MoodMusic: A Method for Cooperative, Generative Music Playlist Creation

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ABSTRACT

Music is a major element of social gatherings. However, creating playlists that suit everyone's tastes and the mood of the group can require a large amount of manual effort. In this paper, we present MoodMusic, a method to dynamically generate contextually appropriate music playlists for groups of people. MoodMusic uses speaker pitch and intensity in the conversation to determine the current 'mood'. MoodMusic then queries the online music libraries of the speakers to choose songs appropriate for that mood. This allows groups to listen to music appropriate for their current mood without managing playlists. This work contributes a novel method for dynamically creating music playlists for groups based on their music preferences and current mood.

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ACM Classification Keywords: H.5.2. User Interfaces: Natural language. H.5.3 Group and Organization Interfaces: Collaborative computing.

General Terms: Design, Human Factors

INTRODUCTION

Music is a major element at social gatherings [6]. Whether people are gathering for a quiet dinner or having a loud raucous party, suitable music is expected. To pick music that is fitting for a social gathering, two factors should be considered: 1) the music preferences of the group's members and 2) music that is appropriate for the specific mood, or the mood that the host hopes to achieve. Previously, music playlists have been created for groups using a variety of collaborative filtering techniques. These techniques include analyzing the structural components of music to discover similarities in the song structure [5], co-occurrences of preferences between users [1], or selecting songs based on similarities in their metadata (i.e., *tags)*. While these methods are useful for selecting music that caters to the tastes of a group in general, they do not adapt to changes in the mood of the group. This means that as the group's mood changes, they must continue to update the playlist to reflect changes in the mood. Previous research has produced music playlists that are appropriate to the current mood of an individual [2,7], however, no research has been conducted to detect the aggregate mood of a group and then provide a music playlist that accommodates the group's music preferences.

To determine the current mood, we utilized Robert Thayer model for describing mood [11]. Other models for describing mood and affect exist [8], but we choose Thayer's because of previous work relating his model to speech [4]. According to Thayer's model, mood has two dimensions: *energy* and *tension* [11]. This means that a person can be *energetic* or *tired* while also being *tense* or *calm* (see Figure 1). MoodMusic selects songs that are associated with moods along these dimensions.

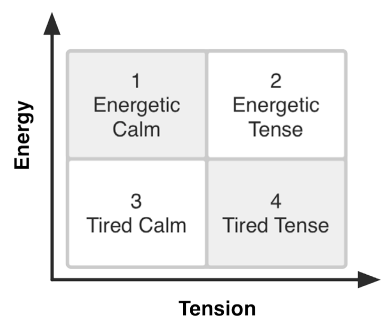

Figure 1: Thayer's mood model. Based on this model, the group's moods can be in one of four quadrants: energetic calm, energetic tense, tired calm and tired tense.

SYSTEM DESIGN

MoodMusic has two distinct components. The first is an interface that performs real-time conversation analysis to determine the current mood and display information about the mood back to the user. The second component is a recommender system that uses the current mood to create playlists that accommodate the mood and the music preferences of the group members. We discuss these two components separately below.

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Real-Time Conversation Analysis

The audio analysis component of MoodMusic uses characteristics of speech to determine mood. We implemented the audio analysis and visual analysis within Processing[1] and utilizing the Krister audio library[2] and a Java FFT library[3]. The interface provides real-time feedback onthe current conversation as well as the corresponding mood within Thayer's mood model (see Figure 2).

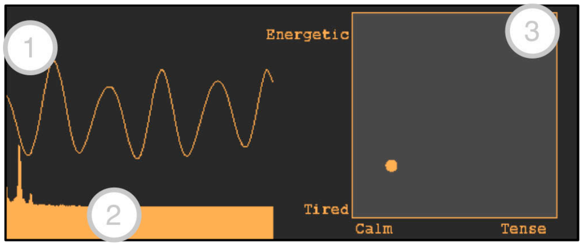

Figure 2: MoodMusic's interface displays three pieces of information: 1) audio as a sound wave, 2) a spectrum, and 3) the current energy and tension detected.

MoodMusic analyzes the audio based on two features: *intensity* and *pitch height*. We choose to use these dimensions because of the previous work associating them to Thayer's mood model for conversational speech [4]. Ilie and Thompson found that intensity and pitch height both contribute to energy, but only intensity contributes to tension. We calculated intensity (volume of the signal) as a rolling average over a 30-second window. We determined pitch height using an Average Magnitude Difference Function algorithm [9]. We then weighted the pitch height and the intensity based on the values that these features were found to influence the participant's perception on the associated dimension in Ilie and Thompsons's work.

Recommender System

MoodMusic's recommender system currently only works for users of the social music website Last.fm[4]. Last.fm logs music its users listen to, thereby creating a library of music preferences for each user. Users can also tag music on Last.fm, which provides a source of metadata about the songs. MoodMusic accesses Last.fm's API to build a list of appropriate music for the group by intersecting the top tags from each individual's music library. MoodMusic determines the mood of a tag by calculating its similarity index with the adjectives from Thayer's *Activation-Deactivation Adjective Check List* [10], synonyms from related work that sought to compare Thayer's model to other mood models, and a corpus of related tags queried from Last.fm's API. Thus, the tags represent a more commonly used list of adjectives [3]. The tags closest to the current mood, are queried using the Last.fm API to get list of songs, associated with the current mood. The resulting playlist represents the intersection of preferred music between the group members for the determined mood.

[1] http://processing.org/
[2] http://www.tree-axis.com/Ess/
[3] http://introcs.cs.princeton.edu/java/97data/
[4] http://www.last.fm/

CONCLUSION AND FUTURE WORK

We presented MoodMusic, a method for creating music playlists for social gatherings based on two components: the group's music preferences and a real-time conversation analysis. Significant work remains in emotion detection—both for groups and individuals—in playlist selection, and in creating metrics for evaluation of group moods. Our next step is to run a user study to evaluate our mood detection and music selection algorithm. Our future goal is to use our system to influence group mood with music. We believe MoodMusic affords a novel, social form of interaction and allows users to explore online music in a new way.

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