A Context and Emotion Aware System for Personalized Music Recommendation

Chen-Ya Wang[1], Yu-Chi Wang[2], Seng-Cho T. Chou[2]

[1] Department of Management & Information, National Open University, Taiwan
[2] Department of Information Management, National Taiwan University, Taiwan
ntuimgrace@gmail.com, r95024@im.ntu.edu.tw, chou@ntu.edu.tw

Abstract

Music recommendation systems are an emerging application that helps users to find their favorite music in numerous archives. Most existing music recommendation methods focus on exploring users' profiles, listening histories and audio signal of music to recommend the most relevant items to users. However, users' preferences may vary in different contexts or in response to changing emotions. In recent years, some studies have affirmed the important roles of context and emotions in music recommendation, and include context or emotions to their system design; however, few studies take both context and emotions simultaneously into consideration. In this paper, we propose an integrated approach to enhance the prediction of a user's preference; this approach incorporates the factors of context and emotion and aims to provide users with a more simple, intuitive and enjoyable listening experience. In addition, we adopt serviced-oriented architecture to implement our music recommendation system to which new innovative services can be easily added or integrated to provide more flexible services in the future. We also present the evaluation results of the prediction accuracy and users satisfaction.

Keywords: Music recommendation, Context, Emotion, Service-oriented architecture

1 Introduction

With the rapid development of digital music technologies, music is ubiquitous and can be easily accessed in our daily life. People listen to music on the radio, TV, the Internet, or portable devices to change their mood, enhance the atmosphere or simply pass the time. Currently, we have numerous choices of music to listen to. However, music listeners often become paralyzed and uncertain how to proceed with the overwhelming number of choices. They are now facing the problem of information overload as people encounter difficulties in finding music that satisfies their preferences and situations. Music recommendation systems (MRS) that help people to find their favorites among the vast amount of available music are now popular commercially and in the academic community. Conventional music recommenders deal with recommendations by mainly exploring two types of information: users and music. However, users' preferences may vary in different contexts or emotional states [1-11]. The effectiveness of MRS will be limited as the recommendation calculations adopt insufficient information [8, 12].

Contextual information has been recognized as an important factor that influences human behavior in many disciplines. From the information behavior aspects, many scholars posited that human perceptions of information behavior are affected by the context where they are situated [10, 13-15]. Information-seeking behavior is affected by the human-in-context factor [14, 16]. In marketing, research on customer decision behavior has demonstrated a similar opinion, namely that the same customer may have different preferences or make different choices in different contexts [17-18]. In the computer science field, contextual information started to be applied in computer systems to provide more relevant services or information to users during the past decade [2, 10, 19-23]. A user's preferences are complex and should be understood in context [22]. Applications can provide information or services that are closer to users' needs by including contextual information. Besides contextual information, emotion is another important factor that will influence users' behavior. The impact of emotions on decision making, consumer behavior and information behavior has been explored in studies in psychology, marketing and information science [24-25]. In human-computer interaction literature, emotion has been recognized as an essential factor that influences users' behavior [26-27]. Within recommendation systems, users' emotional information will be able to recommend more appropriate items matching users' needs [4, 7, 28]. Accordingly, it would be beneficial to incorporate users' contextual and emotional information in the recommendation process.

*Corresponding Author: Chen-Ya Wang; E-mail: ntuimgrace@gmail.com
DOI: 10.3966/160792642018051903013

Researchers in MRS noticed the critical roles of contexts and emotions in people's selection of music and posited that listeners' preferences are strongly related to both factors [4, 6-8, 28]. In the past few years, some studies have taken contextual or emotional information into consideration while making music recommendations [4, 8, 10, 28]; however, few of them provide an integrated method to simultaneously include contextual and emotional information into the recommendation process. In this paper, we propose an integrated approach to enhance the prediction of users' preferences. This approach incorporates the factors of context and emotion and aims to provide users with a simpler, intuitive and enjoyable listening experience. We first filter music from the perspectives of time, location and emotions, based on the time concept hierarchy, the semantic network of ConceptNet, the location classification derived from All Music Guide (AMG, http://www.allmusic.com) and Russell's circumplex model for emotions. Then, we apply a user-based collaborative filtering technique to adjust for the individual differences according to the user's preferences, listening behavior and rating feedbacks, to generate a more personalized music playlist recommendation. As the concept of agile services has received a great deal of attention over the past decade, we adopt serviced-oriented architecture (SOA) to implement our music recommendation system, to which new innovative services can be easily added or integrated to provide more flexible services in the future. To demonstrate the effectiveness of our system, we conducted a series of experiments and measured the prediction accuracy and users' satisfaction.

2 Related Works

2.1 Music Recommendation Systems

As a result of the expanding bandwidth of the internet, the number of people listening to music online is growing with surprising rapidity. Many service providers started to offer music recommendation services to help users find and listen to music that matches their preferences and needs without wasting time on searching for such information. Several popular and successful MRSs which are relevant to our research will be introduced here.

Pandora. Pandora (http://www.pandora.com) was implemented by the Music Genome Project and is a content-based music recommendation service. Its music recommendation engine is primarily based on music content features. Their experts literally collect hundreds of musical characteristics on every track, including: melody, harmony, instrumentation, rhythm, vocals, lyrics, etc. Each song is analyzed using up to 400 musical features, by a trained music analyst. These attributes include the musical identity of a song and the features that are relevant to understanding the listeners' musical preferences. In Pandora, users can query music by inputting artists, song titles or genres. It will respond with songs that are musically similar to the ones provided by users. Since May 3, 2007, Pandora remains for U.S., Australia and New Zealand listening only.

Last.FM. Last.FM (http://www.last.fm) is a collaborative-based music recommendation service that compares the similarity of songs according to users' ratings or preferences. Last.FM uses a music recommender called "Audioscrobbler" to collect a detailed profile of each user's musical taste. Users can tag and label songs, albums and artists with a simple description sentence. Last.FM will aggregate the users' tags and listening history as the basis for music recommendations. Then it presents the users with a list of songs and artists from other users' profiles who share similar music taste with them. Last.FM offers numerous social networking features and can recommend artists that are similar to the users' favorites.

Musicovery. Musicovery (http://www.musicovery.com/) is a content-based music recommendation service. It creates a graphical interface to match users' music listening needs according to their emotions. The "mood pad" displays emotions with two axes: dark/positive and calm/energetic. Every song is analyzed by an expert and labeled with 40 acoustic parameters. Every parameter can record values from around 3 to 20. Every song is mapped to a specific position on the mood pad according to its musical features. Music samples are played when rolling over the mood pad. The listeners can intuitively find the mood and the music they want to launch the playlist from the desired position. Users also can rate the songs in the playlist as feedback.

2.2 Context-Aware Computing

Humans have the ability to express the meanings that they want to convey by using few words because the implications of these words are explained according to the situational information. This indicates that situational information plays an important role in communication. In human-computer interaction, it is also essential to understand users' situational information to provide better services and ensure users' satisfaction. Context is another representative term of situational information which means the information that can be used to characterize the situations relevant to the interaction between users and the applications. In order to use contextual information in an effective way, applications should first address the relationship among context, users and items in applications.

In recent years, some studies have developed context-aware models for computer systems. Korpipää et al. built a well-structured naïve Bayes classification hierarchy to represent the contextual information [29]. Horvitz et al. employed dynamic Bayesian networks

(BNs) and Hidden Markov Models (HMMs) to sense and reason the location information over time and the states of attention that use workload as a random variable [30]. Another method is applying semantic networks (SNs) to represent contextual information. This method links the contextual information as nodes among corresponding concepts, which can be viewed as a directed graph [31]. Adomavicius et al. presented a multidimensional (MD) approach for recommendation systems that include contextual information besides the typical information on users and items [32]. Based on the related knowledge of context, Naganuma et al. proposed an ontology-based modeling method to represent the contextual information of time, space/location and agent/people for an enhanced recommendation service [33]. Han et al. built a music ontology that includes contextual information for music recommendations [28]. Cantador et al. proposed an enhanced semantic method to support the contextualization capabilities for news recommendations [3]. In the music recommendation field, Kim et al. proposed a music recommendation system based on location; it showed good performance [34]. In addition, a context-aware music recommendation system presented by Park et al. also showed that time has a significant influence on music recommendation [35]. Su et al. proposed the Ubiquitous Music Recommender (uMender) that offers music recommendations by mining musical content and context information [8]. Wang et al. employed contextual information collected with mobile devices for music recommendation [10]. Chen et al. proposed a context-aware approach for music recommendations based on a user's emotional state predicted from the article the user writes [4]. We will use location and time as the contextual information in our system.

2.3 Emotion and Music

In psychology-related literature, researchers have attempted to propose some models of human emotions. The two major approaches for emotion modeling are categorical and dimensional methods. The categorical approach allocates each emotion into a small set of mutually exclusive categories. The dimensional approach is a taxonomy that classifies emotions using several dimensions to present the various types of emotions. A suitable emotional model to represent emotions in music is essential for realizing an efficient music recommendation system. We will introduce some emotion models that are useful for mapping emotions with music.

PAD emotional state model. Mehrabian defined the PAD model to describe and measure emotional states [36]. This model classifies emotions according to three distinct dimensions: pleasure- displeasure (P), arousal-nonarousal, (A) and dominance-submissiveness (D). Pleasure-displeasure distinguishes the positive emotional states from negative ones. Arousal-nonarousal refers to a combination of mental alertness and physical activity regarding the intensity of the emotion. Dominance-submissiveness represents control versus lack of control over events or one's surroundings. PAD uses three numerical dimensions to represent all emotions, and any emotion can be viewed as a point in this three-dimensional space. Therefore, every emotion can be mapped onto a 3-dimensional vector space that can be used for similarity calculation in the recommendation process.

Hevner's adjective circle. Hevner's adjective circle mainly focuses on mapping the musical features into a circle of emotional terms [37]. This circle represents emotions with eight groups: spiritual, pathetic, dreamy, lyrical, humorous, merry, exhilarated and vigorous. Hevner further improved this model by exploring six musical features (i.e. mode, tempo, pitch, rhythm, harmony and melody) and redefined the eight groups of the emotional/mood circle as dignified, sad, dreamy, serene, graceful, happy, exciting and vigorous [38]. Meyer extended Hevner's method and proposed an emotional content-based music classification mechanism that can be mapped onto Hevner's Adjective Circle according to five musical features (i.e. mode, harmony, tempo, rhythm and loudness) [39]. This model is suitable for expressing the emotion of music because it defines the relationships between musical features and emotions.

Russell's circumplex model. Russell proposed a circular emotional model by placing eight emotion terms around the two primary dimensions of pleasantness–unpleasantness (horizontal axis) and arousal–sleep (vertical axis) [40]. This model mapped 28 terms of emotions to represent the domain of respective emotions. Russell's circumplex model is a spatial model based on two dimensions of emotion that are interrelated in a very methodical way. Eight emotions fall in a circle with the following order: pleasure (0^0), excitement (45^0), arousal (90^0), distress (135^0), displeasure (180^0), depression (225^0), sleepiness (270^0) and relaxation (315^0). This 360 degree model is useful for exploring the relationships between different emotions and can be used for the similarity calculation in recommendation systems.

In our system, we have to extract the relationships between emotions and songs and then compute the similarity between a user's emotion and the emotional character of a song. We adopt Meyer's mechanism derived from Hevner's method to extract the relationships between emotions and songs. In addition, Cafarella and Cutting provided a mechanism that can map Hevner's Adjective Circle onto Russell's circumplex model [41]. Therefore, we can use Russell's circumplex model to calculate the similarity between a user's emotion and the emotional character of a song.

3 System Design

3.1 System Concept

In this system, we first collect the representative emotion, listening location and listening time of the songs as the basis of our recommending mechanism. Our system adopts the emotional content-based music classification method proposed by Meyers [39] to establish the relationships between emotions and the musical features of a song. Meyers' method maps the emotion of a song to the Hevner's adjective cycle. The listening location is derived from the location classification made by experts in All Music Guides (AMG). For listening time, we build a time concept hierarchy to relate the listening time and songs. Then, we recommend playlists that tally with users' emotions, contextual information and preferences by executing weight computing, music filtering and similarity measure. Figure 1 presents the overview of our system; it includes seven major modules: user interface module, query analyze module, context module, emotion module, user profile module, song info module and recommendation module. In addition, user profiles, songs, emotion of songs, context information and users' ratings of songs are stored in the database.

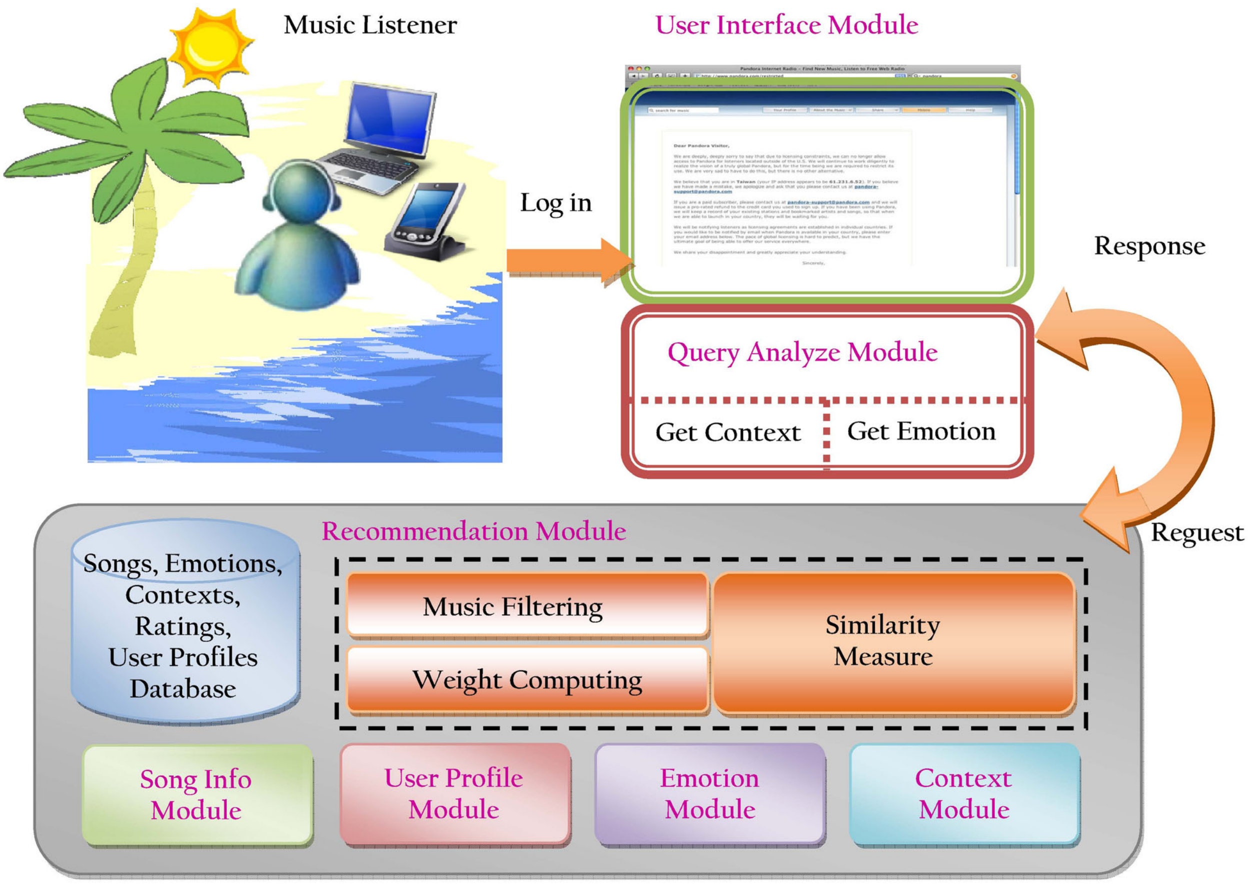

Figure 1. The overview of our system

Our system is simple and easy to use. First, the user connects to our system and then logs in. Second, the user chooses the conditions or input query condition of emotions as shown in Figure 2. Third, our system will automatically generate a playlist for the user and the user can listen to these songs directly on the internet. Users can express their satisfaction by explicit rating of the songs on a scale from 1 to 10 and label the related contextual or emotional information if they think the default information differs from their feelings. These data will be recorded in the database and these feedbacks will be viewed as users' preferences for future music recommendations.

Figure 2. The interface of our system

3.2 System-Oriented Architecture (SOA)

Service-oriented architecture refers to "a style of building reliable distributed systems that deliver functionality as services, with the additional emphasis on loose coupling between interacting services [42]." The business processes or functions are modularized as services and these service interfaces are independent of their implementations because of message-oriented communications. In an SOA environment, business can flexibly add or compose new services under existing IT infrastructure in a loosely coupled manner. These services can be easily accessed from any platform, whether local or remote. We adopted the concept of SOA to build our system in order to provide a ubiquitous, flexible and extendable service.

Web services is one of the most important ways to implement SOA in which requestors can find web services and dynamically bind to them. We designed our system as an SOA-based recommendation service using web services technology. The basic unit of communication in web services is a message rather than an operation. Figure 3 shows the SOA environment of our system. The Service provider offers the recommendation service through well-defined service contracts and has to publish the service contracts for its services in the registry. The service repository provides the possibility to register services and maintains the service registry that acts as a service directory listing. A service contract represents an agreement by the joining parties and binds the users with the service provider. A service consumers can look up the services in the registry and invoke the service by sending messages that meet the service contract format. Then, every user and developer can access the service easily and use the service to develop applications on any platform.

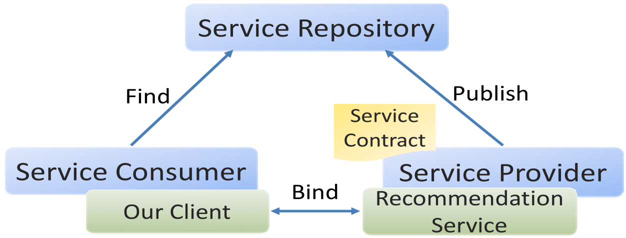

Figure 3. The SOA environment of our system

3.3 System Architecture

Our system is a music recommendation system implemented by the SOA architecture; it takes contextual and emotional information into consideration. Users can get different music playlists according to different context and emotion conditions. Before the calculation of similarity, our system uses the contextual and emotional information as a filter to exclude the songs from different contexts and emotions. Gathering data from several online databases, such as All Music Guide (AMG) and ConceptNet, our system integrates context hierarchy, emotion detection, commonsense computing and collaborative filtering techniques to build a more intuitive and enjoyable music recommendation system. As mentioned above, our system includes seven modules: interface module, query analyze module, context module, emotion module, user profile module, song Info module and recommendation module. The primary design and functions of these modules are described respectively.

User interface module. The user interface module is responsible for all interactions between users and our system through a web-based interface. Users can choose their contextual information (i.e. time and location) and emotions from the lists, or input some text description to represent their emotions. Users also can rate songs in the recommendation playlist to express their satisfaction by explicit rating of the songs on a scale from 1 to 10. They also can label the contextual or emotional characteristics of the song if their cognition of these characteristics differs from the default ones provided by our system. These labels will feedback to this system and be recorded in the database.

Query analyze module. Our system provides three types of query conditions (i.e. time, locations and emotions). Users can choose any or all of them as query conditions. Time is further divided into three parts: morning, afternoon and evening. Location is a list of places derived from AMG database. There are two methods to acquire users' emotions. One is getting the user's choice of his/her emotion from the eight emotions defined by Hevner's adjective cycle [37]. These emotions/tones include: happy, sad, dignified, serene, graceful, exciting, angry, and dreamy. Another method uses the commonsense reasoning techniques and natural language processing to capture the emotion from the query texts inputted by the user.

Context module. Context module deals with two contextual factors: time and location. It retrieves songs according to the time and location information of users' situations. Users also can label the contextual information of the recommendation songs after listening; thus, the contextual characters of these songs can be adjusted on the basis of users' listening situations.

The attributes of listening time are represented as a concept hierarchy which consists of several levels of concepts. The time concept hierarchy is shown as Figure 4. The higher the level, the more generalized it is. However, some nodes in this concept hierarchy may not contain enough information for the recommendation process. Our system will directly inherit the contents of the nodes' parents and use these contents for recommendation computation.

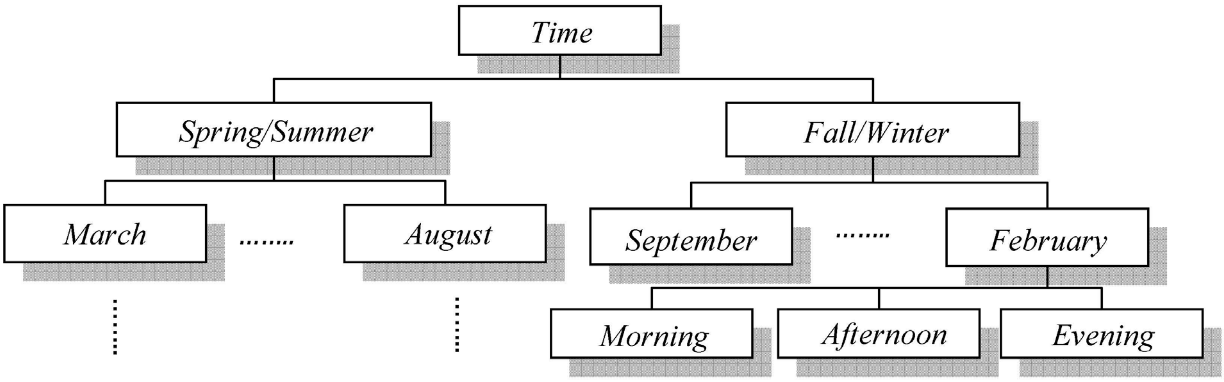

Figure 4. Time concept hierarchy

The location factor is derived from the location classification made by experts in All Music Guide (AMG). AMG categorizes the relationships between locations and music. We retrieve location names from the AMG and then use these names as input to find the relationships between these locations from ConceptNet. ConceptNet is a kind of semantic network which represents the similarity between nodes by computing their inferential distance [43]. We then execute the ConceptNet practical reasoning API to generate the lists of structurally analogous concepts, retrieve the similarities between these locations from the lists and store them into our database.

Emotion module. In the emotion module, we implement Meyer's mechanism [39] to extract the songs' emotions. Meyers proposed an emotional content-based music classification method that analyzes the audio signals using five musical features (i.e. mode, harmony, tempo, rhythm and loudness). Meyers' mechanism maps the emotion of a song to the Hevner's adjective cycle that we also used in the query analyze module to represent a user's emotion. Figure 5 shows the music classification of Meyer's mechanism. Consequently, we extract the songs' emotions by Meyer's musical content classification method and store the results into the database.

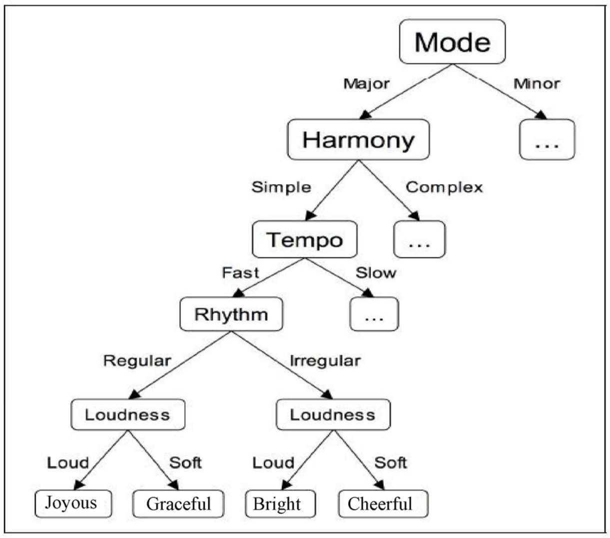

Figure 5. Meyer's musical content classification

Song info module. The song info module is responsible for collecting the meta-data of songs which include: the artists, songs' title, albums, release dates and genres. Our system directly gathers the first four data from the files of songs, and then uses these data as query conditions to find their genres in AMG. The online listening interface which shows the related information is presented in Figure 6.

Figure 6. Online listening interface

User profile module. The user profile module organizes profile data used in this system. A user's profile indicates personal account information, preferences and listening history. These data include: account id, user name, age, gender, e-mail, favorite genres, dislikes genres and listening history list. Specifically, if a user skips listening to a song before the half time of the song, we will ignore the rating for that song when computing the similarity of songs.

Recommendation module. In the recommendation module, our system adopts the hybrid method [44] to integrate all data that come from other modules for music recommendations. The recommendation module includes three sub-modules: weight computing, music filtering and similarity measure. The process flow is shown in Figure 7.

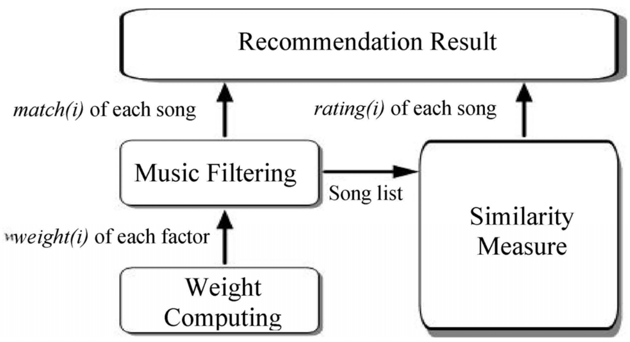

Figure 7. Process flow of recommendation module

(1) *Weight computing:* This sub-module calculates the weighting of one specific factor when users choose more than one factor as their query conditions (i.e. time, locations and emotion). Suppose a user usually uses the emotion factor to generate recommendations and now this user uses both the emotion and location factors; this often indicates that the location factor is more important than the emotion factor in this query. Our system adopts a concept similar to IDF in the TF-IDF (Term Frequency-Inverse Document Frequency) method to measure the weighting of factor *i*. Once a less used factor is chosen, this factor will have a higher weighting for the recommendation calculation. The weighting formula is defined as:

$$w_i = \log \frac{|Q_u|}{|\{q : f_i \ni q\}|} \tag{1}$$

where Q_u is the total number of queries of user u in this system and the denominator is the number of queries of factor i (f_i). Then w_i will be used as the weighting of factor *i*.

(2) *Music filtering:* This sub-module filters the songs according to a user's query condition and extracts the top n songs. The similarity between query condition (i.e. time, locations or emotion) and the characters of song *i* is defined as:

$$m(i,F) = \sum_{f \ni F} w_f \bullet sim_f(i,f) \\ s_{i,f} \sim [+1,+10],\ f \ni F \tag{2}$$

where F is the set of query factors including *emotion, time* and *locations*; w_f is the weighting of each factor in F generated from Equation (1); $sim_f\ (i,f)$ is the similarity between the characters of song *i* and the user's query condition regarding factor *f*; the similarity value $s_{i,f}$ is in the range from 1 to 10; and $m\ (i,F)$ is the similarity between query condition and the characteristics of song *i*. The similarity calculation of every factor $sim_f(i,f)$ is illustrated respectively.

—Location

For the location factor, this system measures the similarity of locations between a user's query condition and the location characteristic of a song based on the ConceptNet. The $sim_{location}\ (i,location)$ value is directly obtained from the relation coefficients of ConceptNet. These coefficients are numeric values which represent the similarity between locations. A sample of similarity value between each location computed by ConceptNet is shown in Table 1 (the original data are calculated to the 12th digit after the point).

Table 1. The sample of location similarity

	Beach	Country	Office	Party	Wedding
Beach	---	6.670	4.067	1.189	3
Country	6.670	---	4.339	1.356	2.377
Office	4.067	4.339	---	1.627	1.5
Party	1.189	1.356	1.627	---	7.13
Wedding	3	2.377	1.5	7.13	---

—Emotion

For the emotion factor, this system uses Meyer's emotional music classification mechanism that maps to the Hevenr's Adjective Cycle. To measure the similarity between a user's emotion and the emotional character of a song, we map the Hevenr's Adjective Cycle into Russell's circumplex model [41], as shown in Table 2. Russell's circumplex model is a 360 degree model that can be used for numeric evaluation. The emotional similarity is defined as:

$$sim_e = |s_e - q_e| \;\; if \;\; sim_e > 180, \; sim_e = 360 - sim_e \quad \textbf{(3)}$$

Table 2. Comparison of three emotional models

Degree	Russell	Schubert	Hevner	Valence	Arousal
0°	Pleasure	(B) Lyrical	(4) Serene (5) Graceful	+	0
45°	Excitement	(A) Bright	(6) Happy	+	+
90°	Arousal	(H) Dramatic	(7) Exciting	0	+
135°	Distress	(I) Tense	(7) Exciting	–	+
180°	Displeasure	(E) Tragic	(2) Sad (3) Dreamy	–	0
225°	Depression	(F) Dark (G) Majestic	(1) Dignified (2) Sad (8) Vigorous	–	–
270°	Sleepiness	(D) Dreamy	(3) Dreamy	0	–
315°	Relaxatuin	(C) Calm	(4) Serene	+	–

－Time

For the time factor, we define three nominal periods: morning, afternoon and night with its mapping hour as shown in Table 3.

Table 3. Definition of time period

Nominal Period	Mapping Time Period (24hr format)
Morning	5-11
Afternoon	11-17
Night	17- 5

If the song's time value, s_t, is in the same time period as the user's query time, q_t, it will be classified as 100% the same. Otherwise, we measure the similarity of time as:

$$sim_t = |s_t - q_t| \;\; if \;\; sim_t > 12, \; sim_t = 24 - sim_t \quad \textbf{(4)}$$

(3) *Similarity measure:* In this sub-module, we first use the user-based collaborative filtering proposed by Shardanand and Pattie [45] to predict the ratings of songs in the list of top n songs generated by Equation (2), then calculate the mean value of matching songs and predict their ratings as our recommendation results.

This sub-module calculates the similarity between users (i.e. $sim(u_a, u)$). Then this sub-module uses $sim(u_a, u)$ to predict the rating of song i for user u_a and normalizes the difference of ratings between individual users; hence, we get the predicted rating $ru_{a,i}$ of song i for user u_a. The collaborative filtering algorithm is defined as:

$$r_{u_a,i} = \overline{r_{u_a}} + \frac{\sum_{u \in U} sim(u_a,u) \bullet (r_{u,i} - \overline{r_u})}{\sum_{u \in U} |sim(u_a,u)|} \quad \textbf{(5)}$$

$$sim(u_a,u) = \frac{Cov(u_a,u)}{\sigma_{u_a}\sigma_u} = \frac{\sum_{s\in S}(r_{s,u_a} - \overline{r_{u_a}})(r_{s,u} - \overline{r_u})}{\sqrt{\sum_{s\in S}(r_{s,u_a} - \overline{r_{u_a}})^2}\sqrt{\sum_{s\in S}(r_{s,u} - \overline{r_u})^2}} \quad \textbf{(6)}$$

where $\overline{r_{u_a}}$ and $\overline{r_u}$ is the average rating of user u_a and user u; U is the set of all users; $sim(u_a, u)$ is the similarity between user u_a and user u which measuring by Pearson correlation; and S is the set of all songs in this system.

Finally, our system computes the harmonic mean of *m(i)* (Equation (2)) and $ru_{a,i}$ (Equation (5)) to derive the final rating value of song i, i.e. $R(i)$. Then we sort the value $R(i)$ to get the music playlist for the user u_a. The harmonic mean formula is defined as:

$$R(i) = \frac{n}{\sum_{i=1}^{n} \frac{1}{x_i}} = \frac{2(m(i) \times r_{u_a,i})}{m(i) + r_{u_a,i}} \quad \textbf{(7)}$$

where n is the total number of considering variables, which are included in the music filtering module and similarity measure module.

4 Evaluation

4.1 Experiment Procedures

The detailed experiment procedures are shown in Figure 8. The experiment includes three steps: data collection and processing, online experiment and experiment evaluation. These steps will be described respectively.

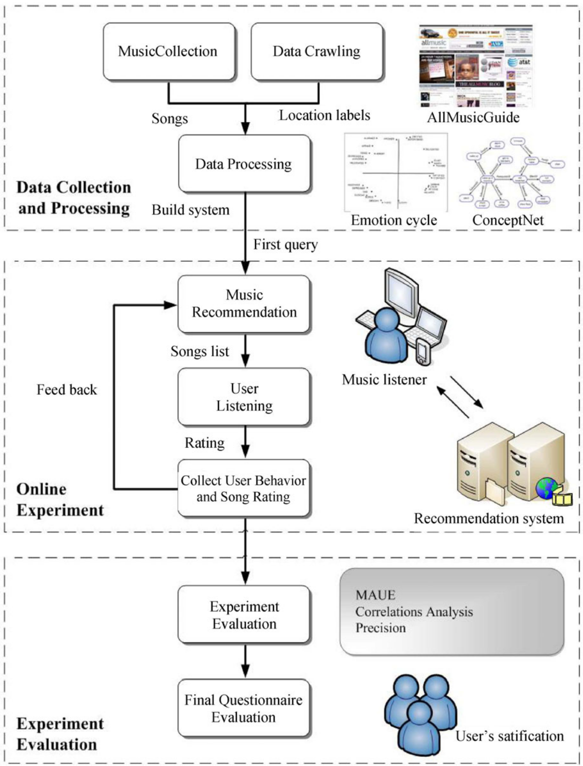

Figure 8. Experiment procedures

Data collection and processing. This system first has to gather related music information and contextual data and then users can listen to music via the internet and give each song a rating and labels. Therefore, we retrieved music information and contextual data from the AMG. The total amount of collected songs for the experiment is 2045 and includes three music genres: Classical, Jazz and Pop/Rock. Among these songs, 1533 belong to Pop/Rock (75%); 359 belong to Jazz (18%); and 152 belong to Classical (7%). Regarding the language of the lyrics, 1281 songs belong to Chinese (63%) and 764 songs belong to English. We randomly sampled 800 songs for the experiment.

For the contextual data, we acquired 83 contextual labels from the AMG and selected 10 of them to be our location labels: Beach, Country, Birthday Party, Night Club, Party, Wedding, Christmas Party, Church, Driving, and Office; 387 songs of the 800 samples have location values matching these ten locations. Among these songs, 43 are Beach (11%); 27 are Birthday Party (7%); 32 are Christmas Party (8%); 23 are Church (6%); 37 are Country (9%); 42 are Driving (10%); 41 are Night Club (10%); 50 are Office (12%); 76 are Party (19%); and 16 are Wedding (4%). The mean of these location values is 38.7 and the standard deviation is 16.667. For the emotional data, after mapping these 387 songs to emotions with Meyer's mechanism, 110 belong to Happy (28%); 89 belong to Exciting (23%); 107 belong to Graceful (28%); 37 belong to Serene (10%); 8 belong to Dreamy (2%); 10 belong to Dignified (2%); 11 belong to Sad (3%); and 15 belong to Angry (4%). More than 80% songs belong to positive emotions, such as Happy, Exciting, Graceful, and Serene. The distribution between emotions and locations is shown in Figure 9.

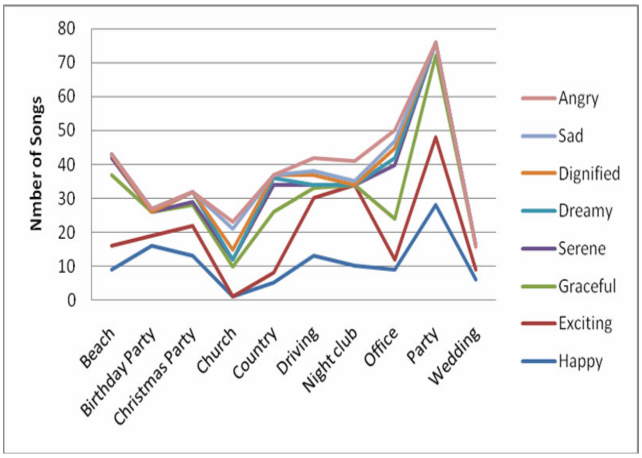

Figure 9. Distribution between emotions and locations

Online experiment. We invited participants to use our system by posting messages on music discussion forums and the famous bulletin board system (BBS). The participants have to register in our system and provide personal information such as age, gender, email address, music preferences, and so on. Then they input the query conditions and get the music recommendation playlist. After listening to a song, the participants can give their rating and label for the song as feedback. The ratings and labels will be entered into the database if the participants listened to more than half of the song. After one month long online experiment, we collected 93 effective users from among 124 registered users. They are between 20 and 28 years of age (average is 24 years of old); 57 (61%) of the effective users are male and 36 (29%) are female.

We further invited 30 participants who have listened to more than 300 songs in Last.FM to join our second stage experiment. This criterion is used to avoid the cold-start problem in Last.FM. The participants had to define at least two scenarios regarding the situations that they want to listen to music. Then we asked the participants to listen to ten songs recommended by Last.FM and our system and to give a rating to every song. We compared the predictive ability of our system with Last.FM. Regarding the comparison target, four popular music listening websites were considered: Last.FM, Pandora, Musicovery and All Music Guide. Pandora does not provide services for listening outside of the U.S and All Music Guide is a categorical website which does not provide the recommendation service. On the other hand, we found that participants had experiences in using Last.FM than in using Musicovery. Consequently, we chose Last.FM as the comparison target.

Experiment evaluation. In the recommendation system literature, the most discussed and used measure is prediction accuracy [46]. Accuracy measures the prediction accuracy of recommendations from a statistical perspective or decision-based perspective [47]. We used the Mean Absolute User Error (MAUE), precision, recall and F1 to evaluate the performance of our system. MAUE is a modified Mean Absolute Error (MAE) method of MAE. MAE measures the average absolute difference between a predicted rating and the actual rating of a user, with every prediction error weighted in the same way [48]. However, the ratings for recommendations show significant differences between heavy raters and cold starters. We therefore used MAUE to ensure that all users have the same weight in the prediction error calculation. MAUE with a low value usually indicates that the prediction accuracy is good. The MAUE equation is defined as:

$$MAUE = \frac{1}{n}\sum_{u=1}^{n}\left(\frac{1}{n_u}\sum_{i=1}^{n_u}\left(\left|p_{u,i} - r_{u,i}\right|\right)\right) = \frac{1}{n}\sum_{u=1}^{n}\left(\frac{1}{n_u}\sum_{i=1}^{n_u}\left(\left|e_{u,i}\right|\right)\right) \quad \textbf{(8)}$$

where n is the total number of users who have rated more than one item; n_u is the number of ratings rated by user u; $p_{u,i}$ is the predicted rating of item i generated by system for user u; $r_{u,I}$ is the actual rating of item i given by user u; and $e_{u,}$ are the differences between predicted rating and actual rating.

Decision-based measures evaluate how well a system recommends items that will be highly rated by the user. Measures of classical information retrieval literature are used here, including: precision, recall and F-measure [4, 8, 49-52]. Decision-based measures evaluate the recommendation list of top-n items for a user. The recommendation items are usually ordered by decreasing relevance. There are four possible outcomes of a recommendation of an item to a user, as shown in Table 4.

Table 4. Possible results of a recommendation of an item to a user

	Relevant	Not relevant
Recommended	True-Positive (TP)	False-Positive (FP)
Not recommended	False-Negative (FN)	True-Negative (TN)

Precision is the percentage of the recommended items that are really relevant items. The equation is defined as:

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

Recall is the percentage of the relevant items that are really recommended by the system. It indicates the coverage of the recommended items. The equation is defined as:

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

F-measure is the weighted harmonic mean of precision and recall. F_1 evenly weights precision and recall, and F_2 weights recall twice as much as precision. We use F_1 to evaluate the performance of our system. The equation is defined as:

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{11}$$

To measure users' satisfaction and perceived usefulness of our recommendations, we asked the participants to answer a questionnaire to collect users' feedback in regard to another perspective. The questionnaire includes three parts: users' chosen factors of recommendation, users' perceived usefulness of this system and users' overall satisfaction regarding this system. The questions are shown in Table 5.

4.2 Experiment Results

The rating results. We collected 934 effective ratings of 372 songs from the experiment. For all of the ratings, the mean value is 7.104 with standard deviation of 1.849. Figure 10 shows the distribution of all ratings with 81% of the ratings located between score 6 and 10. The distribution is skewed on the right side, which means most of the users tend to positively rate our recommendations.

Table 5. Questionnaire for user feedback

Aspect	Number	Description
Concerning factors	1	Do you think emotion is an important factor when choosing music to listen?
	2	Do you think location is an important factor when choosing music to listen?
	3	Do you think time is an important factor when choosing music to listen?
Perceived usefulness	4	Do you think the recommendation results match your emotion?
	5	Do you think the recommendation results match your situations?
	6	Were the recommendations helpful for you?
	7	Do you think our emotion-and-context-based music recommendation system is useful?
Overall satisfaction	8	Overall, are you satisfied with our recommendations?

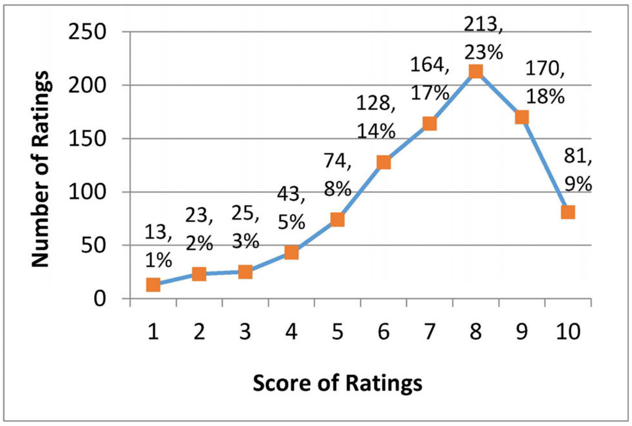

Figure 10. The distribution of all ratings

The number of ratings and the average of users' ratings are accumulated according to the query condition, as shown in Figure 11. Regarding query conditions, 78% use emotion as one of the query conditions, 55% use location as one of the query conditions and 28% use time as one of the query conditions. The results show that most users tend to use the emotion factor as their query condition, which means that emotion is more directly related to users' music listening preferences. People can experience the same kinds of emotions at any time and in any location. For example, we may feel excited at a party, night club, or beach. In this situation, we may choose music according to our emotional states rather than the specific location or time. In Figure 11, except for the queries that only use the time factor as query condition and have lower ratings, most query conditions have good rating scores. The reason may be that our database lacks the ratings of the time factor and therefore the recommendations made by time do not score very well. According to the trend line, we find that users' ratings are higher while combining more factors as their query conditions.

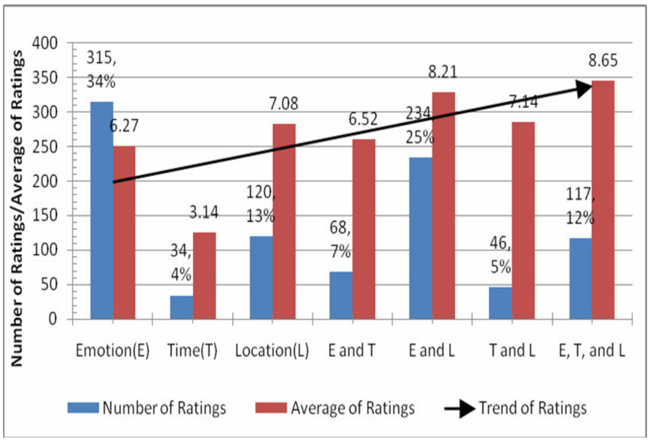

Figure 11. The number and average rating of query conditions

The distribution of ratings for emotions is shown in Figure 12. The ratings regarding negative emotions/tones (i.e. dignified, sad and angry) are only 8% of all ratings. About 92% of the ratings are related to positive or neutral emotions. With a lower number of users, it seems that people rarely listen to music while in a dignified or angry mood. Another possible reason may come to most people rarely feel dignified or angry in daily life. Regarding the lower ratings of happy, it may because happy has a broaden meaning of emotions that it's not easy to define a song as happy and macth the users' situation in the same time. Our results indicate that users usually listen to music while they are experiencing positive or neutral emotions.

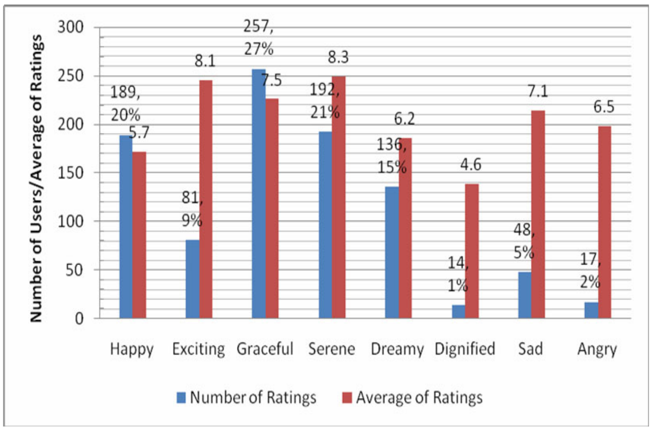

Figure 12. The distribution of ratings for emotions

Prediction accuracy. To evaluate the accuracy of our system, we adopted a well known user-based collaborative filtering algorithm proposed by Resnick et al. [53] and item-based collaborative filtering algorithm proposed by Sarwar et al. [54] as benchmarks to compare with our algorithm. Because this system takes emotion, locations and time into consideration, we had to adapt our data to Sarwar's algorithm for comparison. Therefore, we used a 3-combination of the original factors to derive a format that is comparable to Sarwar's algorithm.

We used MAUE to evaluate the prediction accuracy with the leave-one-out method [55]. A low value of MAUE indicates that the prediction accuracy is good. Figure 13 shows the MAUE of this system and benchmarks with increasing neighborhood size. The reason for having high MAUE in adapted Sarwar's method is that we adapted its data into 3-combinations which cause the sparse data problem. The MAUE of Resnick's method is decreased from 1.2731 to 1.0583 with difference of 0.214, and the MAUE of our proposed method is decreased from 1.2261 to 1.0028 with difference of 0.223. Therefore, as depicted in Figure 13, our method has lower MAUE with higher difference than Resnick's; this indicates that our system has better prediction accuracy than Resnick's benchmark. In our case, the decreasing ratio is significantly ceased when the size of neighborhood is higher than 20.Thus suitable neighborhood of our recommendation system is among 20 to 30 which can considered both of the efficiency and recommending quality. On the other hand, the MAUE shows no significant improvement when the neighborhood size is greater than 30. We therefore set the neighborhood size of our system as 30.

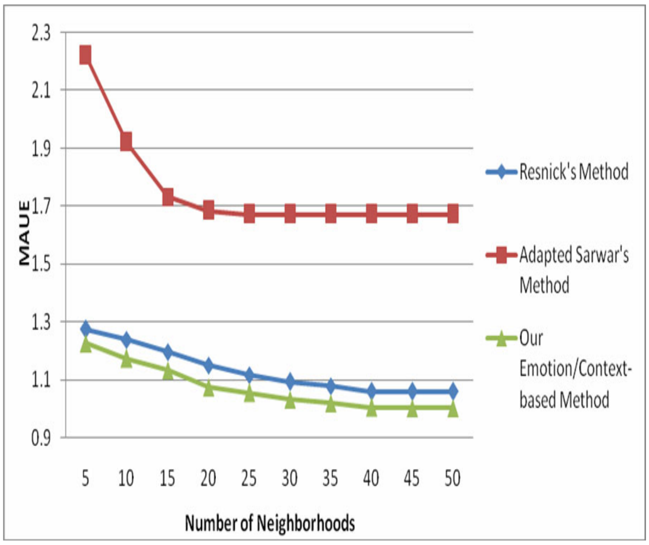

Figure 13. MAUE of different neighborhoods size

Regarding precision and recall, we use 30 as the neighborhood size to measure their value. We define an item as relevant if its actual rating is greater than 7. In addition, an item is recommended if its predicted rating is greater than 7. The results of accuracy measures are shown in Table 6. According to the analysis result of Table 6, our emotion-and-context-based collaborative filtering algorithm has lower MAUE and higher precision, recall and F1 value, which means the average error of our algorithm is lower and our accuracy is better than benchmarks. This ididcated that emotion and context information is very useful in finding the most-relevant songs to facilitate music recommendation. The prediction accuracy of our system performs better than item-based and user-based methods. We will investigate more dimensions of contextual information to improve the quality of our recommendaions.

Table 6. The results of accuracy measures

	Adapted Sarwar's (item-based)	Resnick's (user-based)	Our system
MAUE	1.671	1.0925	1.0323
Recall	0.5717	0.7193	0.7401
Precision	0.6675	0.8011	0.8118
F1	0.6159	0.7580	0.7743

User satisfactions. Finally, 86 users completed the questionnaire. The results are shown in Table 7. For the factors concerned, 79% of the participants think that emotion is an important factor while they are choosing what kind of music to listen to; 63% of the participants think location factor is important and 49% of the participants think the time factor is important. The results indicate that most people take emotion as a critical consideration while listening to music; location and time are not as important like emotion factor. It matches the results of our experiment evaluation in Figure 11 that most users tend to use emotion as one for their query conditions. For the perceived usefulness of this system, 77% participants responded that our recommendations matched their emotional states and 62% participants felt that the recommendations matched their location and time situations. In addition, 75% and 65% of the participants had positive evaluations regarding the helpfulness and usefulness of this system. In the end, the result of question 8 shows that 74% of the participants are satisfied overall with this system.

Table 7. The results of questionnaire

		Responses[a]				
		1	2	3	4	5
Concerning factors	Q1: emotion	0 (0%)	1 (0%)	18 (21%)	41 (48%)	26 (31%)
	Q2: location	0 (0%)	6 (7%)	26 (30%)	37 (43%)	17 (20%)
	Q3: time	0 (0%)	5 (6%)	39 (45%)	34 (40%)	8 (9%)
Perceived usefulness	Q4: match emotion	0 (0%)	3 (3%)	17 (20%)	54 (63%)	12 (14%)
	Q5: match situations	0 (0%)	7 (8%)	25 (29%)	43 (50%)	11 (13%)
	Q6: helpful	0 (0%)	2 (2%)	20 (23%)	48 (56%)	16 (19%)
	Q7: useful	0 (0%)	7 (8%)	23 (27%)	32 (37%)	24 (28%)
overall satisfaction	Q8: overall satisfaction	0 (0%)	5 (6%)	17 (20%)	61 (71%)	3 (3%)

Note. a: The responses represent: 1= strongly disagree, 2=disagree, 3=neutral, 4= agree, 5= strongly agree.

We then used Cronbach's alpha coefficient to examine the internal consistency and reliability of our questionnaire. Cronbach's alpha analyzes the numeric coefficient for measuring the consistency of Likert scale items. Computing by R software, Cronbach's alpha of our questionnaire is 0.775, which is above the recommended value of 0.7 for scale robustness [56]. This result indicates that our questionnaire presents good internal consistency.

Comparison with Last.FM. The proportion of the scenarios chosen by the invited 30 users is shown in Table 8. Figure 14 shows the rating results of Last.FM and our system. The result reveals that users usually rate our recommendations with a higher value than Last.FM, especially in the range of 6 to 10. We can find the rating distribution of Last.FM do not like a normal distribution. Last.FM has many lower ratings at value 1 and 2. This might because the recommended results of Last.FM are easy to be dominant by the music genre. Thus if a user usually listen night club music, when he want to listen the music fit to beach, his recommended song will still have lots relations with night club genre. Here we could not use the MAUE, precision, recall, or F1 measures to compare the performance of our system and Last.FM due to the lack of related information about Last.FM. Therefore, we used the average rating as the comparison index. The average of ratings for Last.FM is 6.296 and the average of ratings for our system is 7.4033; this indicates that our system has better recommendations than Last.FM in some specific situations. Music recommendation services including context information are rapidly development and growth. In the future, we will find more similar services to compare with our system and improve our algorithms.

Table 8. The Proportion of users' scenario choices

Scenarios	Numbers	Percentage
Emotion	16	27%
Location	5	8%
Location + Time	19	32%
Emotion + Time	11	18%
Emotion + Location	9	15%

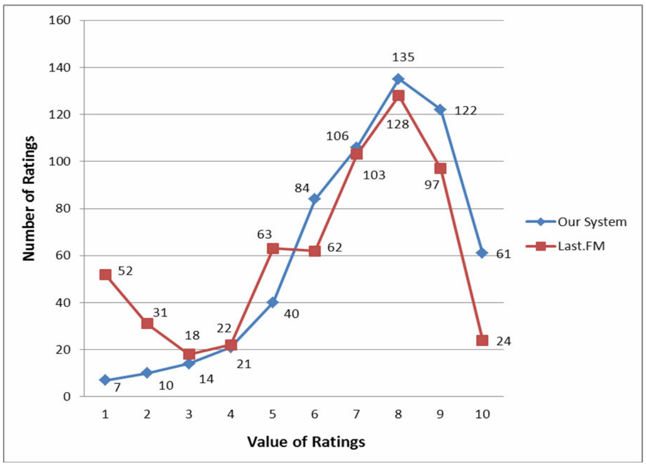

Figure 14. The Distribution of ratings compared with Last.FM

5 Conclusion and Future Works

The approach provided by the general music recommendation system is to recommend a playlist of songs by musical content or users' preferences which may not match users' needs according to their current contextual and emotional information. The aim of this paper was to propose an integrated method for music recommendations that takes context and emotion into consideration. Our context and emotion aware system for personalized music recommendation provides music listeners with a new way to search for music by contextual and emotional information, which most existing MRS do not support. The ultimate goal of this novel system is to integrate people's everyday listening patterns, to enhance the accuracy and users' satisfaction regarding music recommendations. Our contributions are as follows: (1) This paper suggests the direction and method for providing music recommendations. Our system includes contextual and emotional information simultaneously, which was not considered in previous studies. (2) We have verified that emotion and context are important concerns when people listen to music and our system has better accuracy than traditional benchmark methods when the information is combined with a collaborative filtering algorithm. (3) To the best of our knowledge, our music recommender is the first one to transform the nominally contextual and emotional data of music into numeric ones, which can improve the problem of sparse data. (4) To improve the cold start problem, our system will recommend the most common and acceptable music to users during the cold start phase.

For future work, we will pursue the following research directions. (1) For music analysis, we will delve deeper into the relationship between music and emotion, align lyrics with audio, and learn more from users' skipping behavior. These improvements can help our system to enhance the accuracy of recommendations and know more about users' listening behavior. Consequently we can create a more intelligent playlist that matches users' needs. (2) We will integrate our system with portable devices which can automatically obtain the contextual information and detect the user's emotions by his/her body signals. With this improvement, we can provide a real-time music recommendation service based on the automatically detected contextual and emotional information of the user via his/her portable device.

References

[1] G. Adomavicius, A. Tuzhilin, Context-aware Recommender Systems, in: F. Ricci, L. Rokach, B. Shapira, P. B. Kantor (Eds.), *Recommender Systems Handbook*, Springer, 2011, pp. 217-253.

[2] J. Bobadilla, F. Ortega, A. Hernando, A. Gutiérrez, Recommender Systems Survey, *Knowledge-Based Systems*, Vol. 46, pp. 109-132, July, 2013.

[3] I. Cantador, P. Castells, A. Bellogín, An Enhanced Semantic Layer for Hybrid Recommender Systems: Application to News Recommendation, *International Journal on Semantic Web and Information Systems*, Vol. 7, No. 1, pp. 44-78, January, 2011.

[4] C. M. Chen, M. F. Tsai, J. Y. Liu, Y. H. Yang, Using Emotional Context from Article for Contextual Music Recommendation, in *The 21th ACM international conference on Multimedia*, Barcelona, Spain, 2013, pp. 649-652.

[5] C. Hayes, P. Cunningham, Context Boosting Collaborative Recommendations, *Knowledge-Based Systems*, Vol. 17, No. 2-4, pp. 131-138, May, 2004.

[6] M. Kaminskas, F. Ricci, Contextual Music Information Retrieval and Recommendation: State of the Art and Challenges, *Computer Science Review*, Vol. 6, No. 2-3, pp. 89-119, May, 2012.

[7] Y. Song, S. Dixon, M. Pearce, A Survey of Music Recommendation Systems and Future Perspectives, *The 9th International Symposium on Computer Music Modeling and Retrieval*, London, UK, 2012, pp. 395-410.

[8] J. H. Su, H. H. Yeh, P. S. Yu, V. S. Tseng, Music Recommendation Using Content and Context Information mining, *IEEE Intelligent Systems*, Vol. 25, No. 1, pp. 16-26, January-February, 2010.

[9] X. Tian, G. Xu, X. Li, Z. Feng, D. Sun, Personalized Recommendation Based on Information Flow in Data Intensive Services, *Journal of Internet Technology*, Vol. 14, No. 5, pp. 825-834, September, 2013.

[10] C. Y. Wang, Y. H. Wu, S. T. Chou, Toward a Ubiquitous

Personalized Daily-life Activity Recommendation Service with Contextual Information: A Services Science Perspective, *Information Systems and e-Business Management*, Vol. 8, No. 1, pp. 13-32, January, 2010.

[11] X. Wang, D. Rosenblum, Y. Wang, Context-aware Mobile Music Recommendation for Daily Activities, *The 20th ACM international conference on Multimedia*, Nara, Japan, 2012, pp. 99-108.

[12] M. Schedl, G. Widmer, P. Knees, T. Pohle, A Music Information System Automatically Generated via Web Content Mining Techniques, *Information Processing & Management*, Vol. 47, No. 3, pp. 426-439, May, 2011.

[13] C. W. Choo, B. Detlor, D. Turnbull, A Behavioral Model of Information Seeking on the Web: Preliminary Results of a Study of How Managers and IT Specialists Use the Web, *The 61st Annual Meeting of the American Society for Information Science*, Pittsburgh, 1998, pp. 290-302.

[14] N. Godbold, Beyond Information Seeking: Towards a General model of Information Behavior, *Information Research*, Vol. 11, No. 4, p. 269, July, 2006.

[15] K. E. Pettigrew, R. Fidel, H. Bruce, Conceptual Frameworks in Information Behavior, *Annual Review of Information Science and Technology*, Vol. 35, pp. 43-78, 2001.

[16] J. D. Johnson, An Impressionistic Mapping of Information Behavior with Special Attention to Contexts, Rationality and ignorance, *Information Processing and Management*, Vol. 45, No. 5, pp. 593-604, September, 2009.

[17] J. R. Bettman, E. J. Johnson, J. W. Payne, Consumer Decision Making, T. Robertson, H. Kassarjian (Eds.), in: *Handbook of consumer behavior*, Prentice-Hall, 1991, pp. 50-84.

[18] N. M. Klein, M. S. Yadav, Context Effects on Effort and Accuracy in Choice: An Enquiry into Adaptive Decision Making, *Journal of Consumer Research*, Vol. 15, No. 4, pp. 411-421, March, 1989.

[19] W. P. Lee, C. Kaoli, J. Y. Huang, A Smart TV System with Body-gesture Control, Tag-based Rating and Context-aware Recommendation, *Knowledge-Based Systems*, Vol. 56, pp. 167-178, January, 2014.

[20] H. Liu, P. Singh, ConceptNet: A Practical Commonsense Reasoning Took-kit, *BT Technology Journal*, Vol. 22, No. 4, pp. 211-226, October, 2004.

[21] N. Lv, L. Qin, J. H. Park, J. Zhou, Y. Mao, Using Contextual Information to Assist Desktop Search, *Journal of Internet Technology*, Vol. 14, No.3, pp. 517-528, May, 2013.

[22] D. Vallet, P. Castells, M. Fernandez, P. Mylonas, Y. Avrithis, Personalized Content Retrieval in Context Using Ontological Knowledge, *IEEE Transactions on Circuits and Systems for Video Technology*, Vol. 17, No. 3, pp. 336-346, March, 2007.

[23] L. Zhang, C. Qing, Hybrid-Context-Aware Web Service Selection Approach, *Journal of Internet Technology*, Vol. 14, No. 1, pp.57-69, January, 2013.

[24] R. P. Bagozzi, M. Gopinath, P. U. Nyer, The Role of Emotions in Marketing, *Journal of the Academy of Marketing Science*, Vol. 27, No. 2, pp. 184-206, April, 1999.

[25] I. Lopatovska, I. Arapakis, Theories, Methods and Current Research on Emotions in Library and Information Science, Information Retrieval and Human-computer Interaction, *Information Processing & Management*, Vol. 47, No. 4, pp. 575-592, July, 2011.

[26] S. Brave, C. Nass, Emotion in Human–computer interaction, in: J. Jacko, A. Sears (Eds.), *Handbook of Human–Computer Interaction*, Lawrence Erlbaum Associates, 2003, pp. 81-96.

[27] R. W. Picard, E. Vyzas, J. Healey, Toward Machine Emotional Intelligence: Analysis of Affective Physiological State, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 23, No. 10, pp. 1175-1191, October, 2001.

[28] B. J. Han, S. Rho, S. Jun, E. Hwang, Music Emotion Classification and Context-based Music Recommendation, *Multimedia Tools and Applications*, Vol. 47, No. 3, pp. 433-460, May, 2010.

[29] P. Korpipää, M. Koskinen, J. Peltola, S. M. Mäkelä, T. Seppänen, Bayesian Approach to Sensor-based Context Awareness, *Personal and Ubiquitous Computing*, Vol. 7, No. 2, pp. 113-124, July, 2003.

[30] E. Horvitz, C. Kadie, T. Paek, D. Hovel, Models of Attention in Computing and Communication: From Principles to Applications, *Communications of the ACM*, Vol. 46, No. 3, pp. 52-59, March, 2003.

[31] L. Gong, Can web-based Recommendation Systems Afford Deep Models: A Context-based Approach for Efficient Model-based Reasoning, *The 13th international World Wide Web Conference on Alternate Track Papers & Posters*, New York, NY, 2004, pp. 89-93.

[32] G. Adomavicius, R. Sankaranarayanan, S. Sen, A. Tuzhilin, Incorporating Contextual Information in Recommender Systems Using a Multidimensional Approach, *ACM Transactions on Information Systsems*, Vol. 23, No. 1, pp. 103-145, January, 2005.

[33] T. Naganuma, M. Luther, M. Wagner, A. Tomioka, K. Fujii, Y. Fukazawa, S. Kurakake, Task-oriented Mobile Service Recommendation Enhanced by a Situational Reasoning Engine, in: R. Mizoguchi, Z. Shi, F. Giunchiglia (Eds.), *The Semantic Web – ASWC 2006, ASWC 2006, Lecture Notes in Computer Science*, Vol. 4185, Springer, pp. 768-774, 2006.

[34] J. H. Kim, C. W. Song, K. W. Lim, J. H. Lee, Design of Music Recommendation System Using Context Information, in: Z. Z. Shi, R. Sadananda (Eds.), *Agent Computing and Multi-Agent Systems, PRIMA 2006, Lecture Notes in Computer Science*, Vol. 4088, Springer, pp. 708-713, 2006.

[35] H. S. Park, J. O. Yoo, S. B. Cho, A Context-aware Music Recommendation System Using Fuzzy Bayesian Networks with Utility Theory, in: L. Wang, L. Jiao, G. Shi, X. Li, J. Liu (Eds.), *Fuzzy Systems and Knowledge Discovery, FSKD 2006, Lecture Notes in Computer Science*, Vol. 4223, Springer, Berlin, Heidelberg, pp. 970-979, 2006.

[36] A. Mehrabian, Pleasure-arousal-dominance: A General Framework for Describing and Measuring Individual Differences in Temperament, *Current Psychology*, Vol. 14, No. 4, pp. 261-292, December, 1996.

[37] K. Hevner, Experimental Studies of the Elements of Expression in Music, *The American Journal of Psychology*, Vol. 48, No. 2, pp. 246-248, April, 1936.

[38] K. Hevner, The Affective Value of Pitch and Tempo in Music, *The American Journal of Psychology*, Vol. 49, No. 4, pp. 621-630, October, 1937.

[39] O. C. Meyers, *A Mood-based Music Classification and Exploration System*, MSc Thesis, Massachusetts Institute of Technology, Cambridge, CA, 2007.

[40] J. A. Russell, A Circumplex Model of Affect, *Journal of Personality and Social Psychology*, Vol. 39, No. 6, pp. 1161-1178, December, 1980.

[41] M. Cafarella, D. Cutting, Building Nutch: Open Source Search, *Queue*, Vol. 2, No. 2, pp. 54-61, April, 2004.

[42] L. Srinivasan, J. Treadwell, *An Overview of Service-Oriented Architecture, Web Services and Grid Computing*, HP Software Global Business Unit, 2005.

[43] H. Liu, P. Singh, Commonsense Reasoning in and over Natural Language, *The 8th International Conference on Knowledge-Based Intelligent Information & Engineering Systems*, Wellington, New Zealand, 2004, pp. 293-306.

[44] R. Burke, Hybrid Recommender Systems: Survey and Experiments, *User Modeling and User-Adapted Interaction*, Vol. 12, No. 4, pp. 331-370, November, 2002.

[45] U. Shardanand, P. Maes, Social Information Filtering: Algorithms for Automating "Word of Mouth", *The SIGCHI Conference on Human Factors in Computing Systems*, Denver, Colorado, 1995, pp. 210-217.

[46] G. Shani, A. Gunawardana, Evaluating Recommendation Systems, in: F. Ricci, L. Rokach, B. Shapira, P. B. Kantor (Eds.), *Recommender Systems Handbook*, Springer, 2011, pp. 257-297.

[47] G. Adomavicius, A. Tuzhilin, Towards the Next Generation of Recommender Systems: A Survey of the State-of-the-art and Possible Extensions, *IEEE Transactions on Knowledge and Data Engineering*, Vol. 17, No. 6, pp. 734-749, June, 2005.

[48] P. Massa, P. Avesani, Trust-aware Recommender Systems, *The 1st ACM Conference on Recommender Systems*, Minneapolis, MN, 2007, pp. 17-24.

[49] M. Buckland, F. Gey, The Relationship between Recall and Precision, *Journal of the American Society for Information Science*, Vol. 45, No. 1, pp. 12-19, Janauary, 1994.

[50] O. Celma, *Music Recommendation and Discovery: The Long Tail, Long Fail, and Long Play in the Digital Music Space*, Springer-Verlag Berlin Heidelberg, 2010.

[51] G. Salton, M. J. McGill, *Introduction to Modern Information Retrieval*, McGraw-Hill, 1986.

[52] C. J. Van Rijsbergen, *Information Retrieval*, Butterworth, 1979.

[53] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, J. Riedl, GroupLens: An Open Architecture for Collaborative Filtering of Netnews, *The International ACM Conference on Computer Supported Cooperative Work*, Chapel Hill, North Carolina, 1994, pp. 175-186.

[54] B. Sarwar, G. Karypis, J. Konstan, J. Riedl, Item-based Collaborative Filtering Recommendation Algorithms, *The 10th International Conference on World Wide Web Conference*, Hong Kong, China, 2001, pp. 285-295.

[55] J. Han, M. Kamber, *Data Mining: Concepts and Techniques*, 2nd ed., Morgan Kaufmann, 2006.

[56] J. C. Nunnally, *Psychometric Theory*, 2nd ed., McGraw-Hill, 1978.

Biographies

Chen-Ya Wang is an Assistant Professor in the Department of Management & Information, National Open University. She received her Ph.D. in Information Management from the National Taiwan University. She has worked as a system analyst and product manager. Her current research interests are user behavior, service innovation, electronic commerce, recommendation systems, data analytics, and knowledge management.

Yu-Chi Wang received his M.S. in Information Management from the National Taiwan University. He current works as a business consultant to deliver the value of information technology to fields.

Seng-Cho T. Chou is a Professor in Information Management at National Taiwan University. He received his B.Sc. from the Chinese University of Hong Kong, M.S. from the University of California, and Ph.D. in Computer Science from the University of Illinois at Urbana-Champaign. His current research interests are Web technologies and service innovation, information & knowledge management, and data analytics.