Associating Emoticons with Musical Genres

Jukka Holm
Tampere University of Technology
Human-Centered Technology
P.O. Box 589, 33101 Tampere
Finland
+358 44 2008646
jukka.holm@tut.fi

Harri Holm
Nokia D R&D
Visiokatu 3, FIN-33720 Tampere
Finland
+358 40 8032820
harri.j.holm@nokia.com

Jarno Seppänen
Nokia Research Center
P.O. Box 407, FI-00045 NOKIA
GROUP
Finland
+358 50 4835879
jarno.seppanen@nokia.com

ABSTRACT

Music recommendation systems can observe user's personal preferences and suggest new tracks from a large online catalog. In the case of context-aware recommenders, user's current emotional state plays an important role. One simple way to visualize emotions and moods is graphical emoticons. In this study, we researched a high-level mapping between genres, as descriptions of music, and emoticons, as descriptions of emotions and moods. An online questionnaire with 87 participants was arranged. Based on the results, we present a list of genres that could be used as a starting point for making recommendations fitting the current mood of the user.

Keywords

Music, music recommendation, context, facial expression, mood, emotion, emoticon, and musical genre.

1. INTRODUCTION

The music business is undergoing a large change due to the digitization of music. The amount of new music has become overwhelming for any individual to follow, with hundreds of new tracks appearing every day. Although we have a large body of music, efficient distribution services, and consumers who are used to purchasing music online, we are faced with the music discovery problem: how to find personally relevant and interesting music. Music recommendation systems are developed for solving this problem by observing the personal preferences of users, modeling the properties of a music catalog, and suggesting music based on the model.

Mobile music players have capabilities that enable the creation of context-aware music recommendations, that is, suggestions of music to match the current situation of the listener. As context information typically includes location, time, and activity [1], context-aware recommendations can adapt to the location and time of music listening, in addition to the user in question. Another very important piece of context is the emotional state of the listener. In practical systems, the emotions or moods of the listener cannot be directly measured with sensors, but they can for example be asked from the user.

In this study, we researched a high-level mapping between genres, as descriptions of music, and emoticons, as descriptions of emotions and moods. An online questionnaire with 87 participants was arranged, and the participants had to map seven emoticons to given genres and emotion/mood words.

2. EMOTIONS, MOODS AND MUSIC

Facial expressions are an important form of nonverbal communication. They can provide information about a person's affective state (emotions and moods), cognitive activity (concentration, boredom, etc.), temperament and personality, truthfulness, etc. [2] Emotions differ from moods in three ways: 1) They last for a shorter time, 2) have an identifiable stimulus event (whereas moods do not), and 3) are accompanied by distinct facial expressions (whereas moods are not) [3]. In this paper, both terms have been used.

In [3], Sloboda describes the most prominent approaches (prototype, categorical, and dimensional) to conceptualizing emotion. The prototype approach is based on categorizing emotions based on resemblance to prototypical emotions. An important part of the categorical approach, on the other hand, is the concept of basic emotions, meaning that *"there is a limited number of innate and universal emotion categories from which all other emotional states can be derived."* The number of basic emotions varies slightly depending on the used reference. In [4], Ekman has proposed six universally recognized emotions (anger, disgust, fear, joy or happiness, sadness, and surprise).

The dimensional approach focuses on *"indentifying emotions based on their placements on a small number of dimensions, such as valence, activity, and potency."* [3] The most widely used dimensional emotional scale is Russell's circumplex model [5] (Figure 1), which maps *y*-axis to activation level and *x*-axis to valence. Emotions are located in such manner that the opposite emotions (e.g. sad and happy) face each other. The model also includes certain terms (e.g. sleepy) that most researchers do not consider as emotions.

The relationship between music and emotion has been studied e.g. in [6]. There is strong evidence that music can affect people's mood, facial expressions, and physiological reactions. Music is often used to, e.g., motivate certain tasks such as exercise, for relaxation, mood enhancement, and moderating arousal levels. According to [7], *"…preferred levels of arousal depend on whether people are in an arousal-reducing (telic) or arousal-seeking (paratelic) mode. … People in a state of unpleasantly high arousal (for example, while driving in heavy traffic) generally prefer quiet, relaxing music, while people who are in a state of pleasantly high arousal (for example, exercising, working out) will prefer loud, energizing music."*

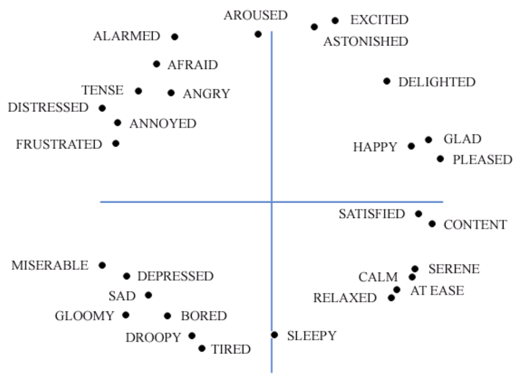


Figure 1. Russell's circumplex model of emotions [5].

The experts at All Music Guide [8] have mapped a large number of songs and albums to "mood" terms such as happy, sad, complex, lazy, smooth, and aggressive. In services such as Last.fm [11], the moods can be tagged by the users themselves. There are also numerous studies focusing on how individual musical parameters such as tempo, timbre, harmony, articulation, and mode (major/minor) contribute to expressing emotions. For example, Berg [9] has studied mapping musical parameters to happiness and sadness, and Juslin [10] has mapped them to a 2D valence-activity space. For a summary on musical parameters and emotion, see e.g. [10] or [12].

3. ONLINE QUESTIONNAIRE

To study what type of emoticons people associate with different musical genres, we arranged an online questionnaire with 87 participants. The participants had to map seven emoticons to given musical genres and emotion/mood words.

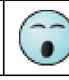
3.1 Selecting Emotion/Mood Words and Designing Emoticons

The selection of facial expressions and emotions/moods was based on Ekman's work [4] and Russell's circumplex model [5]. We first created the following list of 24 emotions and moods: *afraid, aggressive, angry, annoyed, bored, delighted, depressed, disgusted, excited, feeling energetic, feeling great, feeling ok, frustrated, happy, irritated, neutral, pleased, relaxed, sad, satisfied, sleepy, surprised, tense,* and *tired*. Words from every quarter of Russell's model were included.

After this, we designed seven emoticons illustrating certain emotions and moods (Table 1). We first selected three universally recognized facial expressions: happiness, sadness, and anger. For happiness, we designed one emoticon resembling the traditional smiley (#3 in Table 1) and another one (#6) showing greater joy. Both emoticons were colored with yellow, which is often associated with things like cheer and optimism in the western color symbolism [14]. The sad looking emoticon (#1) was colored with blue, which is sometimes associated with depression, melancholy, etc. [14] For anger, we designed a red, angry face (#2) and a milder expression (#5) that looked more like irritation or frustration. Finally, we drew emoticons for representing neutral (#4) and sleepy (#7) moods. The neutral emoticon was colored with green to symbolize that the user is currently online and open to new music. The sleepy emoticon was colored with blue, which is often associated with tranquility, passivity, and the like [14].

Due to the small size of emoticons (32x32 pixels), we had to concentrate on the most characteristic and distinctive features of each facial expression. For this, Ekman [4] was of great help. Inspired by [13], we used exaggerated expressions that are easier to recognize than the realistic ones.

Table 1. Emoticons used in the questionnaire

#1	#2	#3	#4	#5	#6	#7
						

3.2 Selecting Musical Genres

To find a small but representative set of musical genres, we listed the categories used in 14 online music services (e.g. stores, recommendation services, guides, and web radios) and earlier research such as [15]. After analyzing the list, we selected the following 17 genres for our questionnaire: *1. alternative & indie, 2. blues, 3. classical, 4. country, 5. electronica & dance, 6. folk, 7. gospel, 8. hip-hop & rap, 9. jazz, 10. Latin, 11. metal, 12. new age, 13. pop, 14. reggae, 15. rock, 16. soul, rnb & funk,* and *17. world music*. Criteria used for making the selections included, e.g., the target user group of our software, current market trends, genre definitions [8] [15], and MP3 ID3v2 genre list [16]. The selected set of genres was biased towards the American and European consumers.

3.3 Participants

The call for participation was sent to circa 200 employees of a large international company. Participation was voluntary, and the participants did not receive any compensation for participating in the study. 87 persons answered the questionnaire, and 68% of them were male and 32% female. 76% were Finnish, 7% British, and the rest from various other countries. 93% of participants were 25-45 years old and the majority had an engineering background. On the average, participants listened to five of the listed genres. Table 2 shows the percentage of participants listening to each genre.

Table 2. Musical genres listened to by the participants

Genre	%	Genre	%
Alternative & Indie	48	Latin	20
Blues	32	Metal	49
Classical	34	New Age	23
Country	15	Pop	67
Electronica & Dance	54	Reggae	31
Folk	17	Rock	82
Gospel	2	Soul, RnB & Funk	48
Hip-Hop & Rap	29	World Music	16
Jazz	37		

4. RESULTS

4.1 Recognizing Emoticons

In the case of each emoticon, the participants were first asked the question *"In your opinion, what emotion or mood does this facial expression represent?"* This was done to make sure that our emoticons were well designed and recognized correctly. The emotion/mood had to be selected from the list of 24 predefined words. In addition, the participants were able to select from options *"I can't answer because I don't recognize the facial expression"* and *"No opinion."*

All emoticons except #4 were recognized well and mapped to those emotion/mood words that we expected. The first emoticon was mostly associated with "sad" (76% of participants) and "depressed" (21%). As these terms are close to each other in Russell's model, we conclude that the emoticon was recognized correctly. The second emoticon was associated with "angry" (66%) and "aggressive" (20%), as well as closely related but milder terms "irritated", "tense", and "annoyed." Emoticon #3 was associated with positive terms such as "happy" (71%), "delighted" (9%), "feeling great" (8%), and the like.

The fourth emoticon was only a partial success. While 43% of participants voted for "neutral", there was a lot of confusion among the participants. One person thought that the eyes were too wide to be neutral, and another one commented that green color is often used in comics when the character is feeling sick. Thus, emoticon #4 should be modified slightly (and tested again to verify the results) or replaced with, e.g., a green circle.

In the case of emoticon #5, most votes were given to closely related terms "annoyed" (29%), "frustrated" (22%), and "irritated" (20%). In addition, "tense" got 9%, "disgusted" 6%, "angry" 8%, and "aggressive" 2%. The sixth emoticon was mostly associated with terms "feeling great" (40%), "delighted" (30%), "happy" (18%). "Excited" and "feeling energetic" also got a couple of votes each, while the rest got none. In the case of emoticon #7, 47% of participants associated the yawning person with the term "sleepy", 24% with "bored", and 22% with "tired." From our point of view, boredom differs slightly from the other two emotions. Also, according to Russell's model it is slightly more active and negative than the others. Therefore, we conclude that 69% of participants recognized the emoticon accurately enough for our purposes.

4.2 Mapping Emoticons to Genres

After selecting an emotion/mood word describing the shown emoticon, the participants were asked to *select what type of music they listen to when feeling that way*. The genre(s) had to be selected from our predefined list. Options *"I can't answer because I don't recognize the facial expression"*, *"No opinion"*, *"My mood does not affect what type of music I listen to"*, and *"I never listen to music when I am in that mood"* were also available.

In the following charts, the "% of participants" bars show the percentage of participants voting for a given genre. However, as we were mostly interested in the opinions of actual fans of each genre, another set of bars titled "% of fans" was added. Only values ≥15% or ≥20% are shown, and gospel was excluded entirely due to the small number of fans of that genre.

When in the mood shown by the first emoticon, 29% of participants liked to listen to blues music (Figure 2). While 32% of participants were blues fans (Table 2), 54% of these fans preferred to listen to blues when feeling sad. From our music player's point view, it would thus be a good starting point to recommend blues music to blues fans that have selected emoticon #1 to represent their current mood. Many participants who selected some other genre than blues explained that that type of music makes them feel better. While 9% never listened to any music when feeling sad, 13% answered that their mood does not affect what type of music they listen to.

Let us imagine that there is a user that likes all musical genres and is currently feeling sad. If the genres were arranged in a decreasing "% of fans" order, the music recommender system could pick most songs from the blues genre, a couple of alternative & indie and classical songs, and so on. In the case of a user that likes only a subset of the listed genres, the songs would be selected from the subset in a similar way.

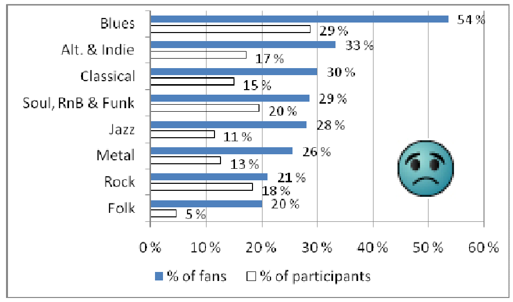


Figure 2. Mapping emoticon #1 to genres.

In the case of emoticon #2, the winners were metal (51% of participants and 84% of fans) and rock (36% and 39%, respectively). While both genres can be considered to be energetic and sometimes even aggressive, such songs are also found from the next popular genres (electronica & dance and alternative & indie). Most of participants who gave extra comments to us mentioned that they listen to metal to maintain and maximize the angry feeling, i.e., the participants were in the arousal-seeking mode [7]. One participant saw metal as *"a good way to channel out frustration, aggressive thoughts and maybe even depressions."* Surprisingly few participants used "happier" and "lighter" music such as soul or Latin to calm them down. For example, only 1% listened to soul when feeling angry although the genre was very popular within the participants. 13% never listened to music when feeling angry, and 6% felt that mood did not affect their choice of music.

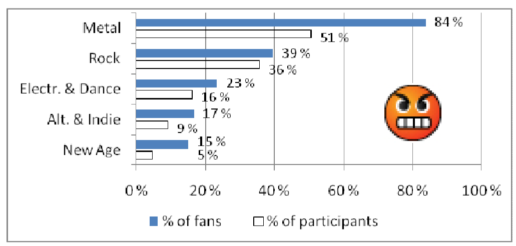


Figure 3. Mapping emoticon #2 to genres.

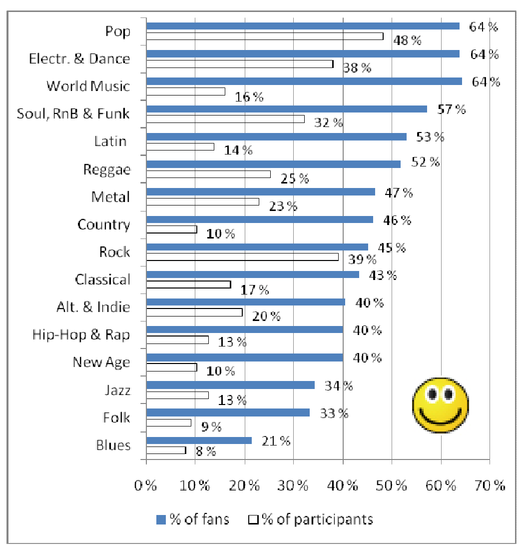


Figure 4. Mapping emoticon #3 to genres.

When feeling happy, participants listened to a lot of all types of music (Figure 4). For every genre except blues, folk, and jazz, the % of fans value was higher than 40%. Reasons for making the selections included, e.g., *"favorite genre"*, *"supports the happy feeling"*, and *"makes me even happier."* Only one participant never listened to any music when feeling happy, and 12% felt that mood did not affect their choice of music. Some participants mentioned that in this mood they are more willing to experiment and try new music. In general, "happier" genres such as pop and Latin were favored over "aggressive" genres such as metal or rock.

As the majority of participants did not recognize emoticon #4, it is not justifiable to make any conclusions about participants' listening habits in that case. Thus, as a starting point for emoticon #4, our music player should recommend songs from every genre that the user likes to listen to.

Emoticon #5 showed a milder negative feeling than anger and this was also reflected in the results. The four winning genres were the same as in the case of emoticon #2, but the percentage values were somewhat lower. Thus, when implementing an emoticon-based music player, one could consider using only either emoticon #2 or #5. Likewise, the "% of fans" values of emoticon #6 were almost identical to those of emoticon #3. The only exceptions were world music (drop from 64% to 43%), reggae (drop from 52 to 33), and classical (drop from 43 to 30).

In the case of emoticon #7, there was quite a lot scattering among the results and all "% of fans" values were <50% (Figure 5). In general, the participants seemed to prefer relaxing and not too aggressive music. Genres with strong beats (e.g. reggae, hip-hop & rap, and Latin) were often avoided and this was also expressed in participants' comments. While 13% answered that they never listen to music when feeling sleepy, 12% did not have any opinion on the matter. 13% answered that mood does not affect what type of music they listen to. Some participants commented that their selection of music in this mood depends on whether they want to cheer up or fall asleep.

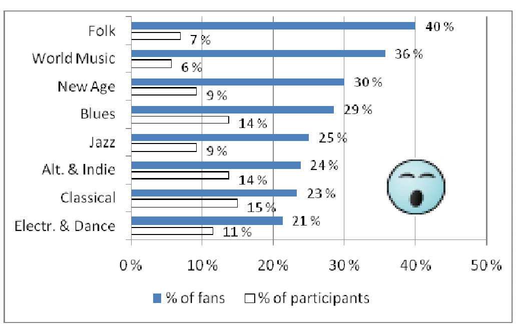


Figure 5. Mapping emoticon #7 to genres.

5. CONCLUSION AND FUTURE WORK

In this study, we researched a high-level mapping between genres, as descriptions of music, and emoticons, as descriptions of emotions and moods. An online questionnaire with 87 participants was arranged, and the participants had to map seven emoticons to given genres and emotion/mood words.

Based on the results, we presented a list of genres that could be used as a starting point for making recommendations fitting user's current mood. The results will be used in our forthcoming context- and mood-aware music recommender system, where the users will be able to set their mood by clicking on one of the emoticons. The system will then make recommendations based on the presented genre lists, user's listening history, etc. A user trial has also been planned, and its findings should be compared to the results of this paper.

In addition to genres, other musical parameters such as tempo could be taken into account when making the recommendations. For example, several authors have already shown that fast tempi are generally associated with happiness and slow tempi with sadness.

6. REFERENCES

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