Comparison of Emoticon Recommendation Methods to Improve Computer-Mediated Communication

Yuki Urabe, Rafal Rzepka and Kenji Araki

Abstract This paper describes the development of an emoticon recommendation system based on users' emotional statements. In order to develop this system, an innovative emoticon database consisting of a table of emoticons with points expressed from each of 10 distinctive emotions was created. An evaluation experiment showed that our proposed system achieved an improvement of 28.1 points over a baseline system, which recommends emoticons based on users' past emoticon selection. We also integrated the proposed and baseline systems, leading to a performance improvement of approximately 73.0 % in the same experiment. Evaluation of respondents' perceptions of the three systems utilizing an SD scale and factor analysis is also described in this paper.

Keywords Emoticon · Affect analysis · Recommendation method · Smartphone application

Y. Urabe (✉) · R. Rzepka · K. Araki
Hokkaido University, Graduate School of Information Science and Technology, Sapporo, Japan
e-mail: y_urabe@media.eng.hokudai.ac.jp

R. Rzepka
e-mail: rzepka@ist.hokudai.ac.jp

K. Araki
e-mail: araki@ist.hokudai.ac.jp

Ö. Ulusoy et al. (eds.), *Recommendation and Search in Social Networks*, Lecture Notes in Social Networks, DOI 10.1007/978-3-319-14379-8_2

1 Introduction

Social Network Services (SNS) have grown rapidly throughout the world, such as Facebook[1] and Twitter,[2] which now handle 1.19 billion[3] and 232 million[4] monthly active users, respectively. Such services have dramatically increased social user interaction on the Internet in comparison to the days when only email and online chatting systems existed. However, due to a lack of nonverbal cues such as facial expressions, body movements, and emotional tones, computer-mediated communication (CMC) often fails to present personal dispositions that are transparently expressed in face-to-face communication. These nonverbal cues account for about 93 % of our daily communication [1], a fact that we should not ignore. Hence, users compensate for these shortcomings by using emoticons.

Emoticons are composed of letters and symbols and represent facial marks or movements. These emoticons can be divided into two styles: a horizontal style (e.g., "(^ _ ^)") and a vertical style (e.g., ":)"). The horizontal style is especially popular in Asian countries such as Japan, South Korea, and China, while the vertical style is mainly used in Western countries [2]. The number of emoticons in the horizontal style is increasing day by day, so much that a Japanese online emoticon dictionary [5] now includes more than 58,000 different types of emoticons, while the vertical type only consists of around 260 emoticons. These emoticons are sophisticated enough to express users' feelings and intentions in CMC; therefore, they are added to sentences in order to express intentions that cannot be expressed by words alone, to enhance the sentence and to express sarcasm and humor [3, 4]. Users insert emoticons by creating them on their own using keypads and keyboards, copying and pasting from online emoticon dictionaries or from emoticon dictionaries installed in devices like smartphones. However, these approaches are not efficient, because many symbols and letters are not simple to type. For example, 58,000 emoticons described in the previous paragraph contain only about 23.6 % of letters and symbols that can be entered from a computer keyboard. Also, choosing one emoticon from emoticon dictionaries that contain hundreds or thousands of emoticons is extremely inconvenient. In order to solve these problems, we propose an emoticon recommendation method that recommends emoticons according to an emotion type analyzed from users' statements. As Kato et al. [5] demonstrated in his research that emoticons are chosen depending on the valence of input (i.e., positive emoticons are chosen with positive contexts, and vice versa), we believe that recommending emoticons depending on the emotion type of the input would be very useful to users.

---

[1] https://www.facebook.com/.

[2] https://twitter.com/.

[3] http://thenextweb.com/facebook/2013/10/30/facebook-passes-1-19-billion-monthly-active-users-874-million-mobile-users-728-million-daily-users/, retrieved on Nov. 25, 2013.

[4] http://www.businessinsider.com/one-half-of-twitters-active-users-tweet-monthly-2013-11, retrieved on Nov. 25, 2013.

[5] http://www.kaomoji.sakura.ne.jp/, retrieved on Nov. 25, 2013.

Our proposed system utilizes two main features: an affect analysis system, ML-Ask [6], and an originally created emoticon database. Our emoticon database contains 59 emoticons, each emoticon showing the extent of each of 10 distinctive emotions (joy/delight, anger, excitement, sadness/gloom, fear, fondness/liking, relief, shyness, surprise/amazement, dislike) on a 5-point scale. We performed a comparison experiment of our proposed method and a baseline method used in the Japanese keypad in iOS. The baseline method recommends emoticons according to the user's past selections. An experiment proved that participants chose emoticons that were among the top five of those recommended by our proposed system, at 28.1 points higher than that of the baseline system. Also, the result was improved to approximately 73.0 % (an improvement of 43.5 points over the baseline method) in the same experiment when we integrated both methods. We also discovered that users' attitudes toward the integrated system and the proposed system were more positive than the baseline system, by conducting evaluation using the semantic differential (SD) method and factor analysis.

2 Related Works

In the field of sentiment analysis, Ptaszynski et al. [7] created an affect analysis system for emoticons: "CAO". "CAO" extracts an emoticon from a sentence and analyzes the specific emotion type according to the theory of kinesics. This system is capable of analyzing more than three million emoticons. Additionally, Emura and Seki [8] proposed an emoticon recommendation method based on the estimation of emotions, communication types, and action types written by users. This research revealed the importance of recommending emoticons according to not only the emotion type provided by the input but also communication types (e.g., greetings and gratitude), and action (e.g., sleep, run, etc.), achieving 66.7 % suitable emoticon recommendations to users. The emoticons in the databases of these systems were gathered from online dictionaries, wherein emoticons are categorized to certain emotion types by administrators, but it has not yet been assessed whether these express the correct emotion types. Meanwhile, Kawakami [9] created an emoticon database which is numerically categorized according to certain emotion types. Kawakami concentrated on how much an emoticon expresses each emotion and investigated how much the emotion emphasizes the sentence. The research revealed that some emoticons express plural emotion types strongly.

In order to create an emoticon database for our proposed system, we employed Kawakami's [9] work in order to develop a more accurate emoticon recommendation system. Creating a database of emoticons showing a numerical expression of each emotion could be a step toward the creation of a system that can recommend emoticons that express the users' complicated emotional state.

3 Emoticon Recommendation Method

The system utilizes two main procedures (Fig. 1). First, the system analyzes the emotion in the user input. We used an affect analysis system, ML-Ask [6] (More details of the ML-Ask are described on 3.1). Second, the system rearranges the emoticon database in the order of suitability to the emotion specified by ML-Ask and recommends the emoticons from top of the list to the user. We created the emoticon database originally by performing a survey of 60 Japanese university students. Next, the user chooses an emoticon that matches the input (the system accordingly registers the frequency of the chosen emoticon in the database, incrementing by one each time an emoticon is selected). Lastly, the system inserts the emoticon right after the input. We implemented the procedure on the iPhone (iOS 7.0) (Fig. 2).

3.1 ML-Ask

Ptaszynski et al. [6] developed ML-Ask for analyzing emotions from Japanese texts. ML-Ask separates emotive utterances from nonemotive utterances and determines the specific emotion types in the emotive utterances. This system is able to specify 10 distinctive emotion types as defined by Nakamura [10]. These are: joy/delight, anger, excitement, sadness/gloom, liking/fondness, fear, relief, dislike, surprise/amazement, and shyness. Our emoticon recommendation method utilizes the result of the emotion types obtained from ML-Ask and reorders the emoticon database.

The values shown in Fig. 3 are averages of ratings given by 60 Japanese university students from the previous work presented in [11]. Students were asked to rate 59 emoticons according to each of 10 distinctive emotion types on a 5-point scale. Figure 4 shows an example rating. From the total ratings, we found that 35 out of 59 emoticons express plural emotion types. Figure 5 shows the number of emoticons

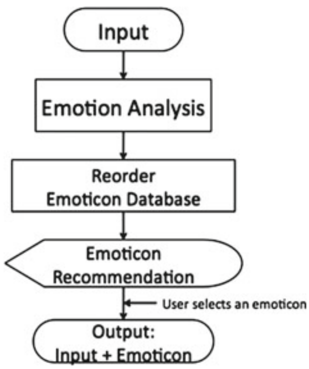

Fig. 1 System procedure

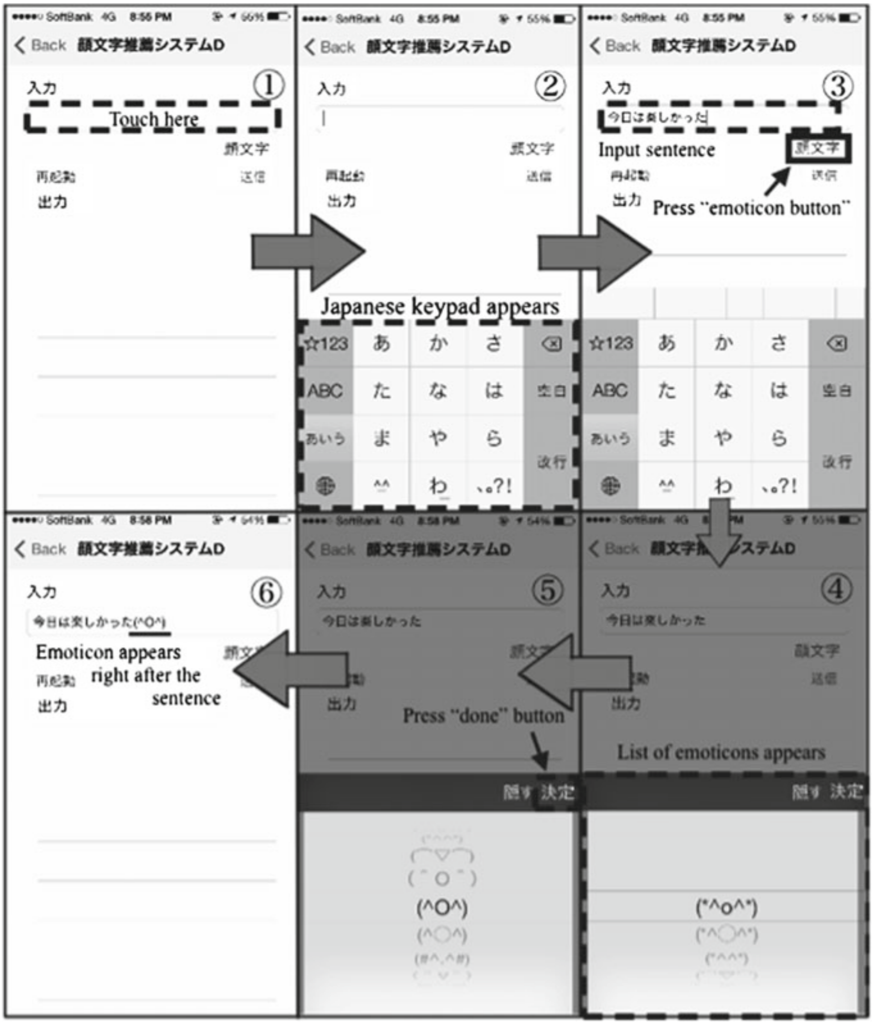

Fig. 2 Application procedure (Device: iPhone 5S, iOS 7.0.4). 1. Touch the *squared* area (①). 2. Japanese keyboard appears (②). 3. Input sentence and press “emoticon button” (③). 4. List of emoticons appears (④). 5. After choosing an emoticon, press the “done” button (⑤). 6. The emoticon is inserted right after the sentence (⑥)

that scored more than 3.0 for each of the 10 emotion types. As can be seen in Fig. 5, the number of emoticons expressing positive emotions (joy/delight, fondness/liking, and relief) was much more than other emotion types. From this result, we can assume that there are many more symbols and letters which can be used to create positive facial expressions than negative ones.

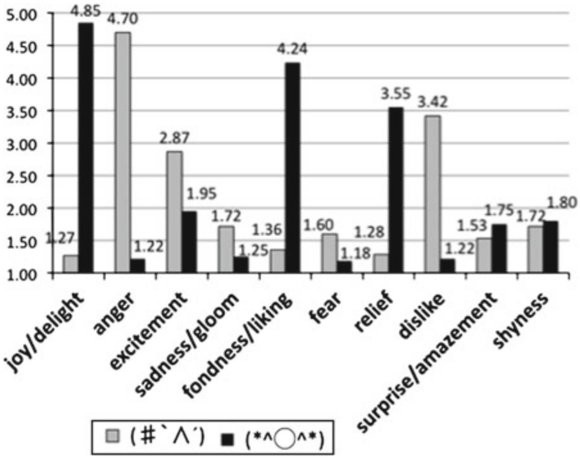

Fig. 3 Example of average rated values for two emoticons. Bars colored in *gray* and *black* are an average of rating of (#‘ ∧ ’) and (* ^ ◯ ^ *), respectively

Fig. 4 Example of emoticon ratings in each of the 10 emotions

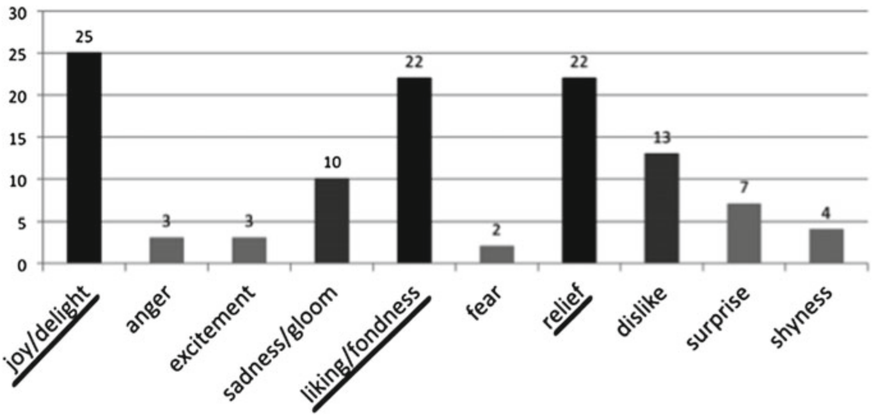

Fig. 5 Number of emoticons rated more than 3.0 for each emotion type

3.2 Integrating Proposed and Baseline Methods

The baseline method and the proposed method have their own advantages in recommending emoticons to users. The baseline method, currently used in the Japanese keypad in iOS, is useful in recommending emoticons that users choose frequently. On the other hand, the proposed method is capable of recommending emoticons according to the emotion type of the content. Therefore, we integrated the proposed and the baseline methods to use the benefits of both. The process of our integrated system is as follows: first, the system utilizes ML-Ask to analyze the emotion type of the input. Then, it sorts the selection frequency of the emoticons according to the emotion type estimated by ML-Ask, and then by the emoticon points for the emotion type. This system first collects emoticons that express similar emotions based on the input and especially considers users' emoticon preferences, so we anticipate that it may be a more user-friendly system than the two aforementioned systems.

4 Determining the Optimal Emoticon Recommendation Method

We compared the proposed method, the baseline method, and the integrated method. In order to exclude any differences in operation, we designed an application for the baseline method and the integrated method with the same operation as the proposed method (Fig. 2). These applications are usable on the iPhone (from iOS 7.0 to the latest at the time of writing). The device we used for the experiment was the iPhone 5S (iOS 7.0.4) due to its compatibility with the latest iOS at the time of writing. The experiment was carried out over 8 days from October 31, 2013 to November 8, 2013 with the cooperation of 30 Japanese undergraduate and master's students. We investigated the efficiency and user impressions of each system from (a) the ratio of emoticons chosen among the top five recommendations, (b) evaluation using the semantic differential (SD) scale and factor analysis, and by (c) asking the participants to rank the three systems based on the systems' performance and the participant's preferences for each system.

4.1 Semantic Differential Scale

The semantic differential (SD) scale was designed by Osgood et al. [12] in order to investigate user attitudes toward an object (e.g., a system, place, etc.). Briefly, the SD scale utilizes a number of scales consisting of polar opposite words such as "good–bad," "strong–weak," and "active–passive" to differentiate the meaning of concepts. Our experiment employed the SD scale with 22 bipolar words (Table 1) and the subjects' perceptions quantified on a 7-point scale. We determined the bipolar words based on our past research [11].

Table 1 22 bipolar word pairs

22 image-word pairs (translated from Japanese used in experiment)
Boring–Fun, Not impressive–Impressive, Unfriendly–Friendly
Difficult to use–Easy to use, Slow–Fast, Inconvenient–Convenient
Unnecessary–Necessary, Heavy–Light, Obscure–Clear, Dislike–Like
Old–New, Complicated–Simple, Not interested–Interested
Common–Noble, Inaccurate–Accurate, Useless–Useful
Difficult to see–Easy to see, Difficult–Easy, Difficult to choose–Easy to choose
Ordinary–Special, Dumb–Smart, Unsatisfied–Satisfied

4.2 Evaluation Experiment

4.2.1 Participants

The experiment was undertaken with the cooperation of 30 students (undergraduates and graduates). The group consisted each of 15 men and women. Their average age was 22.4 years (SD = 1.8). Among the 30 participants, 60.0 % of the students possessed an iPhone or iPad, 33.3 % possessed an Android device, and the rest possessed feature phones. Moreover, 86.7 % of the students reported that they "very often" or "somewhat often" send emails daily, and 90.0 % use emoticons "very often" or "somewhat often" when sending email.

4.2.2 Procedure

The procedure of the experiment was as follows:

1. Participants first filled out basic information (their university year group, sex, age, faculty, whether they possess a smartphone, whether they send emails daily, and whether they use emoticons in sending messages daily).
2. Participants tested one of the three systems. The order in which a participant tested the three systems was decided by random selection in order to examine the difference between participants using each of the systems at the beginning.
3. Participants rated the system using 22 bipolar words on a 7-point scale (Table 1).
4. Participants tested the other two systems as written above in Steps 2 and 3.

The contents of the input were decided in advance. We prepared a list of 15 sentences that each included one emotive word, and showed it to the participants, asking them to enter each sentence in each of the three systems. The sentences for the list were selected from participants' inputs from a previous experiment [11]. These were typed by the participants on the sole condition of using only one emotive word in each sentence. We performed a preliminary experiment to examine how strongly the chosen sentences express one of the 10 emotion types by asking 10 Japanese subjects

Table 2 Example of sentences shown to participants

Japanese sentence	Transliteration	Translation	Emotion
その漫画は好きだよ。	*Sono manga wa suki desu yo*	I like this comic book	Liking/fondness (4.9) (positive)
それはちょっと恥ずかしい。	*Sore wa chotto hazukashi*	This is a little embarrassing	Shyness (4.3) (neutral)
怯えてしまう。	*Obiete shimau*	I am frightened	Fear (4.8) (negative)

to rate them on a 5-point scale (minimum: 1.0, maximum: 5.0; average points collected from respondents are written after the emotion types in Table 2). The list was comprised of three five-sentence groups, each group expressing one of the positive emotions, a random selection from joy/delight, relief, and liking/fondness, one of the neutral emotions, a random selection from surprise/amazement, excitement, and shyness, and one of the negative emotions, a random selection from fear, sadness/gloom, anger, and dislike (examples shown in Table 2).

5 Results and Discussions

5.1 Proportion of Emoticons Chosen Among the Top Five from Each System

Table 3 shows the results of the proportion of emoticons chosen among the top five recommended by each system. Our proposed system scored 57.6 % and our integrated (baseline + proposed) system scored the highest at 73.0 %, both of which are major improvements over the baseline system. From these results, we can assert that recommending emoticons depending on the emotion type of the input is effective for users. Also, when we examined users' chosen emoticons, it seemed that users have their own emoticon preferences for each emotion type; therefore, the performance improves when we integrate users' past selection data (baseline method) with the emotion-based recommending method (proposed method).

We broke down the overall results into positive (joy/delight, liking/fondness, and relief), negative (sadness/gloom, anger, fear, and dislike), and neutral (surprise/amazement, excitement, and shyness) to investigate whether there is a difference in choosing emoticons by the valence of the input (Tables 4, 5 and 6). We discovered that the results of the baseline method for the negative statements (Table 5) were a little lower than that of positive and neutral statements. This is due to the fact that negative emoticons were placed lower in order at the very beginning so users had to scroll down to find emoticons. This can also be said for the emoticon database in the iOS Japanese keypad, that is, many positive emoticons are placed at the top, whereas negative emoticons are arranged in the lower part in the database. Therefore, replacing emoticon recommendation depending on the valence of the input is necessary in order to improve the quality of the performance. We also determined that our integrated system performs slightly better for negative statements (Table 5) than other statement types. This result comes from the smaller number of negative emoticons than that of positive emoticons in the database. The number of emoticons for surprise/amazement, shyness, and excitement in the database was also smaller than that of positive emoticons; however, it did not give a result (Table 6) as high as that of negative statements, because most of these emotions also imply either positive or negative contexts in the statement (e.g., "She was thrilled to death to get the flowers" (excitement and joy/delight), "I was shocked to see a ghost" (fear and surprise/amazement), etc.). Therefore, we should consider whether the statement is weighted toward positive or negative when the statement contains these three emotion types.

5.2 Participants' Attitudes from SD Scale

Next, we collected and calculated the average of respondents' attitudes toward each of the three systems using an SD scale (Fig. 6). In Fig. 6, numbers closer to one have strong impressions of the words on the left, whereas numbers closer to seven are better characterized by the words on the right. The averages are shown under each system.

From the results shown in Fig. 6, we discovered that our integrated system scored the highest among the three systems for 15 word pairs out of 22 word pairs. The overall average of the integrated system was 5.4 points, which was slightly higher than the proposed system (5.3 points). The baseline system scored 4.1 points, therefore, we verified that methods recommending emoticons according to emotion types from input are more effective than the baseline method. We also found that our integrated system (4.9 points) and our proposed system (5.4 points) scored lower than the baseline system (5.6 points) for the word pair "complicated–simple." We assume that most participants rated this by considering the process of the system recommending emoticons to them.

Table 3 Proportion of emotions chosen among the top five recommendations

	Baseline (%)	Proposed (%)	Integrated (baseline + proposed) (%)
Overall	29.5	57.6	**73.0**
Men	26.0	59.5	**74.9**
Women	33.3	55.6	**71.0**

Table 4 Proportion of emotions chosen among the top five recommendations (Positive)

	Baseline (%)	Proposed (%)	Integrated (baseline + proposed) (%)
Overall	32.2	57.5	**71.6**
Men	30.1	60.6	**75.3**
Women	34.2	54.8	**68.0**

Table 5 Proportion of emotions chosen among the top five recommendations (Negative)

	Baseline (%)	Proposed (%)	Integrated (baseline + proposed) (%)
Overall	23.9	67.4	**76.7**
Men	17.1	65.3	**76.4**
Women	31.7	69.4	**77.0**

Table 6 Proportion of emotions chosen among the top five recommendations (Neutral)

	Baseline (%)	Proposed (%)	Integrated (baseline + proposed) (%)
Overall	32.9	50.0	**71.1**
Men	31.5	56.2	**73.2**
Women	34.2	44.0	**69.0**

5.2.1 Factor Analysis of the SD Scale Ratings

We carried out a factor analysis of the SD scale ratings in order to condense a large number of variables into a few interpretable underlying factors and summarize the respondents' perception toward each of the three systems. The factor analysis resulted in three factors with eigenvalues exceeding 1.0 which accounted for 66.4 % of the variance. Table 7 shows the varimax rotation factor loadings for the 22-bipolar word pairs.

The first factor is made up of 16 scales and can be described as "users' impression of the system" (e.g., whether they feel the system is difficult or easy to use, whether they are satisfied with the system, etc.). The second factor is made up of three scales (common–noble, ordinary–special, and old–new). These word pairs can be summarized as "novelty of the system." The third factor was also comprised of three factors (slow–fast, heavy–light, and complicated–simple); therefore, we named this factor "system performance."

We plotted the 22 bipolar word pairs with groups of respondents categorized by system and gender (Figs. 7 and 8). As shown in Fig. 7, we discovered that our integrated system ("I" in Fig. 7) demonstrated the highest novelty and the most positive impression among the three systems, whereas the baseline system ("C" in Fig. 7) was ranked by far the lowest in both these aspects. Our proposed system ("C" in Fig. 7) also produced a positive impression similar to our integrated system, and slightly positive in terms of system novelty. When we consider the difference between

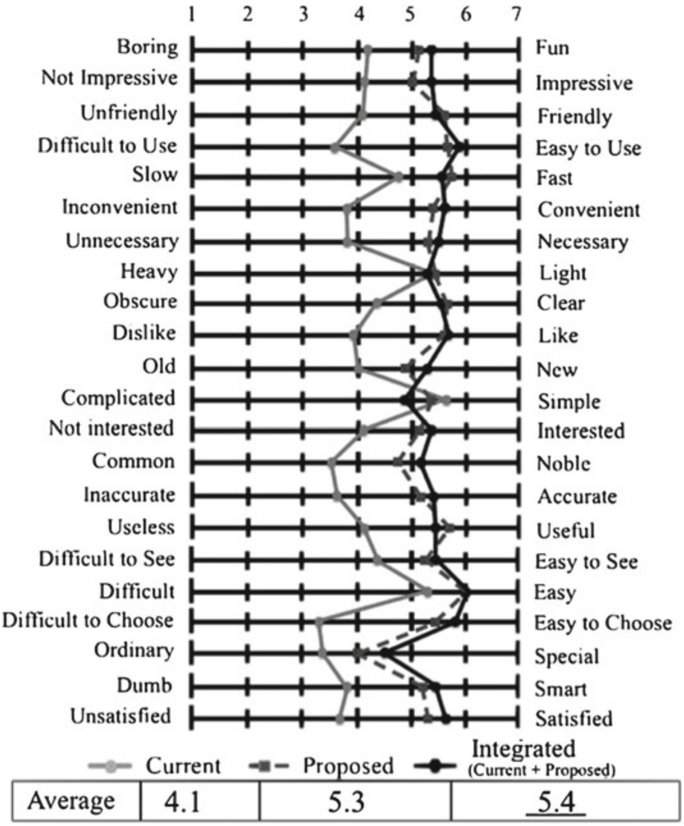

Fig. 6 Results of evaluation using SD scale

genders, it is apparent that the male users have the most positive perceptions toward the integrated system ("M" circled with "I" in Fig. 7) among the three systems, while the female users seemed to like the proposed system ("F" circled with "P" in Fig. 7) the best, however, the female users reported their highest impression of novelty ("F" circled with "I" in Fig. 7) for the integrated system. For the third factor, "system performance," we discovered that the users felt that our proposed system ("P" in Fig. 8) seemed to perform the fastest and the lightest of all systems. We also compared the perceptions of system performance according to gender and found that the female users felt that the proposed system ("F" circled with "P" in Fig. 8) performs the best, while the male users preferred the baseline system ("M" circled with "C" in Fig. 8). Our integrated system produced a relatively lower impression ("I" in Fig. 8) for this factor, probably due to the complexity of the method of recommending emoticons compared to the proposed and the baseline methods.

Table 7 Factor Loadings of each of the 22 bipolar word pairs in the SD scale (≧ 0.3)

22-Bipolar word pairs (Name given to pair)	Factor 1 (Impression of the system)	Factor 2 (Novelty of the system)	Factor 3 (System performance)
Difficult to use–Easy to use (ETU)	0.88		
Unsatisfied–Satisfied (SAT)	0.88	0.32	
Inconvenient–Convenient (CON)	0.86		
Unnecessary–Necessary (NEC)	0.82		
Difficult to choose–Easy to Choose (ETC)	0.82		
Dislike–Like (LIK)	0.82		
Useless–Useful (USE)	0.80		
Unfriendly–Friendly (FRI)	0.72	0.32	
Dumb–Smart (SMA)	0.72	0.50	
Inaccurate–Accurate (ACC)	0.71		
Obscure–Clear (CLE)	0.67		0.40
Not interested–Interested (INT)	0.64	0.54	
Difficult to see–Easy to see (ETS)	0.63		
Not impressive–Impressive (IMP)	0.60	0.51	
Boring–Fun (FUN)	0.58	0.42	
Difficult–Easy (EASY)	0.53		0.39
Common–Noble (NOB)	0.38	0.80	
Ordinary–Special (SPE)		0.72	
Old–New (NEW)	0.44	0.71	
Slow–Fast (FAS)			0.75
Heavy–Light (LIG)			0.72
Complicated–Simple (SIM)			0.31
Eigenvalues	12.6	1.8	1.3
% of total cumulative variance	41.5	57.7	66.4

5.3 Rankings Based on the Systems' Performance and Users' Preference

We also asked the respondents to rank the three systems based on performance and which of the three systems they prefer. Tables 8 and 9 show the results of this ranking. As shown in Table 8, 23 out of 30 participants ranked our integrated system

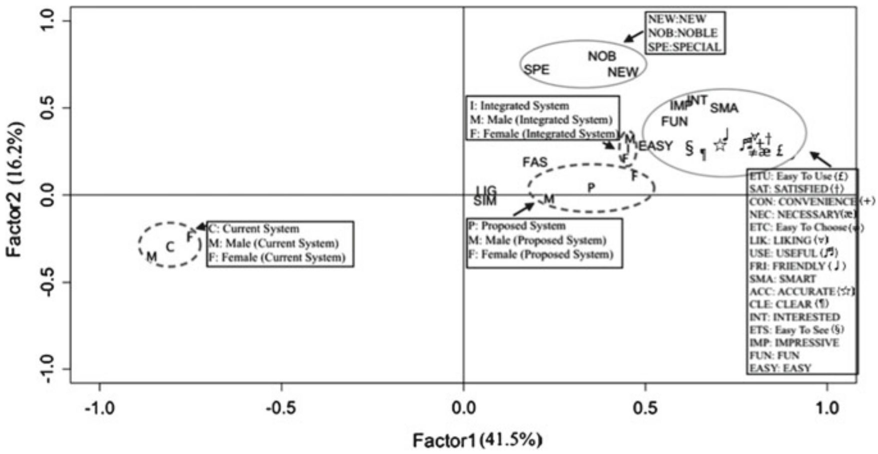

Fig. 7 Biplot of the two factor models for Factor 1 and 2. X-axis is Factor 1 (Factor 1 explains 41.5 % of the total variance), y-axis is Factor 2 (Factor 2 explains 16.2 % of the total variance)

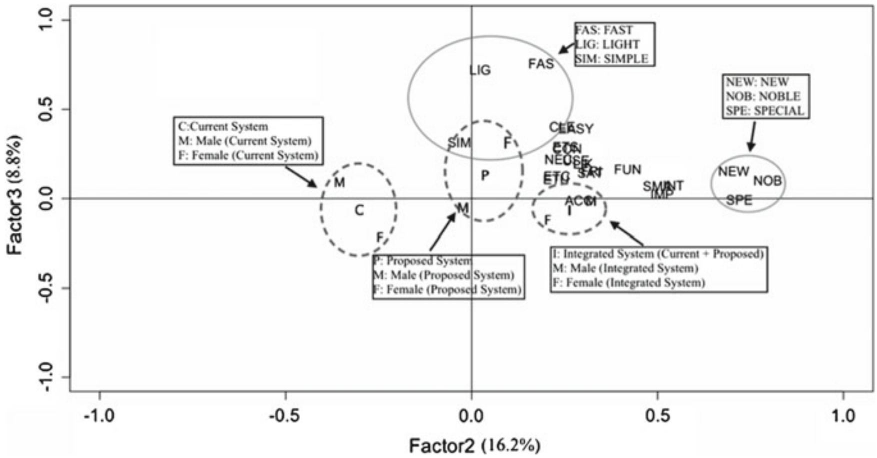

Fig. 8 Biplot of the two factor models for Factor 2 and 3. X-axis is Factor 2 (Factor 2 explains 16.2 % of the total variance), y-axis is Factor 3 (Factor 3 explains 8.8 % of the total variance)

as performing the best, 16 out of 30 participants ranked the proposed system as second, and 21 out of 30 participants ranked the baseline system as third. As shown in Table 9, the ranking was in descending order of: our integrated system (21 out of 30 participants), our proposed system (14 out of 30 participants), and the baseline system (19 out of 30 participants). From these results, we concluded that our integrated system achieved a great improvement over the baseline system in terms of system performance and user preferences.

Table 8 Ranking based on the systems' performance (numbers are the total of people)

System	1st	2nd	3rd
Integrated	**23**	6	1
Proposed	6	**16**	8
Baseline	1	8	**21**

Table 9 Proportion of emotions chosen among the top five recommendations (Neutral)

System	1st	2nd	3rd
Integrated	**21**	8	1
Proposed	6	**14**	10
Baseline	3	8	**19**

6 Conclusions

In this paper, we presented two emoticon recommendation methods based on users' past emoticon selection and emotional statements contained in the input. The main procedures of these two methods share the same process of analyzing emotions from user-entered sentences by using the affect analysis system ML-Ask, but differ in their methods of reordering the emoticon database and recommending appropriate emoticons to users. Our originally created database utilized an idea by Kawakami [9], and comprised of 59 emoticons with the points expressed from each of 10 distinctive emotions.

Evaluation experiments were performed to compare the performance of the three systems. We discovered that approximately 73.0 and 57.6 % of chosen emoticons were among the top five recommendations by our integrated system (the incorporation of the baseline and the proposed systems) and our proposed system, respectively. On the other hand, the baseline system used in the Japanese iPhone keypad only scored 29.5 % in the same experiment. We also confirmed that our integrated and proposed systems scored 5.4 points and 5.3 points, respectively, in evaluation using a semantic differential scale, which was relatively larger than the baseline system of 4.1 points. Furthermore, the results of a factor analysis demonstrated that users perceived the highest novelty and had the most positive impression towards our integrated system, whereas the baseline system was rated the lowest in these factors. The overall ranking of the three systems was in descending order of: our integrated system, our proposed system, and the baseline system, in terms of system performance and users' preferences. From the overall results, we confirmed that emotion plays a major role when recommending appropriate emoticons to users. Furthermore, users have their own preferences when selecting emoticons with their input, therefore, the integrated method is the most user-friendly.

We believe that we can expect further improvements in recommending more appropriate emoticons to users. First of all, in future work, we could recommend more suitable emoticons for inputs expressing neutral emotion types (surprise/amazement, shyness, and excitement) by analyzing whether the input is weighted toward either positive or negative. For example, a sentence like “She was thrilled to death to get the flowers” expresses both excitement and joy/delight and so is weighted toward a positive statement, however, a sentence like “I was shocked to see a ghost” expresses both surprise/amazement and fear, and so is weighted to a negative statement. Second, we intend to apply an existing machine learning method to learn which kinds of emoticons are preferred for which words in the sentence, so that our system will also work with sentences with no emotive words. Lastly, expansion of the emoticon database is necessary in order to allow larger numbers of emoticons to be inserted easily. Also, more emoticons in the database will be helpful for discovering the types of symbols that articulate each emotion type, and create a system to automatically generate emoticons suitable to the input.

The emoticon recommendation system is not only useful for assisting users to choose an appropriate emoticon for Japanese messages, but also can be utilized in various ways. First, the system can be utilized for any language, though the emoticon database may need a little adjustment to the emotional strength value due to the difference in interpreting emoticons across cultures [2]. Second, our approach is also capable of working with pictograms that are input along with characters using mobile phones. Third, it is possible to use our system with a text-based dialogue system in order to express the feeling using emoticons and show friendliness toward the interlocutor.

References

1. Mehrabian A (1971) Silent messages, 1st edn. Wadsworth, Belmont
2. Park J, Barash V, Fink C, Cha M (2013) Emoticon style: Interpreting differences in emoticons across cultures. In: The 7th international AAAI conference on weblogs and social media. AAAI Press, Palo Alto, pp 466–475
3. Derks D, Bos AER, Grumbkow JB (2008) Emoticons in computer-mediated communication: social motives and social context. In: Cyberpsychology & Behavior, vol 11(1). Mary Ann Liebert, New York, pp 99–101
4. Lo SK (2008) The nonverbal communication functions of emoticons in computer-mediated communication. In: Cyberpsychology & Behavior, vol 11(5). Mary Ann Liebert, New York, pp 595–597
5. Kato S, Kato Y, Scott D (2009) Relationships between emotional states and emoticons in mobile phone email communication in Japan. In: International journal on e-learning, vol 8(3). AACE Press, Waynesville, pp 385–401
6. Ptaszynski M, Dybala P, Rzepka R, Araki K (2008) Effective analysis of emotiveness in utterances based on features of lexical and non-lexical layer of speech. In: The 14th annual meeting of the association for natural language processing, pp 171–174
7. Ptaszynski M, Maciejewski J, Dybala P, Rzepka R, Araki K (2010) CAO: A fully automatic emoticon analysis system based on theory of kinesics. IEEE Trans Affect Comput 1:46–59
8. Emura Y, Seki Y (2012) Facemark recommendation based on emotion, communication, and motion type estimation in text. IPSJ Sig Notes 85:1–7
9. Kawakami M (2008) The database of 31 Japanese emoticon with their emotions and emphasis. In: The human science research bulletin of Osaka Shoin Women’s University, vol 7, pp 67–82

10. Nakamura A (1993) Dictionary of emotive expressions (Kanjyo Hyogen Jiten) (in Japanese). Tokyodo Publishing, Tokyo
11. Urabe Y, Rzepka R, Araki K (2013) Emoticon recommendation for Japanese computer-mediated communication. In: The proceedings of 2013 IEEE seventh international conference on semantic computing, Irvine, pp 25–31
12. Osgood CE, Suci GJ, Tannenbaum PH (1957) The measurement of meaning. University of Illinois Press, Urbana