

# Music recommendation hybrid system for improving recognition ability using collaborative filtering and impression words

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**Abstract:** Music therapy for improving recognition ability may be more effective when the favorite music of each person is adopted. In the proposed system, first, the recommendation process using collaborative filtering is terminated when no users in the reference list have the same preference of recommended music as that of a new user. Then, the second recommendation process finds the most similar music, from the scores for impression words, to those successfully recommended among music not recommended up to the moment. The average number of recommended songs for each user by the proposed system was 12.1, whereas that of collaborative filtering was 4.3. The recommendation accuracy of the proposed system was 70.2%, whereas that of collaborative filtering was 62.1%. The ratings of songs can be added on a user-by-user basis in the recommendation process, and this increased number of cases improves the recommendation accuracy and increases the number of recommended songs.

**Keywords:** Collaborative filtering, Music recommendation, Music therapy, Impression word, and Recognition ability.

## 1 INTRODUCTION

In Japan, the average age of the population has been increasing, and this trend is expected to continue. Recently, music therapy has been used for improving the recognition ability of people, particularly older people. Music therapy may be more effective when the favorite music of each person is adopted. We have been developing music recommendation methods aimed at improving recognition ability [1]. However, it is not easy to recommend much music to a user using the initially developed method. To overcome this difficulty, we proposed a music recommendation method that combines collaborative filtering and our initial music recommendation process based on impression words [2].

For this study, we further improved the method reported in [2] by adding a function that adds the ratings of songs on a user-by-user basis in the recommendation process to increase both the recommendation accuracy and the number of recommended songs by increasing the number of cases. We implemented the updated method on a personal computer and evaluated the proposed system by using children's songs, which tend to be familiar to older people.

## 2 MUSIC RECOMMENDATION METHOD USING IMPRESSION WORDS

We use ten pairs of impression words (Table 1) [3]. As an example, we show the user scores for one pair of impression

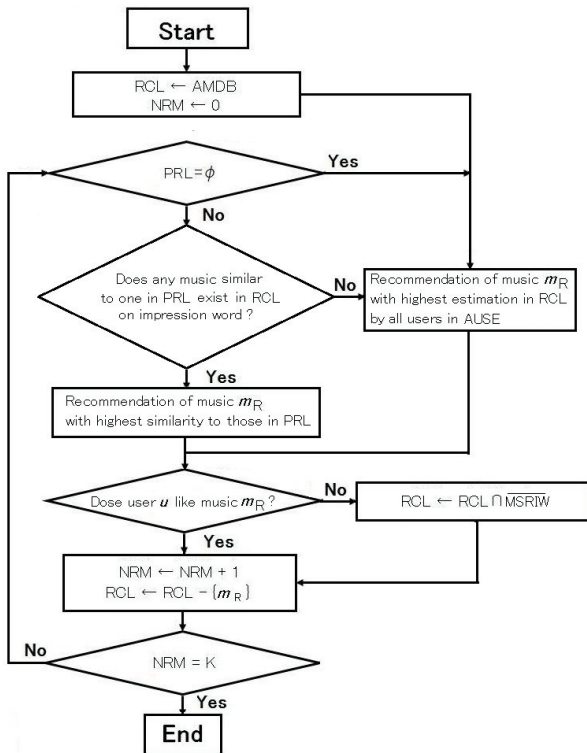
words (quiet - busy). A user scores the word pairs according to seven levels, which are then transformed to three levels, as shown in Table 2 [2]. In a music database, 52 songs were assigned scores  $i$  ( $-3 \leq i \leq 3$ ) for each pair of impression words evaluated by the participants. Fig. 1 shows a flowchart of the music recommendation based on impression words. When music not recommended to a user has the same values except "0" as that for at least one recommended music having a high evaluation by the user on the three-level score for at least five impression words, the music is treated as having a positive evaluation by the user. In contrast, when music not recommended to the user has the same scores except "0" as that for another music just recommended to the user and having a negative evaluation by the user on the

**Table 1.** Pairs of impression words [3]

quiet - busy
bracing - heavy
easy - uneasy
cheerful - gloomy
refreshing - depressing
happy - sad
comforting - harmful
calm - elevating
clean - dirty
magnificent - superficial

**Table 2.** Scores for pairs of impression words quiet – busy [2]

Score	Three-level score	impression
3	-1	very busy
2		busy
1	0	slightly busy
0		neutral
-1		slightly quiet
-2	1	quiet
-3		very quiet



**Abbreviations ;**

- AMDB : set of all music in data base
- RCL : set of music in recommendation candidate list
- AUSE : set of all users with subjective estimation
- NRM : number of recommended music
- PRL : set of music having 3.5 or higher than 3.5 of score given by user *u* in AMDB ∩ RCL
- MSRIW : set of music having similarity to recommended music *m<sub>R</sub>* on impression words

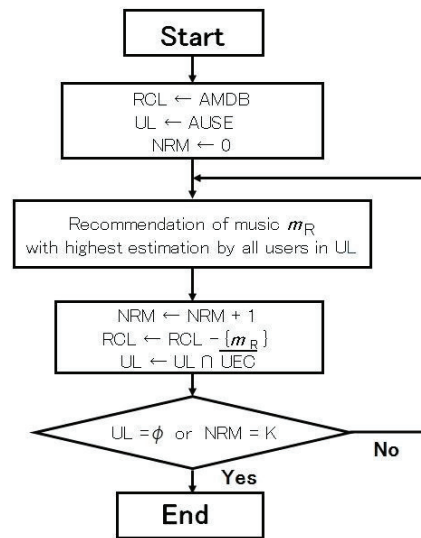
**Fig. 1.** Flowchart of music recommendation by using impression words [2]

three-level score for at least seven impression words, the music is treated as having a negative evaluation by the user. In Fig. 1, when none of the not recommended music receives a positive evaluation by the user, another recommendation is performed by using the subjective estimations of all users whose subjective estimations are stored in the database. It is expressed by “with highest similarity” in Fig. 1 that the music has the highest

proportion of the same three-level scores except “0” as that of other music recommended to the user and given a positive evaluation by the user among the music not yet recommended to the user. In Fig. 1, the “set of music with a similarity to the recommended music based on impression words” (MSRIW) is decided by using at least seven pairs of impression words in the case of a negative evaluation.

**3 PROPOSED SYSTEM**

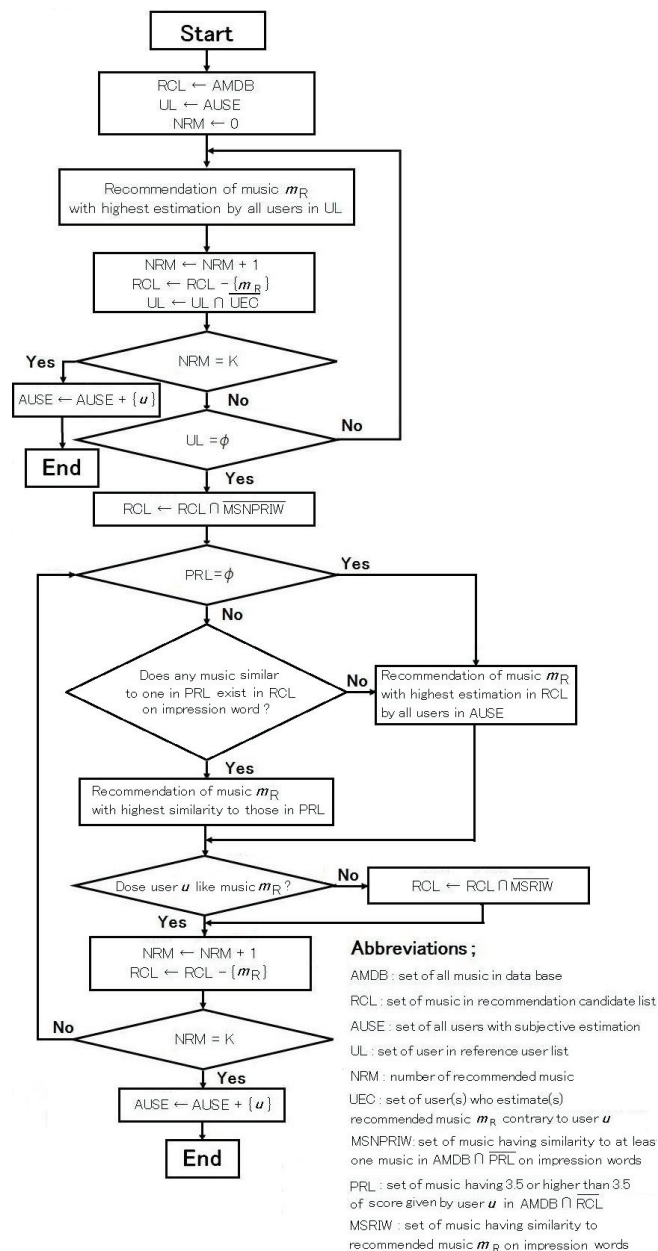
Figs. 2 and 3 show two music recommendation methods. Method 1 (Fig. 2) is collaborative filtering only, and Method 2 (Fig. 3) is the proposed system, which combines collaborative filtering and our music recommendation process based on impression words. In the proposed system, the recommendation process using collaborative filtering is terminated when the number of users is zero in the reference list of users showing exactly the same evaluation for the recommended music as that of the user up to that moment. Then, the recommendation process performs by finding out the most similar music, from the viewpoints of three-level scores except “0” on impression words, to that successfully recommended among music not yet recommended. The proposed system recommends music stored in the database to user *u*, as shown in Fig. 3. Both



**Abbreviations ;**

- AMDB : set of all music in data base
- RCL : set of music in recommendation candidate list
- AUSE : set of all users with subjective estimation
- UL : set of user in reference user list
- NRM : number of recommended music
- UEC : set of user(s) who estimate(s) recommended music *m<sub>R</sub>* contrary to user *u*

**Fig. 2.** Flowchart of music recommendation by collaborative filtering [2]



**Fig. 3.** Flowchart of music recommendation used in the proposed system

the recommendation process using collaborative filtering and that using the proposed system are terminated when the number of recommended songs reaches the upper limit  $K$ , decided previously. Just before finishing the recommendation process, the database of users with subjective estimations of the music is updated by adding the subjective estimations of the user for whom the proposed system recommends music.

In the flowcharts of Method 1 and Method 2 shown in Figs. 2 and 3, respectively, the estimation of user  $u$  for song  $m_R$  is set as 1 when the score of user  $u$  for song  $m_R$  is 4 or 5 (“slightly favorite” or “favorite”), and it is set

as 0 when the score is 1 to 3 (“dislike,” “slightly dislike,” or “neutral”).

For programming, we used Visual C++ 6.0 (Microsoft) on a PC (Dell Latitude E6599, CPU: Intel Core 2 Duo P8700 2.54 GHz, main memory: 4.00 GB, and OS: Windows 7, Microsoft) for the experiment.

## 4 PERFORMANCE EVALUATION

### 4.1 Conditions

Because older people tend to prefer children’s songs [4], we selected a CD described as an anthology of older songs enjoyed by older people with dementia [5], and then we selected 52 songs on the CD that were also included in a music textbook database for elementary schools [6]. To evaluate the music recommendation methods, all 52 of the selected songs in the database were assigned scores  $s$  ( $1 \leq s \leq 5$ ) by 12 users of different ages (teens: 1, twenties: 6, fifties: 5). For evaluating the proposed system, we chose each of the 12 users as user  $u$  and put the remaining users in the reference user list UL described in Fig. 3. Thus, each user was user  $u$  one time and in the reference list 11 times. We used 15 as the value of  $K$  in the evaluations of both Method 1 and Method 2. In addition, all 52 of the selected songs in the database were assigned scores  $i$  ( $-3 \leq i \leq 3$ ) for each pair of impression words by five subjects of different ages (twenties: 3, forties: 1, fifties: 1). Of the five subjects, the one who was in his fifties was also one of the users who assigned scores  $s$ . The average of scores  $i$  obtained from the five subjects for each pair of impression words was used as scores  $i$  for the performance evaluation. The 15 songs having the values except “0” as the three-level score for one impression word at most were not recommended in the process of recommendation based on impression words because they did not have distinct characteristics from the viewpoints of impression words.

Then, we obtained the result of the music recommendation for each new user for each method described in Section 3. To evaluate the two music recommendation methods described in Section 3, 10 new users (user Nos. 1 to 10) participated in the experiment without the updating of the AUSE, which is the set of all users with subjective estimations in Fig. 3, just before finishing the recommendation process, and then one user who had the worst accuracy of recommendation among the new 10 users was selected for additional recommendations with the updating of the AUSE. Moreover, 14 older users,

Nos. 11 to 24 of different ages (seventies: 2, eighties: 8, nineties: 4) participated in the experiment with the user-by-user updating for the AUSE.

#### 4.2 Results and discussions

The number of recommended songs for users previously registered in the AUSE by the proposed system was 15 per user. In this case, the recommendation process by collaborative filtering was not terminated because the number of users staying in the UL did not become zero. Therefore, the proposed system recommended the most songs under the condition that the upper limit  $K$  of recommended songs was 15. The mean value of the recommendation accuracy of the proposed system was 93.9%, whereas that of the random recommendation (i.e., not using Method 1 and/or Method 2) was 47.9%.

As an example, Table 3 shows the process of the music recommendation for user No. 8. As shown in Table 3, Method 2 tended to recommend more music than did Method 1.

**Table 3.** Music recommendation process for user No. 8

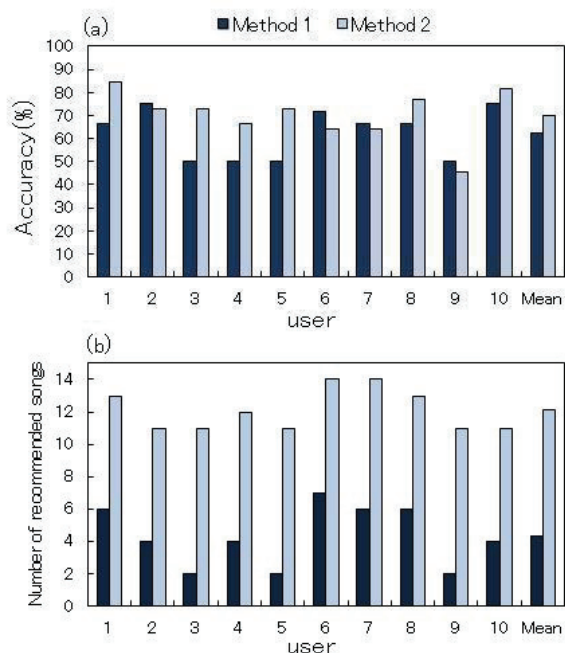
**[Method 1]**

Order	Recommended music No.	Acceptance	User No. in UL
1	52	○	1,2,3,4,5,7,8,9,10,11,12
2	41	○	1,2,3,4,5,7,8,9,10,11,12
3	50	○	1,2,3,4,5,7,8,9,10, 12
4	21	○	1,2,3,4,5,7,8,9,10, 12
5	26	×	12
6	23	×	none

**[Method 2]**

Order	Recommended music No.	Acceptance	User No. in UL
1~6	Same as Method 1		
7	5	○	/
8	17	○	
9	36	○	
10	43	×	
11	18	○	
12	13	○	
13	6	○	

Fig. 4 shows the performance of the two methods in the experiment, where updating of the AUSE was not performed in the proposed system. The mean value of the number of recommended songs by Method 2 in the



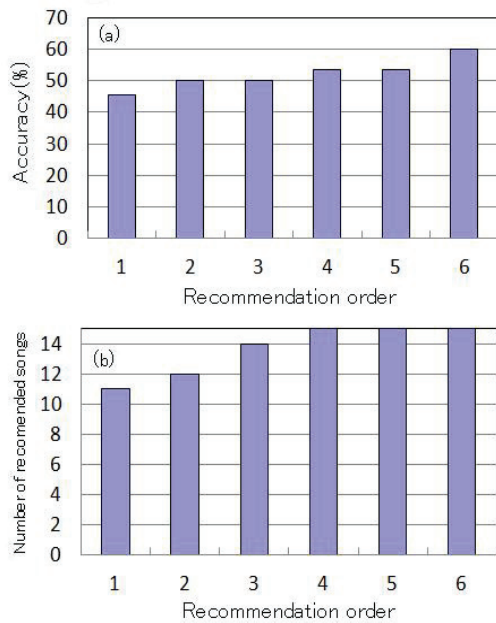
**Fig. 4.** Performance of music recommendation methods:

- (a) recommendation accuracy,
- (b) number of recommended songs

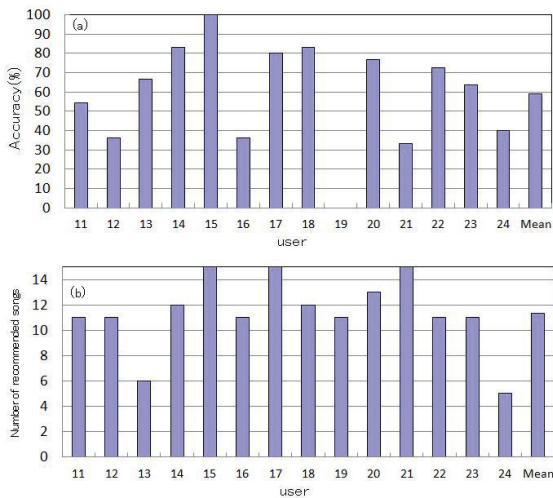
proposed system was 12.1 per user, whereas that of only collaborative filtering (Method 1) was 4.3 per user. The mean value of the recommendation accuracy of the proposed system was 70.2%, whereas that of only collaborative filtering was 62.1%. In the collaborative filtering (Method 1), the recommendation process was terminated because the number of users staying in the UL became zero. In contrast, in Method 2, the recommendation process was performed while the recommendation using the impression words was possible under the condition shown in Fig.3. As compared with only using the collaborative filtering (Method 1), we could increase the number of recommended songs while achieving a better accuracy of the recommendation than with Method 1 by combining the recommendation based on the impression words with the collaborative filtering.

Fig. 5 shows the effect of updating the AUSE for user No. 9. By updating the AUSE, the accuracy of the recommendation improved (Fig. 5(a)) and the number of recommended songs also increased (Fig. 5(b)).

Fig. 6 shows the performance of the proposed system, with the updating of the AUSE for users Nos. 11 to 24. User No. 19 stated that he disliked all children's songs. As a result, the accuracy of the recommendation was 0% for user No. 19. The mean value of the number of recommended songs for users Nos. 11 to 24 was 11.4 per user. The mean



**Fig. 5.** Effect of updating the AUSE using user No. 9:  
 (a) recommendation accuracy,  
 (b) number of recommended songs



**Fig. 6.** Performance of the proposed system:  
 (a) recommendation accuracy,  
 (b) number of recommended songs

value of the recommendation accuracy for users Nos. 11 to 24 was 59.1%, whereas that without user No. 19 was 63.6%.

The mean value of the recommendation accuracy of the proposed system was 93.9% for users previously registered in the AUSE. Moreover, updating of the AUSE was effective for both the improved accuracy of the recommendation and the increase in the number of recommended songs. Therefore, to improve the performance of the proposed system, we should use the proposed system with updating of the AUSE for more

people, particularly those who are older and/or have a cognitive impairment.

## 5 CONCLUSION

We propose a music recommendation system that combines collaborative filtering and music recommendation based on impression words. We showed that the proposed system was more effective for music recommendation than the system of only collaborative filtering when used on a music database composed of children's songs. The function by which the ratings of songs can be added on a user-by-user basis in the recommendation process was effective for both improving the accuracy of the recommendation and increasing the number of recommended songs.

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