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Music Playlist Generation System for Changing a Listener's Mood to a Positive State

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Abstract: The purpose of this study is to propose an automatic music playlist generation system that places the listener into a positive mood. The system uses two types of playlist: mood-boosting and mood-stabilizing. Both types have four patterns, with a different structure that shifts the listener's mood. To create a playlist, the system calculates the probability of an impression of all audio tracks by using a multinomial mixture model. In addition, the system chooses audio tracks for the playlist based on such probability. For a calculation using the model, in this study 30 types of music feature data were extracted from 1,500 pieces of sample tracks. Tagged data expressing five impressions of these tracks from 13 Japanese listeners were also received. Every four patterns of the playlist of mood-boosting and mood-stabilizing tracks were evaluated using the multiple mood scales method. For all playlists, the results showed that the indicator of a negative mood after listening to a playlist decreased from the index as compared to before the track was played. In addition, the index of liveliness in the playlists of mood-boosting tracks and the index of well-being in the playlists of mood-stabilizing tracks increased. In conclusion, the results indicate that the proposed system can design playlists of both mood-boosting and mood-stabilizing tracks that place the listener in a positive mood.

Keywords: Automatic playlist generation, Positive computing, Recommender system, Psychological estimation

1. INTRODUCTION

This paper describes a music playlist generation system for placing a listener into a positive mood. Recent studies have suggested that music affects a change in mood [1, 2]. Many people have stated that this effect is one of the purposes for listening to music. They select and enjoy playlists "for relaxation" on online music streaming services. However, they may lose interest in a playlist when listening to it many times because the audio tracks on the playlist are fixed. Therefore, listeners look for automated playlists that change their moods by selecting appropriate music from music online streaming services.

Other researchers have proposed various playlist generating techniques [3, 4]. There are three main approaches that favor the generation of a playlist. First, a playlist composed of similar music is created by smoothing the transitions between audio tracks. Such a playlist is for listeners who want to listen to music in the same category or from the same musicians. However, the impression of all records in such a playlist does not vary widely. Therefore, it is difficult to create a significant change into a positive mood in the listener. Second, a playlist is built by adapting to the listener's feedback online. The listeners can hear their favorite music through the playlist. However, the playlist is not suited for listeners who want to discover new tracks that are not similar to their favorite music. In addition, the playlist may not shift the listener toward a positive mode. Third, it learns from manually generated playlists. There are variety of playlists of this type, such as "for a sad mood" or "for a happy mood." This study picks up the existing playlists that move the listeners into a positive mood, and designs a new playlist of tracks selected based on these existing playlists. We also need to evaluate whether the playlist can shift the listener toward a positive mood using a psychological method.

In this paper, we present a system that generates a music playlist for shifting the listeners toward a positive mood. The system designs two types of playlist: mood-boosting and mood-stabilizing. Both types have four patterns, with a different structure that shifts the listener's mood. To lead to a smooth change in the listener's mood, all playlists developed by the system gradually change the impression of the audio tracks. To create a playlist, the system calculates the probability of an impression of all audio tracks by using a multinomial mixture model. In addition, it chooses the audio tracks for the playlist using this probability. To evaluate the model, in this study, 30 types of music feature data were extracted from 1,500 pieces of sample tracks. The tagged data expressing the five impressions of these tracks were also received from 13 Japanese subjects.

This study evaluated the designed playlists to determine whether it shifted the Japanese listeners toward a positive mood using a psychological estimation method. This study evaluated every four patterns of the mood-boosting and mood-stabilizing playlists using the multiple mood scales method [5]. For all playlists, the results showed that the indicator of a negative mood after listening to a playlist decreased from that prior to listening to the playlist. In addition, the index of liveliness in the moodboosting playlists and the index of well-being in the mood-stabilizing playlists were shown to increase.

In conclusion, the results indicate that the proposed system can design both mood-boosting and moodstabilizing playlists that shift the listener toward a positive mood.

In the following, section 2 describes how the system shifts a listener toward a positive mood. In section 3, we explain and discuss the subjective evaluation results of the developed playlists using psychological estimation methods. Finally, section 4 provides some concluding remarks regarding this research.

2. SYSTEM

We developed a music playlist generation system for moving the listener into a positive mood.

2.1 Impression estimation of an audio track

The system uses five impression words to represent the musical contents of the audio tracks. The five words are "low (very quiet)," "middle-low (slightly light)," "middle (light)," "middle-high (slightly swinging)," and "high (extremely swinging)."

This system calculates every probability of the five impressions for a single audio track. This study defines the impression with the highest probability as the main impression of the track. As shown in Table 1, to calculate the probability, ten clustering models were created using a multinomial mixture model. As shown in Figure 1, to estimate the probability of a single impression, four of the ten clustering models were selected and used to calculate the probability of the impression of a track. The average probability of the four clustering models is applied as the
 Table 1: Ten clustering models used to estimate the probability of an impression

| The clustering model | Precision | Recall | F-measure |
|----------------------|-----------|--------|-----------|
| MM or LL | 0.82 | 0.95 | 0.88 |
| MM or HH | 0.85 | 0.91 | 0.89 |
| ML or MM | 0.96 | 0.61 | 0.75 |
| MH or MM | 0.92 | 0.64 | 0.76 |
| LL or HH | 0.86 | 0.73 | 0.79 |
| LL or ML | 0.84 | 0.53 | 0.65 |
| MH or LL | 0.83 | 0.92 | 0.87 |
| HH or ML | 0.94 | 0.96 | 0.95 |
| HH or MH | 0.85 | 0.87 | 0.86 |
| ML or MH | 0.91 | 0.86 | 0.89 |

Note) LL: Low, ML: Middle-Low, MM: Middle, MH: Middle-High, HH: High

| An audio track | | | | | |
|---|---|---------------------------------|---------------------------------|---------------------------------|--|
| | | | | | |
| | | | | | |
| Impression: LL | Impression: ML | Impression: MM | Impression: MH | Impression: HH | |
| MM or LL | ML or MM | MM or LL | MH or MM | MM or HH | |
| LL or HH | LL or ML | MM or HH | MH or LL | LL or HH | |
| LL or ML | HH or ML | ML or MM | HH or MH | HH or ML | |
| MH or LL | ML or MH | MH or MM | ML or MH | HH or MH | |
| | Calculate the average of the probability of four models | | | | |
| Calculate the average of the probability of four models | | | | | |
| The probability of LL is 0.9 | The probability of LL is 0.7 | The probability of LL is 0.5 | The probability of LL is 0.3 | The probability of LL is 0.2 | |
| Note) LL: Low ML: Middle-Low MM: Middle-High HH: High | | | | | |

ain impression track

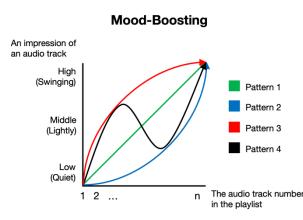
Figure 1: Method for calculating every probability of five impressions concerning a single audio track

probability of one impression of the track. For example, the probability that the impression of the audio track will be "low (quiet)" is obtained based on the average of the four probabilities, namely, "low or middle-low," "low or middle," "low or middle-high," and "low or high." To create the clustering models, the system received the tagged data expressing the five impressions of the tracks from the 13 Japanese subjects. It also extracted 30 types of audio feature data from 1,500 pieces of sample tracks using JAudio [6] and MIR toolbox [7]. The data were compressed using a principal component analysis and the compressed data were applied to create a model.

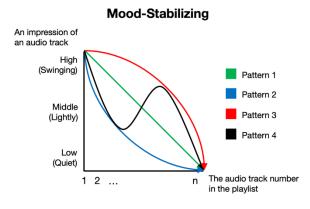
2.2 Design of playlist used to shift to a positive state

The system designs two types of playlist: moodboosting and mood-stabilizing. The mood-boosting playlist raises a depressed spirit into a lively mood. The mood-stabilizing playlist brings a restless spirit down to a calm mood. Figure 2 shows the structure of the four patterns for both types of playlist.

Table 2 also shows the structure for shifting the impression of an audio track within the four moodboosting patterns. The mood transition structure of the



Four patterns of the mood transition structure in mood-boosting playlist



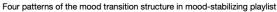


Figure 2: Four patterns of mood transition structure for mood-boosting and mood-stabilizing playlists

playlist gradually changes the impression of the audio tracks. The gradual change is designed based on the impression of an audio track and the probability of its impression.

The system selects the audio track most appropriate for the structure of the impression transition in the playlist based on the following three rules.

The first rule is for the first track. The system randomly selects one track from all audio tracks whose main impression is equal to the impression of the first track in the playlist. The second and third rules are for after the second track.

The second rule is for regarding the part in which tracks of the same impression continue except for the first track. In this case, the system selects an audio track whose main impression is equal to the impression of the playlist and whose probability of the main impression is lower than that of the previous track. In addition, the audio track is one whose probability concerning the next impression is higher than that of the previous track. By way of exception, if there is no next impression, i.e., the impression is "low" or "high," the system selects the audio track that has the

| Table 2: Structure of shifting impression of audio track | KS |
|--|----|
| in four mood-boosting patterns | |

| Track | Pattern | | | |
|---|---------|----|----|----|
| | 1 | 2 | 3 | 4 |
| 1 | LL | LL | LL | LL |
| 2 | LL | LL | ML | LL |
| 3 | ML | LL | MM | ML |
| 4 | ML | ML | MM | ML |
| 5 | ML | ML | MH | MM |
| 6 | MM | ML | MH | MM |
| 7 | MM | ML | MH | MH |
| 8 | MM | ML | MH | MM |
| 9 | MH | MM | MH | MM |
| 10 | MH | MM | HH | MH |
| 11 | HH | MH | HH | HH |
| 12 | HH | HH | HH | HH |
| Note) LL: Low, ML: Middle-Low, MM: Middle | | | | |

MH: Middle-High, HH: High

probability of the main impression being higher than the that of the previous track.

In this case, the system selects an audio track whose main impression is equal to the impression of the playlist, and whose probability of being the main impression is greater than 0.8. In addition, the audio track is one in which the probability concerning the previous impression is higher than that of the other tracks.

3. EVALUATION

This study evaluated the design for every four patterns in both playlists to determine whether it could have shifted the Japanese listener toward a positive mood or not using a psychological estimation method. The subjects of this experiment were 11 men and two women. The average age of the 13 subjects is 22 (SD of 1.2) and all are college students. This study used a psychological evaluation method for Japanese listeners: the multiple mood scales method. Each subject listened to the playlist of every four mood-boosting and mood-stabilizing patterns. This experiment did not set a limitation on the behavior of the subjects except for the interval of the listening playlist, which was over one hour. They listened to the playlist on their favorite device with a headphone or speaker.

Table 3 and Table 4 show the result from the multiple mood scales method. For all playlists, the results showed that the indicator of a negative mood after listening to a playlist decreased from that prior to listening. In addition, the index of liveliness of the mood-boosting playlist and the index of well-being of the mood-stabilizing playlist

Table 3: As for the multiple mood scales method, the transition of the negative feeling and the liveliness feeling before and after listening to the mood-boosting playlist (N=13)

| | Negative f | Negative feelings | | Liveliness | |
|---------|------------|-------------------|---------|------------|--|
| Pattern | Average | S.D. | Average | S.D. | |
| 1 | -5.23 | 5.13 | 2.38 | 2.13 | |
| 2 | -4.30 | 2.15 | 2.15 | 2.28 | |
| 3 | -3.07 | 2.69 | 2.69 | 2.46 | |
| 4 | -3.46 | 4.44 | 3.00 | 2.11 | |

Note: The average value is calculated based on the evaluated point after listening to the playlist minus the evaluated point before listening to it.

Table 4: The transition of negative and liveliness feelings before and after listening to the mood-stabilizing playlist based on the multiple mood scales method (N = 13)

| | Negative feelings | | Well- | Well-being | |
|---------|-------------------|------|---------|------------|--|
| Pattern | Average | S.D. | Average | S.D. | |
| 1 | -3.46 | 3.71 | 4.07 | 3.02 | |
| 2 | -2.93 | 3.75 | 3.84 | 4.07 | |
| 3 | -4.69 | 4.37 | 4.15 | 2.98 | |
| 4 | -2.46 | 4.28 | 3.00 | 5.21 | |

Note: The average value is calculated based on the evaluated point after listening to the playlist minus the evaluated point before listening to it.

both increased. In conclusion, the results indicate that the proposed system can design both mood-boosting and mood-stabilizing playlists that move a listener toward a positive mood.

4. CONCLUSION

This paper described a music playlist generation system used to shift a listener toward a positive mood. This system designs four patterns of both mood-boosting and mood-stabilizing playlists. The system designs a playlist with a smooth mood transition structure by gradually changing the impression of the audio tracks. Based on the results of a psychological evaluation, both the moodboosting and mood-stabilizing playlists can move the listener into a positive mood.

In a future study, we plan to customize the system to create playlists that fit individual listeners.

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