Towards Providing Music for Academic and Leisurely Activities of Computer Users

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Abstract. This paper uses brainwaves to recognize the computer activity of the user and provides music recommendation. Twenty-three (23) hours of data collection was performed by asking the computer user to wear a device that collects electroencephalogram (EEG) signals from his brain as he performed whatever tasks he wanted to perform while listening to music. The features of the preferred song given the activity of the user is used to provide songs for the user automatically. Activities were classified as either academic or leisure. The music provision model was able to predict the music features preferred by the user with accuracy of 76%.

Keywords: support provision, brain-computer interface, intention recognition, behavior recognition.

1 Introduction

This presents a music provision system that automatically provides music for a computer user given the computer activity of the person (i.e., academic or leisurely). The music played while the computer user is engaged in an activity helps his well-being however, the user may not have the time to preselect songs that he or she would like to listen to. Thus, automating the music selection for the user based on the activities performed offloads the user the task of having to select his songs that matches his given activity. This research assumes that the song features are indicators of the type of songs the user prefers to listen to while performing an activity.

A more straightforward solution in providing music support for the computer user is by looking at the applications that are being run. However, this is only plausible if there is a complete listing of all the possible applications and websites that can be used by the user and there is a corresponding annotation for each that indicates which type of music is preferred given these applications. Hence, this paper classifies the activity using the brainwaves of the computer user.

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2 Data Gathering Sessions

The researchers interviewed a group of students without revealing that the interview is to find out whether they listen to music as they perform their activities. Among the students interviewed, only one subject was selected based on how the user plays music as he performs his computer activities.

The music database from [2] was used alongside the activity-music tracker program in order to gather data. The researchers elicited data from the subjects for a total of forty-six (46) sessions where each session lasted for thirty (30) minutes. Twenty-three (23) hours of data gathering was performed.

The subject chose to listen to one hundred ninety-two (192) songs. The subject was seated in front of a computer while wearing the Emotiv EPOC Neuroheadset EEG. The sessions were held in an isolated room where the subject is accompanied only by one researcher.

The subject was given the free rein to choose whichever activity he wants to perform. The Music Tracker software logged all the applications used as well as the sites visited and music listened to by the user. Music that was skipped by the user, meaning, the user did not finish the song (i.e., song is played for less than 20 seconds), are considered to be inappropriate songs played given the current context (i.e., activity type and specific activity of the user). This approach was also applied in the works of [3] where it is assumed that if the user cancels an action, the action is not preferred by the user. The music that is not skipped by the user is assumed to be music that the user deems acceptable or tolerable. After 30 minutes of data gathering, the subject was asked to annotate the activities that were performed as academic or leisurely.

3 Music Provision System

The inputs for the Music Provision System are the EEG signals of the computer user. The EEG signals of the computer user are segmented, and then bandpass filtering and FFT are applied and feature extraction ensues. After the features are extracted, these are then classified as academic activity or leisure activity brainwaves based on the Brainwaves-Activity Model [1].

C4.5, the classifier used, generated a tree that makes use of the music features to identify the activity type. The tree describes the type of music that is deemed to be something that the user does not find to be distracting (i.e., music with features that is similar to music that was not skipped the user before). The tree generated gives the rules for music (i.e., features of music associated to the type of activity) that can be played for a certain activity. Hence, the activity type can now be used to find the matching features that are used for an activity type (song features for activity type). The rules that were generated from the Music Features-Activity Type Model[1] are then used to provide the music. There are however, many rules that can be derived for a general activity, hence, the specific activity is also used to extract rules (i.e., song features for a specific activity) from the Music Features-Specific Activity[1]. This takes into account the specific activity of the user. From this specific activity, music rules are derived and these rules serve as basis for the music that is provided. Each set of song features for general activity will be assessed based on its similarity to the set of song features for the specific activity. Similarity is measured using the Manhattan Distance.

A distance score is computed for each set of rule of the general activity. The rule with the least value will be used as the best rule and its set of song features will be used to get the suggested song. The distance score is computed as the summation of the results of the Manhattan Distance discussed earlier between the set of song features of the general activity rule and the sets of song features of the specific activity rules.

After acquiring the best rule among the general activity rules, its set of song features will be compared to every set of song features of every song in the music repository to get the closest song to the rule. Another distance score is assigned to each song in the music repository. Manhattan Distance Algorithm will be used to compute the distance score of each song. The song with the least distance score will be suggested to the user.

3.1 Static Rule Learning

In order for the system to know that a song was previously rejected by the user, the distance score discussed previously is modified in a way that past events will be considered in the calculation. The Distance Score will be updated so that the new Distance Score will also consider the past feedback of the user. The Learning Score ranges from 0 to 1, the Maximum Learning Score therefore is 1. This Learning Score will be used in calculating the new Distance Score of a given rule. The new computation for the Distance Score is shown in Equation 1. The function uses Learning Scores assigned to each rule of the General Activity rules.

$$\text{Distance Score} = \alpha\,(D\_Score) - (1-\alpha)\,L\_Score \tag{1}$$

where, D_Score is the Distance Score and the L_Score is the Learning Score. α ranges from $0 < 1$ inclusive. If α approaches 1, the Distance Score or the basis of the song decision will be solely dependent on the Distance Score, therefore there is no learning involved. If $\alpha = 0$, the new Distance Score will be solely dependent on the Learning Score, therefore this considers only the full learning. When a song is rejected by the user, the system deducts 0.2 from the Learning Score of its rule. Clicking the Next button in the system is interpreted as rejection of the song provided for the user [3]. As seen from the Equation 1, having a lower Learning Score lowers the chances of it being suggested. Initial value of Learning Score is 1.

Tests were conducted where 4 exact copies of brainwaves were used as an input to the system. Following the algorithm, the songs should vary if the user continues to click next for all the four instances. The result of the tests shows that if $\alpha > 0.6$, the songs are not varying, therefore the system is not learning. Learning here is the ability of the system to adapt. The system uses $\alpha = 0.6$.

This gives the Distance Score priority, so that the system will be using the right rule given the situation, but is also closely considering the Learning Score which covers the past feedbacks of the user.

3.2 Test Results for Static Rule Learning

To test the accuracy of the model, the model was evaluated according to the correctness of its output compared to the actual song of the given instance in the test set (2-hour unseen data). If the Manhattan Distance of the songs is below the threshold 1, then the predicted song is close to the actual. If the distance approaches 0, then the song features of the songs being compared become closer. Refer to Equation 2.

$$Accuracy = \frac{\text{Accepted Comparisons}}{\text{Total Instances}} * 100\% \tag{2}$$

The Brainwave-Activity model is 54% accurate. Given that the accuracy of the Brainwave-Activity model is such, the accuracy of the Static Rule Learning is 66%. If the Brainwave-Activity model is omitted and the activity is just manually provided hence, this is 100% accurate, the accuracy of Static Rule Learning is 76%.

4 Conclusion

This paper presents the results for music provision using the user's brainwaves, specific activities and activity types. This paper shows that the music preference of the user given the user's activities may be provided automatically using the features used in [2]. The experiment conducted shows that the model was able to accurately provide the music preference of the user with the accuracy of 76% given that the brainwaves were able to characterize the type of the activity correctly.

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