INTRODUCING A DATASET OF EMOTIONAL AND COLOR RESPONSES TO MUSIC

Matevž Pesek[1], Primož Godec[1], Mojca Poredoš[1], Gregor Strle[2], Jože Guna[3], Emilija Stojmenova[3], Matevž Pogačnik[3], Matija Marolt[1]

[1]University of Ljubljana, Faculty of Computer and Information Science
[matevz.pesek,primoz.godec,mojca.poredos,matija.marolt]@fri.uni-lj.si

[2]Scientific Research Centre of the Slovenian Academy of Sciences and Arts, Institute of Ethnomusicology
gregor.strle@zrc-sazu.si

[3]University of Ljubljana, Faculty of Electrotechnics
[joze.guna,emilija.stojmenova,matevz.pogacnik]@fe.uni-lj.si

ABSTRACT

The paper presents a new dataset of mood-dependent and color responses to music. The methodology of gath-ering user responses is described along with two new inter-faces for capturing emotional states: the MoodGraph and MoodStripe. An evaluation study showed both inter-faces have significant advantage over more traditional methods in terms of intuitiveness, usability and time complexity. The preliminary analysis of current data (over 6.000 responses) gives an interesting insight into participants' emotional states and color associations, as well as relationships between musically perceived and induced emotions. We believe the size of the dataset, in-terfaces and multi-modal approach (connecting emo-tional, visual and auditory aspects of human perception) give a valuable contribution to current research.

1. INTRODUCTION

There is no denial that strong relationship exists between music and emotions. On one hand, music can express and induce a variety of emotional responses in listeners and can change our mood (e.g. make us happy – we consider mood to be a longer lasting state). On the other hand, our current mood strongly influences our choice of music - we listen to different music when we're sad than when we're happy.

It is therefore not surprising that this relationship has been studied within a variety of fields, such as philosophy, psychology, musicology, anthropology or sociology [1]. Within Music Information Retrieval, the focus has been on mood estimation from audio (a MIREX task since 2007), lyrics or tags and its use for music recommendation and playlist generation, e.g. [2-5].

To estimate and analyze the relationship between mood and music, several datasets were made available in the past years. The soundtracks dataset for music and emotion contains single mean ratings of perceived emotions (labels and values in a three-dimensional model are given) for over 400 film music excerpts [6]. The MoodSwings Turk Dataset contains on average 17 valence-arousal ratings for 240 clips of popular music [7]. The Cal500 contains a set of mood labels for 500 popular songs [8], at around three annotations per song, and the MTV Music Data Set [9] a set of 5 bipolar valence-arousal ratings for 192 popular songs.

In this paper, we introduce a new dataset that captures users' mood states, their perceived and induced emotions to music and their association of colors with music. Our goals when gathering the dataset were to capture data about the user (emotional state, genre preferences, their perception of emotions) together with ratings of perceived and induced emotions on a set of unknown music excerpts representing a variety of genres. We aimed for a large number of annotations per song, to capture the variability, inherent in user ratings.

In addition, we wished to capture the relation between color and emotions, as well as color and music, as we believe that color is an important factor in music visualizations. A notable effort has been put into visualizing the music data on multiple levels: audio signal, symbolic representations and meta-data [10]. Color tone mappings can be applied onto the frequency, pitch or other spectral components [11], in order to describe the audio features of the music [12], or may represent music segments. The color set used for most visualizations is picked instinctively by the creator. To be able to provide a more informed color set based on emotional qualities of music, our goal thus was to find out whether certain uniformity exist in the perception of relations between colors, emotions and music.

The paper is structured as follows: section 2 describes the survey and it design, section 3 provides preliminary analyses of the gathered data and survey evaluation and section 4 concludes the paper and describes our future work.

2. ONLINE SURVEY

We gathered the dataset with an online survey, with the intention to reach a wide audience and gather a large number of responses. We started our survey design with a preliminary questionnaire, which provided some basic guidelines for the overall design. We formed several research questions to drive the design and finally implemented the survey which captures the user's current emotional state, their perception of colors and corresponding emotions, as well as emotions perceived and induced from music, along with the corresponding color. After the first round of response gathering was completed, we performed a new survey designed to evaluate different aspects of user experience with our original survey.

2.1 Preliminary study

Although there exists some consent that a common set of basic emotions can be defined [13], in general there is no standard set of emotion labels that would be used in music and mood researches. Some authors choose labeled sets intuitively, with no further explanation [14]. In contrast, we performed an initial study in order to establish the relevant set of labels. For the purpose of eliminating the cultural and lingual bias on the labelling, we performed our survey in Slovenian language for Slovene-speaking participants.

The preliminary questionnaire asked the user to describe their current emotional state through a set of 48 emotion labels selected from literature [15-17] , each with an intensity-scale from 1 (inactive) to 7 (active). The questionnaire was solved by 63 participants. Principal component analysis of the data revealed that first three components explain 64% of the variance in the dataset. These three components strongly correlate to 17 emotion labels chosen as emotional descriptors for our survey.

We also evaluated the effectiveness of the continuous color wheel to capture relationships between colors and emotions. Responses indicated the continuous color scale to be too complex and misleading for some users. Thus, a modified discrete-scale version with 49 colors displayed on larger tiles was chosen for the survey instead. The 49 colors have been chosen to provide a good balance between the complexity of the full continuous color wheel and the limitations of choosing a smaller subset of colors.

2.2 The survey

The survey is structured into three parts, and contains questions that were formulated according to our hypotheses and research goals:

- user's mood impacts their emotional and color perception of music;
- relations between colors and emotions are uniform in groups of users with similar mood and personal characteristics;
- correlation between sets of perceived and induced emotions depends both on the personal musical preferences, as well as on the user's current mood;
- identify a subset of emotionally ambiguous music excerpts and study their characteristics;
- mappings between colors and music depend on the music genre;
- perceived emotions in a music excerpt are expected to be similar across listeners, while induced emotions are expected to be correlated across groups of songs and users with similar characteristics.

We outline all parts of the survey in the following subsections, a more detailed overview can be found in [18].

2.2.1 Part one – personal characteristics

The first part of the survey contains nine questions that capture personal characteristics of users. Basic demographics were captured: age, gender, area of living, native language. We also included questions regarding their music education, music listening and genre preferences. We decided not to introduce a larger set of personal questions, as the focus of our research lies in investigating the interplay of colors, music and emotions and we did not want to irritate the users with a lengthy first part. Our goal was to keep the amount of time spent for filling in the survey to under 10 minutes.

2.2.2 Part two - mood, emotions and colors

The second part of our survey was designed to capture information about the user's current mood, their perception of relation between colors and emotions and their perception of emotions in terms of pleasantness and activeness.

The user's emotional state was captured in several ways. First, users had to place a point in the valence-arousal space. This is a standard mood estimation approach, also frequently used for estimation of perceived emotions in music. Users also indicated the preferred color of their current emotional state, as well as marked the presence of a set of emotion labels by using the *MoodStripe* interface (see Figure 1).

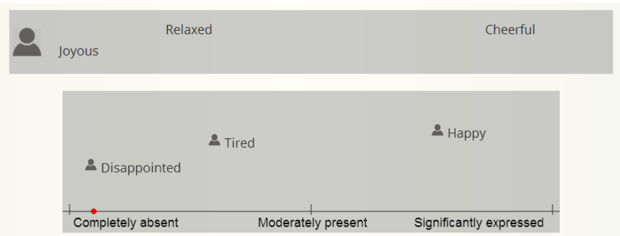

Figure 1: The *MoodStripe* allows users to express their emotional state by dragging emotions onto a canvas, thereby denoting their activity

To match colors with emotions, users had to pick a color in the color wheel that best matches a given emotion label (10 labels were presented to each user). Finally, users had to assess how they perceive the pleasantness and activeness of emotions by placing a set of emotion labels into the valence-arousal space using the *MoodGraph* (see Figure 2). This enables us to evaluate the variability of placement of emotion labels in terms of their activeness and pleasantness and compare it to data gathered in part three, where users described musical excerpts in a similar manner.

2.2.3 Part three - music in relation to colors and emotions

In the third part of our survey users were asked to complete two tasks on a set of ten 15-second long music excerpts. These were randomly selected from a database of 200 music excerpts. When compiling the database, we strived for a diverse, yet unknown set of music pieces, to avoid judgments based on familiarity with the content. The database contains 80 songs from the royalty free online music service *Jamendo*, representing a diverse variety of “standard” genres, with songs unknown to the wider audience. 80 songs were included from a dataset of film music excerpts [6], 20 from a database of folk music and 20 from a contemporary electro-acoustic music collection.

After listening to an excerpt, users were first asked to choose the color best representing the music from the color wheel. Next, users were asked to describe the music by dragging emotion labels onto the valence-arousal space using the *MoodGraph* interface (Figure 2). Two different sets of labels were used for describing induced and perceived emotions, as different emotions correspond with respective category[19], and at least one label from each category had to be placed onto the space. shown and

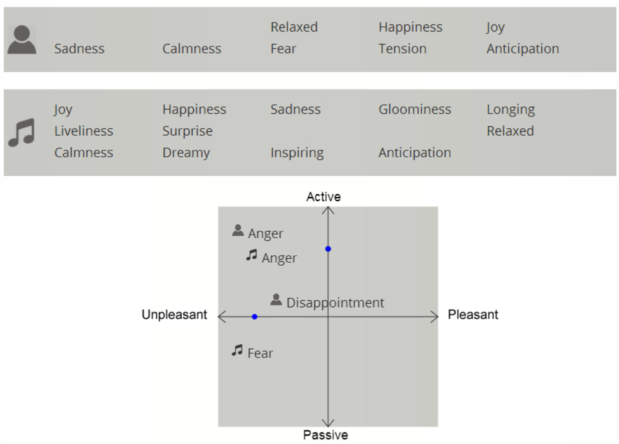

Figure 2: The *MoodGraph:* users drag emotion labels onto the valence-arousal space. Induced emotions are marked with a person icon, perceived emotions with a note icon.

2.3 Evaluation survey

After responses were gathered, we performed an additional evaluation survey, where we asked participants to evaluate the original survey. Although the survey was anonymous, users had the opportunity to leave their email at the end, which we used to invite them to fill in the evaluation questionnaire. Participants were presented a set of twelve questions about different aspects of the survey: user experience, complexity of the questionnaire, and aspects of our new *MoodGraph* and *MoodStripe* interfaces. Some of the questions were drawn from the existing evaluation standard NASA load task index [20], while others were intended to evaluate different aspects of our interfaces.

3. RESULTS

The survey was taken by 952 users, providing 6609 mood/color-perception responses for the 200 music excerpts used. We thus obtained a large number of responses per music excerpt (each has 33 responses on average), including sets of induced and perceived emotion labels, their placement in the valence-arousal space, as well as the color describing the excerpt. To our knowledge, no currently available mood-music dataset has such a high ratio of user annotations per music excerpt. The data, as well as music excerpts will be made public as soon as the second round of response gathering, currently underway, will be finished.

In the following subsections, we provide some preliminary analyses of our data.

3.1 Demographic analysis

The basic demographic characteristics of the 952 participants are as follows. The average age of participants was 26.5 years, the youngest had 15, the oldest 64 years. 65% of participants are women, 66% are from urban areas. 50% have no music education, 47% do not play instruments or sing. The amount of music listening per day is evenly spread from less than 1 hour to over 4 hours. 3% claimed they were under the influence of drugs when taking the survey.

3.2 Colors and emotions

In the second part of the survey, participants indicated their emotional state within the valence-arousal space, as well as by choosing a color. Relations between the color hue and location in the valence-arousal space are not very consistent, but overall less active emotional states correspond more with darker blue-violet hues, while the more active ones to red-yellow-green hues. There is also a statistically significant positive correlation between color saturation and value (in a HSV color model) and activeness, as well as pleasantness of emotions: the more positive and active the user’s emotional state is, the more vivid the colors are.

Colors attributed to individual emotion labels, as well as the placement of labels in the valence-arousal space are visible in Figure 3. Associations between colors and emotions are quite consistent and in line with previous research [21-24]. Fear (A) and anger (F) are basic negative emotions and have dark blue/violet or black hues. Sadness (I) and relaxation (J), interestingly are also very similar, although different in valence. Energetic (C) as a very active mood is mostly red, joy (B) and liveliness (G) somewhat less (more yellowy, even green). Another interesting outcome is that similar red-yellow-green hues are also prevalent for disappointment (E) and discontent (H). Happiness (D) is very distinct, in pastels of green and blue (similar to [21-24]). As these hues are often related to inner balance (peace), their choice for happiness, by some definitions a state where ones needs are satisfied, reflects the participants' notion that happiness and inner balance are related[21, 24].

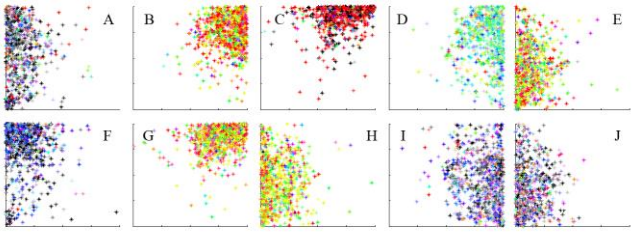

Figure 3: position of emotions in the valence-arousal space, and their colors. *A: fear, B: joy, C: energy, D: happiness, E: disappointment, F: anger, G: liveliness, H: discontent, I: relaxation, J: sadness*

3.3 Relationships between induced and perceived emotions

In part three of the survey participants were asked to mark induced and perceived emotions for individual music excerpt by dragging emotion labels from the respective categories onto the valence-arousal space (see Figure 2). Here, we focus on the relationship between induced and perceived emotions.

Figure 4 shows the centroids (averages) for induced-perceived emotion pairs of participants' ratings for each music excerpt: 'anger', 'relaxed', 'happiness', 'joy', 'sadness', 'calmness', 'anticipation' and 'fear'. Positions of induced-perceived emotion pairs (Figure 4) loosely correspond to the positions of participant's emotional states in the valence-arousal space from Figure 3, with some obvious differences. For example (with respect to B, D and I on Figure 3), positive induced-perceived emotion pairs, such as relaxed, happiness and joy (B, C and D in Figure 4) occupy a more central space in the 'pleasant/active' quadrant of valence-arousal space. Similarly, negative emotion pairs (A, E and H in Figure 4) are also more central on the 'unpleasant' quadrants than corresponding emotions on Figure 3, but have significantly larger variance and spread on valence-arousal space compared to positive emotions (apart from relaxed (B)), especially along arousal dimension.

Let us compare the relationships in Figure 4. There is a noticeable variance between induced and perceived emotions for negative emotions, such as fear (H), anger (A) and sadness (E), as they spread over both arousal and valence axes. The central position of sadness (E) along the arousal dimension is especially interesting, as it is typically associated with low arousal (compare to J in Figure 3). Furthermore, all three negative emotions (A, E and H) are in certain musical contexts experienced or perceived as pleasant. On the other hand, positive induced-perceived emotion pairs, such as joy (D) and happiness (C), tend to be more similar on both valence (positive) and arousal (relatively high) dimension and consequently have less variance. More neutral emotions, such as calmness (F) and anticipation (G), occupy the center, with relaxed (B) untypically potent on the arousal dimension.

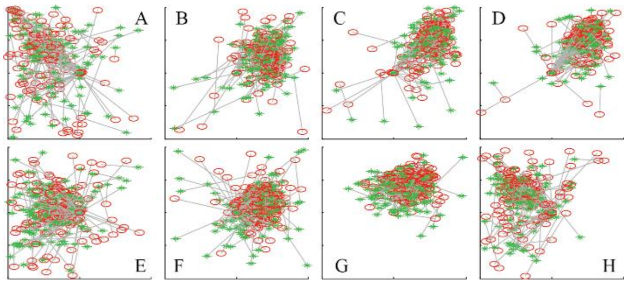

Figure 4: Representation of relationships between induced-perceived emotion pairs of all music excerpts (induced centroid: green star, perceived centroid: red circle). *A: anger, B. relaxation, C. happiness, D: joy, E: sadness, F: calmness, G: anticipation, H: fear*

Discriminating between induced and perceived emotions in music is a complex task and to date there is no universally agreed upon theory, or emotional model, that would best capture emotional experiences of listeners (see e.g. [19, 25-29]). Many argue (e.g. [6, 19, 28, 30, 31]) that simple valence-arousal dimensional model (one that *MoodGraph* is based on) might be too reductionist, as it ignores the variance of emotions and results in inherently different emotions occupying similar regions of valence-arousal space (e.g., compare regions of fear (H), anger (A) and sadness (E) in Figure 4). Our preliminary results nevertheless show some interesting aspects of induction and perception of musical emotions. For example, the representations of relationships among and within induced-perceived emotion pairs shown in Figure 4 support Gabrielsson's theory of four basic types of relationship between induced and perceived emotions in relation to music: positive/in agreement, negative/opposite, non-systematic/neutral and absent/no relationship [25]. Positive relationship is the most common (e.g., when music perceived to express sad emotions also evokes such emotions in the listener), resulting in the overlap (in some cases above 60%; see e.g. [19, 26, 29]) of induced-perceived emotion pairs. In one study [32], researchers found extremely strong positive correlation for induced and perceived emotions on both valence and arousal dimensions, and concluded that results show "listeners will typically feel the emotions expressed by the song" [p. 93]. However, our preliminary results do not support this claim. There is a significant variance among induced-perceived emotion pairs, particularly among negative emotions. Furthermore, while effects of positive correlation between induced and perceived emotions are evident (especially in positive emotions), other types of relationships are equally significant: from negative/opposite, non-matching, to complex and neutral. The preliminary results clearly show differential variance across induced and perceived emotions (in line with recent findings [33]).

When analyzing the induced-perceived emotion pairs in *MoodGraph*, we've found that: a) they do not necessarily positively correlate, b) they occupy different regions and c) even when they fall into the same region of valence-arousal space, both rotation and standard deviation within each induced-perceived emotion pair are significantly larger than reported in some of the previous studies (e.g., [32]). This shows that participants understood both concepts (i.e. induced vs. perceived emotion) and were able to differentiate emotions from both categories on the valence-arousal space.

One reason for large amount of variance in representations of induced/perceived pairs is probably due to the model itself, as participants can rate both induced and perceived emotions together and directly onto *MoodGraph* after listening to the music excerpt. Another advantage, we argue, is the construction of the *MoodGraph* itself. While bearing similarity with traditional approach to dimensional modeling (a classic example being Russell's circumplex model of affect [15]), the *MoodGraph* has no pre-defined and categorically segmented/discrete regions of valence-arousal space, hence avoiding initial bias, while still offering an intuitive interface – the participant is free to drag emotion labels onto MoodGraph according to her preferences and interpretation of the valence-arousal space.

3.4 Evaluation survey

The online evaluation questionnaire was filled-in by 125 users, who all took part in our survey. Results were positive and indicate that the survey was properly balanced and the new interfaces were appropriate. Detailed results can be found in [34]. To summarize, responses show appropriate mental difficulty of the questionnaire, while the physical difficulty seems to be more uniformly distributed across participants. Thus, it can be speculated that the listening part of the questionnaire represents a physical challenge to a significant number of participants. The presented *MoodGraph* interface was quite intuitive; however, it was also time demanding. Considering the task load of the interface (combining three distinctive tasks), this was expected. The number of emotions in *MoodGraph* categories was slightly unbalanced and should be extended in our future work. The *MoodStripe* interface represents a significant improvement over a group of radio buttons, both in intuitiveness and time complexity. Participants also indicated that the set of 49 colors available for labeling emotions may not be large enough, so we will consider enlarging the set of color tones in our future work.

4. CONCLUSIONS

We intend to make the gathered dataset available to the public, including the musical excerpts, data on users' personal characteristics and emotional state, their placement of emotions within the valence/arousal space, their perceived and induced emotional responses to music and their perception of color in relation to emotions and music. This will open new possibilities for evaluating and re-evaluating mood estimation and music recommendation approaches on a well annotated dataset, where the ground truth lies in the statistically significant amount of responses per song, rather than relying on annotations of a small number of users.

Shortly, we will start with the second round of response gathering with an English version of the survey. We also intend to enlarge the number of music excerpts in the music dataset and provide it to the users who have already participated in this study. Thus, we hope to further extend and diversify the dataset.

Preliminary analyses already show new and interesting contributions, and next to answering the questions already posed in section 2.2, the dataset will provide grounds for our future work (and work of others), including:

- previously introduced mood estimation algorithms will be evaluated by weighting the correctness of their predictions of perceived emotion responses for music excerpts. New mood estimation algorithms will be developed, building upon the newly obtained data;
- we will explore modelling of relations between music and colors chosen by users in the survey. Results may be useful for music visualization, provided that correlations between audio and visual perception will be consistent enough;
- music recommendation interfaces will be explored, presenting recommendations in a visual manner with the intent to raise user satisfaction by reducing the textual burden placed on the user. The interface will include personal characteristics and their variability in the decision model;
- the dataset can also be used in other domains, as responses that relate colors to emotions based on the user's emotional state can be used independently.

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