Introducing a dataset of emotional and color responses to music

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ABSTRACT

The paper presents a new dataset of emotional and color responses to music. The methodology of gathering user responses is described along with two new interfaces for capturing emotional states: the MoodGraph and MoodStripe. An evaluation study showed both interfaces 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, interfaces and multi-modal approach (connecting emotional, 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 of mood-dependent perceptual responses to music, based on a set of unknown music excerpts representing a variety of genres. Our goal was to explore emotional and visual aspects of music perception, particularly user's emotional state, her general perception of emotions, relations between perceived and induced emotions for individual music excerpt, and the influence of music preferences and music education. We aimed for a large number of annotations per music excerpt, 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. In most cases, the color set used for visualization is picked instinctively by the creator. To be able to provide a more informed color set based on emotional qualities of music, we first need to assess whether certain uniformity exist in users' perceptions of colors, emotions and music.

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

2. ONLINE SURVEY

An online survey has been used to gather the dataset, with the intention to reach a wide audience and gather a large number of responses. First, we conducted a preliminary study to provide basic guidelines for the overall design and to evaluate different aspects of user experience.

2.1 Preliminary study

While there is a general consent among psychologists on the common set of basic emotions [13], there is no such standard set of basic emotions in music research [25]. Some authors choose labeled sets intuitively, with no further explanation [14]. In order to establish the relevant set of emotion labels, we performed an initial study on users' emotion ratings. For the purpose of eliminating the cultural and lingual bias, the survey was conducted in Slovenian language for Slovene-speaking participants only.

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 of 49 colors, displayed on large tiles, was chosen for the survey instead. The 49 colors 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 in three parts, representing the questions formulated according to our research hypotheses:

- 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;
- correlations between sets of perceived and induced emotions depend both on the personal musical preferences, as well as on the user's current mood;
- 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 and musical preferences;
- mappings between colors and music are to a certain extent genre dependent.

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 captures basic demographics (age, gender, area of living, native language) and user's music characteristics and habits, including music education and proficiency (playing an instrument or singing), the amount of time listening to music and genre preferences. Additional, more detailed questions were omitted, to reduce the load and allow user to focus on emotional, visual and musical aspects in the second and third part of the survey. Our goal was to keep the amount of time spent completing the survey under 15 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 and currently experienced emotions (self-estimation), associations between colors and emotions, and the general perception of individual emotions in terms of pleasantness and activeness.

User's emotional state was captured in several ways. To self-estimate her current mood, user 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. Next, user indicated the preferred color in regard to her current mood, as well as marked the level of activity for individual emotion by positioning a set of emotion labels in the *MoodStripe* interface (see Figure 1).

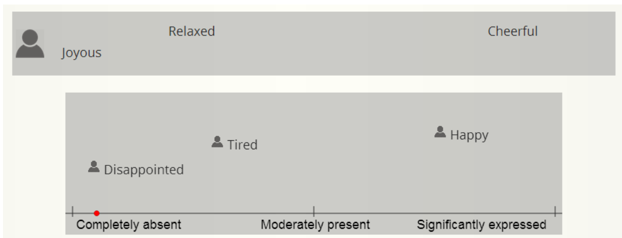

Figure 1: The *MoodStripe* allows users to express their emotional state by dragging emotions onto a canvas, thereby denoting their activity/presence

Moreover, a set of 10 emotion labels is further associated with individual colors by selecting the most appropriate color for individual emotion in the discrete color wheel. Finally, users assess the pleasantness and activity of individual emotions by positioning respective emotion labels onto the valence-arousal space using the *MoodGraph* interface (see Figure 2). This enables us to evaluate the variability of emotions in terms of their activeness and pleasantness and compare the results with valence-arousal dimensions of emotions in music.

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 the music excerpt, user is first asked to select a color from the color wheel that best represents individual excerpt. Next, user rates the excerpts by dragging individual emotion labels onto the valence-arousal space of the *MoodGraph* interface (Figure 2). Two different categories are used to discriminate between induced and perceived emotions, as these emotions are to some extent category-specific [19, 27], and at least one label from each category has to be placed onto the space.

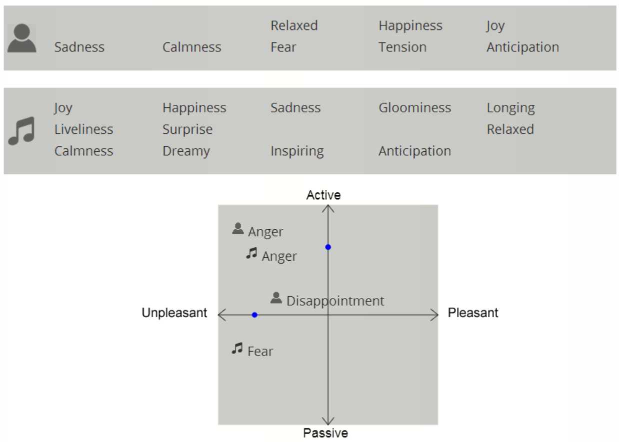

Figure 2: The *MoodGraph:* users drag emotion labels onto the valence-arousal space. Induced emotions are marked with a person icon, perceived emotions with a note icon.

2.3 Evaluation survey

After responses were gathered, we performed additional evaluation of the 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 with a set of twelve questions inquiring about different aspects of the survey: general user experience, complexity of the questionnaire, and user experience of *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.

2.3.1 Evaluation survey results

The online evaluation questionnaire was completed by 125 users, who previously all took part in the survey. Detailed presentation of the results can be found in [34]. Results were generally positive and indicate overall balance of the survey user-friendliness of our interfaces. 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 presents both a physical and mental challenge to a significant number of participants. *MoodGraph* interface was experienced as quite intuitive; however, it was also time demanding. Considering the task load of the interface (combining three distinctive tasks), this was to be expected. According to the evaluation results, the number of emotions given in the survey was slightly unbalanced, and participants also indicated that the set of 49 colors available for labeling emotions may not be large enough. We will consider extending both sets in our future work. The positive user feedback on the *MoodStripe* interface shows a significant improvement over a more traditional Likert scale variation, both in intuitiveness and time complexity.

3. ANALYSIS

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.

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].

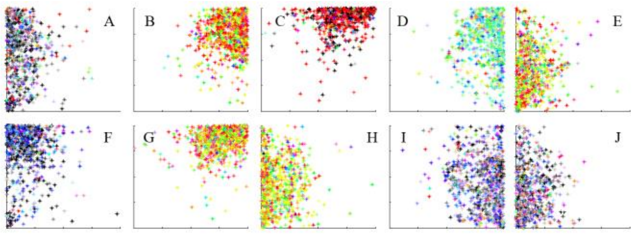

Figure 3: position of emotions in the valence-arousal space, and their colors. *A: fear, B: joy, C: energy, D: happiness, E: disappointment, F: anger, G: liveliness, H: discontent, I: relaxation, J: sadness*

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.

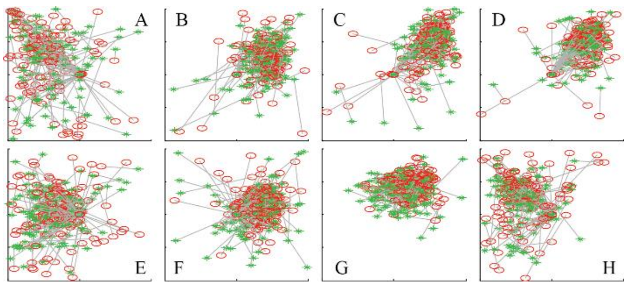

Figure 4: Representation of relationships between induced-perceived emotion pairs of all music excerpts (induced centroid: green star, perceived centroid: red circle). *A: anger, B. relaxation, C. happiness, D: joy, E: sadness, F: calmness, G: anticipation, H: fear*

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.

4. CONCLUSIONS

We intend to make the gathered dataset available to the public, including the musical excerpts, data on users' personal characteristics and emotional states, valence-arousal ratings of emotions, perceived and induced emotional responses to music and 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 gathering responses 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 analysis has already given us some interesting insight into relationships between emotions, colors and music. In our future work, we will focus on answering general research hypotheses presented in section 2.2, and use the dataset to expand on other areas, 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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