset of a chord from zero. This offset tells us that a chord is more probable to be used in a chord progression that induces positive emotions in listeners. For instance, we observe that chords B, Db, Dbm, Eb, Fm, F#, and F#m have relatively higher positive EPA_{prob} values than other chords.

We also observe that 3 out of 4 variants of chord F under consideration have relatively higher EPA_{prob} values. Hence chord F is most likely to appear in "happy" chord progressions. Similarly chords Gm and Em have relatively high negative values of EPA_{prob} and hence are more likely to appear in "sad" chord progressions.

As discussed in section II, one limitation of sentiment extraction model proposed in [1] is that perception of a group of experienced musicians is far from representative of the popular perception. One possible application this study can be to enhance musical knowledge database in aforementioned model to increase the accuracy of emotion mapping. Figure 7 shows the music computation model. We observe that in the "understanding" step, the system refers to a knowledge database which is constructed by interviewing experienced music professionals. For example, the chord progression Dm, G, Cmaj7, F, Bm7, E7, Am is perceived to set a plaintive mood by musicians. Incorporating general perceptions for different musical attributes such as melody, tempo, rhythm, chord, style, tone can extend sentiment mapping to large populations. Figure 8 shows the modified knowledge database containing both, the expert and general perception of musical attributes.

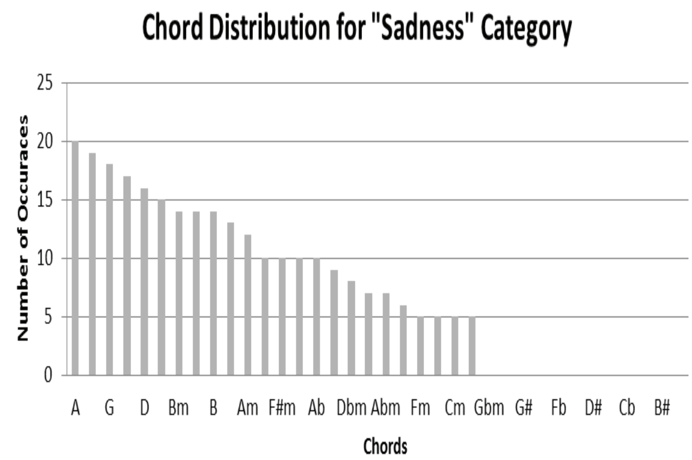

Fig.5. Distribution of chords in sadness category

All the general attributes namely melody, tone, style, rhythm EPA_{prob} can be computed using the technique proposed in this paper. Moreover, it also opens opportunities for research on how the values of different musical attributes are interrelated. For instance, empirical algorithms can be devised that use Chord EPA_{prob} values to determine EPA values for chord-progressions by analyzing the deflections between different chords during transitions.

VI. LIMITATIONS

Categorical analysis of emotions in music requires an exhaustive set of emotional categories. Some music specific emotional models do exist [9] that try to cover the basic musical emotions in an exhaustive manner. Another problem in such a study is that it is hard think of songs under certain emotional categories. However the question remains: What is easier? Listening to music and feeling emotions or seeing emotions and then thinking of a sound that might trigger those emotions. Knowledge of different dimensions when analyzing sentiments will give us deeper insight into affective computing in music.

VII. CONCLUSION

In this paper we identified different emotions associated with musical chords. We introduced the concept of probabilistic EPA and a technique to compute EPA_{prob}. We observed that certain chords were more likely to appear in happy songs and some were more likely to appear in sad songs. We discussed how these results can be applied to existing models to yield more accurate sentiment mapping.

VIII. FUTURE WORK

It would be interesting to see if the analyzed trends hold true when the domain size is increased or when the age group is changed. Also, in this study we only focus on chords individually. If a similar approach is applied to other attributes such as type of instrument, pitch, percussion, transitions, scales etc. we can create a comprehensive database which can be utilized by specially designed algorithms to intelligently compose music having desired emotions. As mentioned in section V, research on how the values of different musical attributes are interrelated can yield interesting results.

Description				D#	Dbm	E	Em	Eb	E#	Ebm	F	Fm	Fb	F#	F#m	Fbm	G	Gm	Gb	G#	Gbm
Ratio of chord under happiness category (R_{happy})			R_{happy}=Occurence of a chord in happiness category/Net occurences of all chords in happiness category	0.00	0.04	0.05	0.03	0.05	0.00	0.01	0.05	0.03	0.00	0.05	0.05	0.00	0.06	0.02	0.00	0.00	0.00
Ratio of chord under sadness category (R_{sad})			R_{sad}=Occurence of a chord in sadness category/Net occurences of all chords in sadness category	0.00	0.03	0.06	0.05	0.03	0.00	0.02	0.06	0.02	0.00	0.03	0.04	0.00	0.07	0.04	0.00	0.00	0.00
EPA HAPPINESS	E_{happy}	2.92	$E_{chord-happy} = E_{happy}*R_{happy}$	0.00	0.12	0.16	0.08	0.14	0.00	0.04	0.16	0.09	0.00	0.14	0.14	0.00	0.17	0.05	0.00	0.00	0.00
	P_{happy}	2.43	$P_{chord-happy} = P_{happy}*R_{happy}$	0.00	0.10	0.13	0.07	0.11	0.00	0.04	0.13	0.08	0.00	0.11	0.11	0.00	0.14	0.04	0.00	0.00	0.00
	A_{happy}	1.96	$A_{chord-happy} = A_{happy}*R_{happy}$	0.00	0.08	0.11	0.06	0.09	0.00	0.03	0.11	0.06	0.00	0.09	0.09	0.00	0.11	0.04	0.00	0.00	0.00
EPA SADNESS																					
	E_{sad}	-1.88	$E_{chord-sad} = E_{sad}*R_{sad}$	0.00	-0.06	-0.10	-0.09	-0.05	0.00	-0.03	-0.12	-0.03	0.00	-0.06	-0.07	0.00	-0.13	-0.07	0.00	0.00	0.00
	P_{sad}	-1.66	$P_{chord-sad} = P_{sad}*R_{sad}$	0.00	-0.05	-0.09	-0.08	-0.04	0.00	-0.03	-0.10	-0.03	0.00	-0.06	-0.06	0.00	-0.11	-0.06	0.00	0.00	0.00
	A_{sad}	-2.06	$A_{chord-sad} = A_{sad}*R_{sad}$	0.00	-0.06	-0.11	-0.10	-0.05	0.00	-0.04	-0.13	-0.04	0.00	-0.07	-0.08	0.00	-0.14	-0.08	0.00	0.00	0.00
EPA PROB	E_{prob}		$E_{chord-happy} + E_{chord-sad}$	0.00	0.06	0.05	-0.01	0.09	0.00	0.01	0.04	0.06	0.00	0.07	0.07	0.00	0.04	-0.02	0.00	0.00	0.00
	P_{prob}		$P_{chord-happy} + P_{chord-sad}$	0.00	0.05	0.04	-0.01	0.07	0.00	0.00	0.03	0.05	0.00	0.06	0.05	0.00	0.03	-0.02	0.00	0.00	0.00
	A_{prob}		$A_{chord-happy} + A_{chord-sad}$	0.00	0.02	-0.01	-0.04	0.04	0.00	-0.01	-0.02	0.03	0.00	0.02	0.02	0.00	-0.02	-0.04	0.00	0.00	0.00

Description				A	Am	Ab	A#	Abm	B	Bm	Bb	B#	Bbm	C	Cm	Cb	C#	Cbm	D	Dm	Db
Ratio of chord under happiness category (R_{happy})			R_{happy}=Occurence of a chord in happiness category/Net occurences of all chords in happiness category	0.06	0.03	0.03	0.00	0.03	0.07	0.05	0.04	0.00	0.02	0.06	0.02	0.00	0.00	0.00	0.06	0.03	0.05
Ratio of chord under sadness category (R_{sad})			R_{sad}=Occurence of a chord in sadness category/Net occurences of all chords in sadness category	0.07	0.04	0.04	0.00	0.03	0.05	0.05	0.05	0.00	0.02	0.07	0.02	0.00	0.00	0.00	0.06	0.04	0.02
EPA HAPPINESS	E_{happy}	2.92	$E_{chord-happy} = E_{happy}*R_{happy}$	0.19	0.09	0.08	0.00	0.09	0.20	0.15	0.13	0.00	0.05	0.19	0.06	0.00	0.00	0.00	0.18	0.07	0.14
	P_{happy}	2.43	$P_{chord-happy} = P_{happy}*R_{happy}$	0.16	0.08	0.07	0.00	0.08	0.17	0.12	0.11	0.00	0.04	0.16	0.05	0.00	0.00	0.00	0.15	0.06	0.11
	A_{happy}	1.96	$A_{chord-happy} = A_{happy}*R_{happy}$	0.13	0.06	0.06	0.00	0.06	0.13	0.10	0.08	0.00	0.04	0.13	0.04	0.00	0.00	0.00	0.12	0.05	0.09
EPA SADNESS																					
	E_{sad}	-1.88	$E_{chord-sad} = E_{sad}*R_{sad}$	-0.14	-0.08	-0.07	0.00	-0.05	-0.10	-0.10	-0.10	0.00	-0.03	-0.13	-0.03	0.00	0.00	0.00	-0.11	-0.07	-0.04
	P_{sad}	-1.66	$P_{chord-sad} = P_{sad}*R_{sad}$	-0.12	-0.07	-0.06	0.00	-0.04	-0.09	-0.09	-0.09	0.00	-0.03	-0.12	-0.03	0.00	0.00	0.00	-0.10	-0.06	-0.04
	A_{sad}	-2.06	$A_{chord-sad} = A_{sad}*R_{sad}$	-0.15	-0.09	-0.08	0.00	-0.05	-0.11	-0.11	-0.11	0.00	-0.04	-0.15	-0.04	0.00	0.00	0.00	-0.12	-0.08	-0.05
EPA PROB	E_{prob}		$E_{chord-happy} + E_{chord-sad}$	0.05	0.01	0.01	0.00	0.05	0.10	0.05	0.03	0.00	0.02	0.06	0.03	0.00	0.00	0.00	0.07	0.00	0.10
	P_{prob}		$P_{chord-happy} + P_{chord-sad}$	0.03	0.00	0.01	0.00	0.04	0.08	0.04	0.02	0.00	0.01	0.04	0.02	0.00	0.00	0.00	0.05	0.00	0.08
	A_{prob}		$A_{chord-happy} + A_{chord-sad}$	-0.03	-0.03	-0.02	0.00	0.01	0.03	-0.01	-0.02	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	-0.03	0.05

Fig.6. EPA_{prob} calculations for different chords

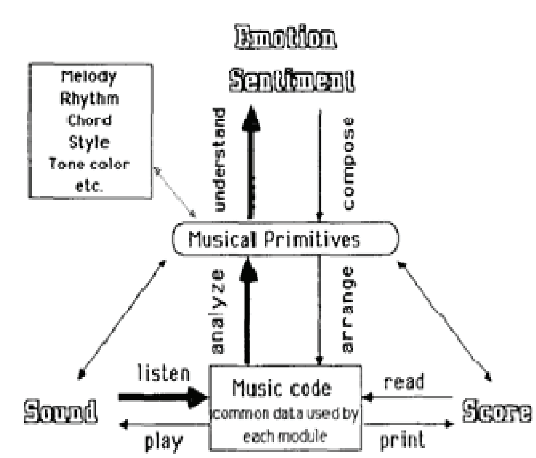

Fig.7. Concept of system for music processing. From: Katayose, Haruhiro, M. Imai, and Seiji Inokuchi. "Sentiment extraction in music." In Pattern Recognition, 1988., 9th International Conference on, pp. 1083-1087. IEEE, 1988

GENERAL PERCEPTION

Melody EPA $_{prob}$
Rhythm EPA $_{prob}$
Chord EPA $_{prob}$
Style EPA $_{prob}$
Tone EPA $_{prob}$

+

EXPERT PERCEPTION

Fig.8. Modified knowledge database

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