MALL: A Life Log Based Music Recommendation System and Portable Music Player

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ABSTRACT

We may like to listen to particular types of tunes under the particular situation or environment, such as events, weather, time, and place. However, it is not always easy to manually choose such particular types of tunes just by looking at metadata such as titles or artist names. It is effective and enjoyable if such tunes are automatically recommended after learning the tendency of the users. This paper presents MALL (Music Adviser with Life Log), a life log based music recommendation system and portable music player. The system records the history of listened tunes with the situation and environment on the Android-based portable music player. It then discovers association rules between the situation or environments and musical feature values of the tunes. Finally, the system recommends particular types of tunes based on the discovered association rules. We names this system MALL because it advises the tunes based on the life logs of the users.

Keywords

life log, music recommendation, musical features, association rules.

1. INTRODUCTION

It has been very easy to store large number of tunes on the personal computers and portable music players recently, due to the evolution of digital hardware, digital network, and multimedia compression algorithms. It may often make more difficult to manually choose preferable tunes on demand from the large collections of tunes. Music recommendation techniques are useful for users to easily play the preferable tunes. We think portability and personalization of music recommendation system is an important and interesting issue.

Users of music player software usually look at metadata (e.g. title, artist name, and genre) displayed on the playlist, while choosing tunes to be listened. On the other hand, we may like to listen to particular types of tunes under the particular situation or environment, such as events, weather, time, and place. We had a questionnaire to 236 university students regarding to the relationship between listened tunes and situation or environments. We had a result that 71% of the answers had experiences of feelings that the listened tunes match to the season, and 62% of them had experiences of feelings that the listened tunes match to the time. Also, we had a result that more than half of them had experiences of feelings that the listened tunes match to the place or weather. This fact denotes that it is effective and enjoyable if particular types of tunes matched to the situation or environment are automatically recommended after learning the preferences of the users. Therefore, we think life log based music recommendation is an interesting research topic, while many of other existing study on music recommendation are based on other factors such as collaborative filtering or musical preference learning.

We also think that musical feature values are very important information for situation-based music recommendation. It is quite natural that many people want to listen to the quiet music at the quiet places, or uplifting music before the sports. We think musical features are useful information to recommend music from the above viewpoints rather than other information such as names of artists or genres.

This paper presents MALL (Music Adviser with Life Log), a personalized music recommendation system which suggests tunes based on the situation and environment of users. Here, we consider digitally recordable situation or environment as life logs of users, including time, season, weather, and events/schedules of users, as references for the personalization of the music recommendation system. The system discovers association rules between the particular events in the life logs and musical feature values, and recommends tunes based on the association rules. We think that the system realizes personalized and situation-customized music recommendation, and even notices users their interesting tendency of listening tunes. Also, we expect that this kinds of music recommendation can be used as social communication tools to effectively share preferable tunes among friends or fans.

We implemented an Android-based portable music player for this music recommendation system. It features a button expected to be pressed by users when they feel listening tunes match to the situation or environment. It records the situation or environment with the names of playing tunes to a log file when users press the button, and frequently send the log file to the recommendation system. The system also

SAC'14 March 24-28, 2014, Gyeongju, Korea.

frequently analyzes the log files to discover the association rules between the events recorded in the log files and musical feature values of the listened tunes.

2. RELATED WORK

2.1 Life Log Based Contents Recommendation

Life log analysis is an effective and interesting approach for personalized contents recommendation, and actually several studies on life log based contents recommendation have been presented. For example, Yin et al. [17] presented a system which gathered daily life information from smart phones and suggested preferable information according to the relevancy with the gathered information. Nakamura et al. [10] presented a system which recommended TV programs based on the logs of users, including Web browsing histories, operations of consumer electronics, and schedulers on the computers. MALL is somewhat similar to this kind of systems, but it is a more music-specific recommendation system.

2.2 Music Recommendation

Automatic recommendation has been very popular since the growth of on-line shopping systems. Many of the recommendation systems are based on collaborative filtering which refer preferences of large number of users and textural information of the contents. Music contents are mostly binary (e.g. audio files) and therefore we may need additional technical components such as feature extraction for the development of effective music recommendation.

Actually, existing music recommendation techniques apply collaborative filtering [2, 14], metadata analysis [12], and learning of user preference and musical features [13]. On the other hand, several techniques have considered situation of users for the music recommendation [6]. MALL is more based on correlation between users' behavior and musical features.

There have been a lot of works on context-based music recommendation [3, 7, 11, 16]. It is quite related to MALL because they also gather users' daily information and associate to particular tunes. However, most of the techniques associates meta information of tunes such as artists or genres from the gathered information.

2.3 Portable Music Player

Portable music players are today widely used to listen to the music; however, it has more hardware-related limitations comparing with personal computers, such as input devices and sizes of displays. Therefore, it is an important research issue to develop easy, helpful, and enjoyable user interfaces to search for preferable tunes from large music collections. Recent evolution of smart phones and tablets has extended the possibility of development of such user interfaces for portable music players.

Lyricon [8] is one of the typical researches for smart user interface on portable music players. It automatically selects multiple icons of tunes not only musical features, but also lyrical keywords, and effectively displays the icons. Users can understand both impression of the sounds and the content of the lyrics, and they can choose songs which is suitable for their feeling based on the visual impression of the icons.

Meanwhile, several researches presented features to record life logs from the operations of portable music players [4]. We think it is a natural idea that preferable tunes can be recommended by analyzing the logs of portable music players.

3. PRESENTED MUSIC RECOMMENDATION SYSTEM

This section introduces system architecture and processing flow of MALL. The server-side component of the system calculates the musical feature values of the registered tunes and stores them into a database as a preprocessing. Meanwhile, the client-side component records situation- and environment-related values or keywords into a log file with the names of played tunes, when users press the corresponding button on the music player application, as shown in Figure 1(Upper). It also frequently sends the log files to the server-side component. The server-side component discovers associated rules between the musical feature values of the played tunes and the situation or environments recorded into the log files. It then sends playlists consisting recommended tunes based on the association rules to the client-side component, as shown in Figure 1(Lower).

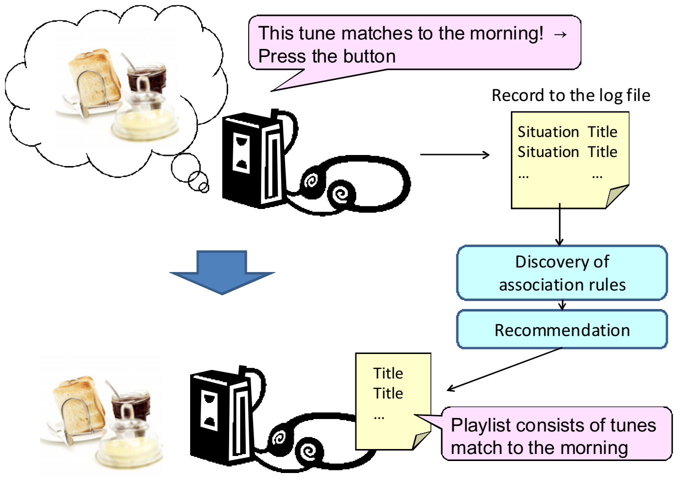

Figure 1: Illustration of use case scenario of MALL. (Upper) Life log information collection. (Lower) Playlist recommended by the system consisting of tunes match to the current situation.

The following sections introduce the processing flow of the each processing block.

3.1 Musical Feature Values

MALL supposes to deal with audio files of tunes, and musical feature values can be calculated from every tune. Our current implementation applies the following musical feature values calculated by "MIRtoolbox" [18].

RMS energy is the root-mean-square of the acoustic energy. This value of recent pop, rock, or electric music tends to be higher, because their acoustic power is controlled as nearly constant by electric effects including compressor or limiter. On the other hand, this value of ballads, classical music, and other non-electric music tends to be lower, because their acoustic power varies along their developments. Consequently, this value is useful to divide electric and acoustic music.

Tempo can be calculated from the cyclic patterns of power peak or harmony change. We believe tempo is an important information to estimate the preference of music listeners, and actually it can be well calculated.
Roll off is the threshold frequency, where the amount of acoustic energy lower than this value occupies 85% of the total acoustic energy. This value is useful to divide tunes according to the tones of main instruments.
Brightness is the ratio of acoustic energy of 1500Hz or higher frequency, which is mainly brought from overtones of instruments. This value is useful to divide tunes according to orchestration or recording settings: it tends to be higher if instruments which sound rich overtones (e.g. violin, saxophone, cymbal) are effectively used by the arrangements of the tunes.
Roughness is the tatio of acoustic energy of inharmonic tones. This value is useful to divide traditional and modern music. Inharmonic tones are relatively often used by modern classical music, jazz, and contemporary pop music.
Mode is the ratio of time occupied by major or minor harmonies. This value is useful to divide enjoyable and sad sounds of the music.

3.2 Recording Life Log

We developed an Android-based music player application which features a button supposed that users press when they feel played tunes match with situation or environment. This application is mainly supposed to be used on portable music players, smartphones, or tablets, because we expect users to press the button anytime and anywhere.

Figure 2 shows a snapshot of the music player application. This application supports a playlist display function which users can select names of albums, artists, and tunes, as well-known music players supports. Also, it supports play, pause, fast-forward, and fast-rewind buttons, as typical music players support.

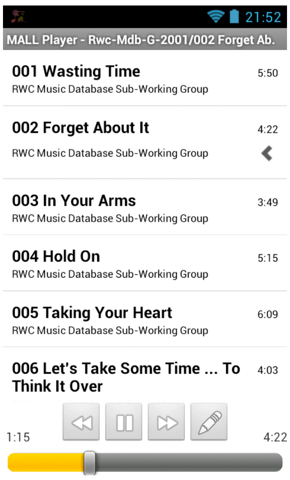

Figure 2: Snapshot of the Android application.

In addition to the above usual GUI widgets, this application features the aforementioned button indicated by an icon of pencil, as shown in Figure 2. When a user presses this button, the application records the title and artist name of the played tune, weather, date, day of the week, and time, into a log file. Our current implementation stores the log files into the SD card of the Android-based devices as CSV format files, and frequently sends to the server-side component.

3.3 Discovery of Association Rules

Preparing musical feature values and log files of users, the server-side implementation discovers associate rules ($A \rightarrow B$). Here, A is equations or inequalities regarding the information recorded in the log files, called "life log conditions" in this paper. B is a set of ranges of musical feature values, called "musical feature conditions" in this paper. Generic data mining techniques discover association rules by calculating "support" and "confidence".
Support is calculated as $P(A, B)$, the probability that A and B occur simultaneously.
Confidence is calculated as $P(B|A)$, the probability that B occurs when A occurs.

Our current implementation applies the following life log conditions derived from weather, month, day of the week, and time, recorded in the log files:

Sunny, Cloudy, Rainy,
Spring, Summer, Autumn, Winter,
month (January to December),
day (Monday to Sunday),
morning (5AM to 10AM), daytime(10AM to 4PM),
evening(4PM to 7PM), night(7PM to 5AM)

MALL discovers association rules between the above listed life log conditions and the musical feature conditions. In other words, the problem we want to solve is discovery of the following association rules:

$$A \rightarrow B_1[a_{1min}, a_{1max}]\&B_2[a_{2min}, a_{2max}]...B_n[a_{nmin}, a_{nmax}]$$

Here, A is a life log condition, and $B_i[a_{imin}, a_{imax}]$ is the i-th musical feature condition described as a range of a musical feature. This problem can be solved by applying quantitative association rule mining algorithms [5, 15].

When new tunes are stored into the server-side component of MALL, it calculates their musical features and checks up the association rules. It calculates the support and confidence values for each combination of the life log conditions and musical feature conditions, and lists the combinations if both the two values exceeds the predefined thresholds. Calculation of the support and confidence is often very costly because of huge number of combinations of A and B. To solve this problem, Apriori algorithm [1, 9] have been widely applied to extract high frequency items and calculate the combinational probabilities of the items.

3.4 Recommendation

MALL recommends tunes based on the association rules discovered by the above mentioned process. It may recommend too large number of tunes if the system has large scale music collection and therefore large number of tunes match the association rules. Our current implementation defines the order of recommendation of tunes for each association rule. When a tune has a n-dimensional feature value vector $(a_1, ..., a_n)$, MALL calculates the distance between the feature value vector and the center of the range of the musical feature condition $(B_1[a_{1min}, a_{1max}], ...B_n[a_{nmin}, a_{nmax}])$.

MALL recommends the predefined number of the tunes which are the closest to the center of the range. Our implementation generates M3U format files as collections of recommended tunes so that we can easily play them on the Android application.

4. EXPERIMENTAL RESULT

We implemented the client application of MALL with Java Development Kit (JDK) 1.6.0, Android Software Development Kit (Android SDK) 2.3.3, and Android Development Tools (ADT) Plugin, and installed on SONY portable music player NW-Z1050. We also implemented the association rule mining part of MALL with JDK 1.6.

We had an experimental test with university students. We asked them to bring the Android music player with them every day for a month, listen to the tunes stored in the Android player, and press the button if they feel that the playing tune matches the situation. We used 313 tunes introduced by RWC Music Database [19].

This experiment excluded association rules regarding seasons because the subjects spent just one month. Also, the experiment explored the association rules consisting of two musical feature conditions only. The reason is as follows. Too many tunes are often recommended if we applied association rules containing one musical feature condition, and we determined it might make user evaluations difficult. On the other hand, support values were quite small if we applied association rules containing three or more musical feature conditions, because our music database was not sufficiently large.

This section introduces the association rules discovered from the log files of two subjects, and subjective evaluation results of the tunes recommended by MALL for the subjects. Tables 1 and 2 show the lists of discovered association rules. MALL generated playlists consist of tunes matching to the discovered musical feature conditions shown in the tables. We asked the subjects to listen to the tunes in the playlists, and evaluate if the tunes match to the life log conditions in 5-grade. The 5-grade evaluation results and comments are as follows.

Evaluation of subject A.

- Night:5. There are a lot of quiet tunes which I feel good to listen in the night.
- Wednesday:4. There are a lot of preferable tunes, but I am not sure why such tunes are recommended for Wednesdays.
- Sunny:4. There are a lot of uplifting or brisk tunes which I feel good to listen on the sunny days.

Evaluation of subject B.

- Morning:5. There are a lot of uplifting or brisk tunes which I feel good to listen in the morning.
- Night:4. There are a lot of slow or dark tunes which I feel good to listen in the night.
- Sunny:3. There are several uplifting or comfortable tunes, while several others are dark.
- Cloudy:4. There are a lot of moderate tunes, which are not too much uplifting or dark.

Table 1: Discovered association rules of the subject A.

Life log condition	Musical feature condition
Night	RMSEnergy [0.04, 0.05] Roughness [5.0, 55.0]
Night	RMSEnergy [0.03, 0.06] Rolloff [1000.0, 2000.0]
Night	Roilloff [1500.0, 2000.0] Brightness [0.16, 0.21]
Night	Rolloff [1000.0, 2000.0] Roughness [5.0, 55.0]
Wednesday	RMSEnergy [0.03, 0.06] Roughness [5.0, 55.0]
Sunny	RMSEnergy [0.04, 0.07] Roughness [55.0, 105.0]

These results suggest that MALL successfully recommended preferable tunes which the subjects felt good for the above life log conditions, except the subject B rated "3" for the life log condition "Sunny". She mentioned that various impression of tunes are mixed in the playlist of "Sunny", and actually two combinations of musical feature conditions associated with "Sunny" for the subject B are quite independent. The first combination of musical feature conditions suggests smaller RMSEnergy and smaller Roughness values. Non-electric tunes applied relatively pure harmony well match with the conditions. On the other hand, the second combination of musical feature condition suggests medium Rolloff and smaller Brightness values. Simply arranged tunes which contain less powerful overtones well match with the condition. We suppose such independent combinations of musical feature conditions brought a set of tunes which have various impressions. We would like to discuss how we can improve such results.

Additionally, we asked the subjects the following two questions.

Q1: What kinds of life log conditions do you feel necessary to implement on the association rule discovery module of MALL?

Both the subjects mentioned feeling or emotion is desirable for this question. One of them also mentioned place is also desirable.

Q2: What kinds of functions do you feel necessary to implement on the Android application of MALL?

The subjects suggested to implement functions to manually generate bookmarks of tunes, and automatically record the preferred tunes, for this question. We think these are important issues and want to address as a future work.

5. CONCLUSION

This paper presented a music recommendation system based on discovery of association rules between life log information and musical features, and a portable music player to gather the life log information. The portable music player can record useful information of users' situation and environment for music recommendation, just when users press a button on an Android-based application.

We named this system MALL (Music Adviser with Life Log) because we aimed to suggest various tunes as if shopping malls displays various items.

Table 2: Discovered association rules of the subject B.

Life log condition	Musical feature condition
Morning	RMSEnergy [0.03, 0.05] Roughness [5.0, 55.0]
Morning	Tempo [100.0, 115.0] Brightness [0.430, 0.480]
Morning	RMSEnergy [0.100, 0.130] Tempo [105.0, 110.0]
Night	RMSEnergy [0.05, 0.07] Rolloff [2000.0, 3000.0]
Night	RMSEnergy [0.05, 0.07] [Mode -0.10, -0.06]
Night	RMSEnergy [0.03, 0.06] Tempo [115.0, 135.0]
Night	RMSEnergy [0.06, 0.08] Roughness [105.0, 155.0]
Night	Tempo [115.0, 135.0] Roughness [5.0, 55.0]
Night	Rolloff [1000.0, 2000.0] Brightness [0.13, 0.18]
Night	Rolloff [1500.0, 2500.0] Roughness [5.0, 55.0]
Sunny	RMSEnergy [0.03, 0.05] Roughness [5.0, 55.0]
Sunny	Rolloff [1500.0, 2000.0] Brightness [0.16, 0.21]
Cloudy	RMSEnergy [0.08, 0.11] Roughness [155.0, 255.0]
Cloudy	RMSEnergy [0.10, 0.13] Tempo [105.0, 115.0]

Potential future issues of our work is as follows.

We would like to test with more various musical feature values in addition to ones introduced in Section 3.1. Especially our current implementation lacks to consider the features regarding melody progress and rhythm patterns. It is not an easily solved issue because we need to develop a fine sound source separation technique to extract melodies and rhythm instruments for the feature calculation; however, we expect to realize to calculate them in the near future thanks to the recent evolution of sound source separation techniques.

We also would like to implement a smart algorithm to automatically determine the appropriate threshold values of support and confidence. Our current implementation manually determine them, but it is obviously a difficult task to determine the appropriate values.

Recording other life log information is another important and interesting issue. We discussed that following additional information will suggest more interesting music recommendation.

Place is one of the interesting information because we may choose tunes based on places. Actually there have been many pop songs tightly related to particular places such as beach and mountain. We would like to extract such information from logs of GPS (Global Positioning System).

Movement is another interesting one. We may choose the tunes based on our movements such as driving and running. We can roughly sense our movement from accelerometers and guess what kinds of semantics of the movement goes on. This information may be also an interesting one for the music recommendation.

Textual information may be also useful one. We can extract events of users on the particular days as textual information from on-line calendars or contents on the blogs. We expect this kind of information may associate to some kinds of tunes.

Emotion is a technically difficult but a very interesting information. We had a result that 93% of the answers had experiences that the listened tunes match to the emotions at the moment, in the questionnaire result introduced in Section 1. Reflecting this result, we would like to discuss how to input the emotion of users while listening to the music and record to the life log files. We expect that more users will be satisfied by the recommendation results when we develop a mechanism to input the emotion.

After these discussion, we would like to have larger user studies with more subjects, and discuss the effectiveness of the recommendation results using the life log files of the subjects. Actually we had the experimental test with more number of subjects, but we could complete the test with only two of the subjects. We could not record the life logs of other subjects due to the runtime errors of the portable devices. We need to develop more robust system for the larger experimental tests. Also, we would like to subjectively compare the experimental tune recommendation results between MALL and meta information (e.g. names of artists or genres) based recommendation techniques, and discuss how musical feature value based music recommendation is useful.

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