PAPER

Personalized Emotion Recognition Considering Situational Information and Time Variance of Emotion

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SUMMARY To understand human emotion, it is necessary to be aware of the surrounding situation and individual personalities. In most previous studies, however, these important aspects were not considered. Emotion recognition has been considered as a classification problem. In this paper, we attempt new approaches to utilize a person's situational information and personality for use in understanding emotion. We propose a method of extracting situational information and building a personalized emotion model for reflecting the personality of each character in the text. To extract and utilize situational information, we propose a situation model using lexical and syntactic information. In addition, to reflect the personality of an individual, we propose a personalized emotion model using KBANN (Knowledge-based Artificial Neural Network). Our proposed system has the advantage of using a traditional keyword-spotting algorithm. In addition, we also reflect the fact that the strength of emotion decreases over time. Experimental results show that the proposed system can more accurately and intelligently recognize a person's emotion than previous methods.

key words: *emotion recognition, situational information, personalized model, human computer interaction, natural language, text*

1. Introduction

Emotion recognition is a thoroughly researched area of artificial intelligence which includes human-computer interaction, cognitive modeling, empathic computing, and affective computing. Areas of research can be subdivided according to modality into voice, facial expressions, brain signals and text. Text is a very informative modality because it can intelligently convey emotional features that the other modalities cannot. A number of computer scientists who are interested in emotion recognition have studied text-based emotion recognition. They have treated the emotion recognition problem as a kind of classification problem typical of that which has been widely used in information retrieval, natural language processing (NLP) and machine learning. However, previous attempts are limited in their ability to recognize emotion, because emotion is very complicated and must be considered in terms of the surrounding situation and the individual's personality [1].

To recognize emotion by considering the situation, we assume the following emotion recognition steps for computer processing. 1) Recognize a given situation. 2) Identify the situation associated with the conditions for emotion occurrence (e.g., anger occurs when facing an aggressive word

or action). 3) If a matching situation exists, emotion is recognized by the emotion occurrence rules in the algorithm. To implement this process, we extracted situational information from natural language text and constructed a situation model using an emotional lexicon dictionary and dependency parser. We also considered the fact that emotions may be different for each person even in the same situation. For example, a hot-tempered person can become angry because of aggressive words and actions, but a placid person may not be angry under the same conditions. Emotion recognition in both cases will be possible if a personalized emotion model is used. To integrate the above ideas, we propose a personalized emotion model using the KBANN (knowledge-based artificial neural network) model. The proposed system has the advantage of using a traditional keyword-spotting algorithm as described in Sect. 3. In addition, we reflect the assumption that the strength of the emotion decreases over time by applying the proposed emotion-decreasing formula. Through these intelligent emotion recognition methods, it is possible to recognize emotion for input sentences that have no emotional keywords (which cannot be recognized using a keyword-spotting algorithm).

2. Related Works

2.1 Emotion Recognition Using Text Modality

Most text-based emotion recognition is based on a keyword-spotting algorithm [2]–[4]. The keyword-spotting method is relatively easy to process because it only handles word-level vocabulary information. However, it cannot reflect syntactic information contained in sentences and can only handle word-level semantic information. This means that a considerable amount of linguistic information is lost. In addition, processing ironic or negative expressions is almost impossible because keyword-spotting only deals with the literal meaning of the sentences. Because of these limitations, we do not think a keyword-spotting algorithm is suitable for high accuracy applications.

Some researchers who have studied the limitations of the keyword-spotting method have tried to utilize syntactic information, semantic information, pragmatic information or other linguistic information. Chung-Hsien Wu et al. [5] proposed a domain-dependent method using semantic labels and a separable mixture model for utilizing syntactic and semantic information. However, their method was domain-dependent at every point. They built their own cor-

pus for training and testing and achieved a recognition accuracy of about 75 percent for three emotions (happy, unhappy, and neutral). Cheongjae Lee et al. [6] used linguistic features, pragmatic features, and domain features for conversational sentences and dealt with eight emotions. Their emotion recognition system was about 90% accurate. However, 73% of the corpus had neutral emotions, and they used a conversational corpus which contained direct emotional keywords, which might have affected the accuracy. One attempt at emotion recognition reflected psychological theories of emotion in text-based situations. Yongsoo Seol et al. [7] used domain knowledge for emotion creation with designed KBANN classifiers and dealt with eight emotions. However, knowledge for emotion creation is expressed using abstract concepts in psychology, in which it is difficult to map natural language text. Although they used a corpus that did not include many emotional keywords, their recognition system was 64% accurate. Previous research did not consider the surrounding situation or personality of a subject. In this study, we attempt to develop a human-like intelligent emotion recognition methodology using these properties.

2.2 Human Emotion Modeling

Previous researchers have created emotion models. Ortony et al. [8] proposed a computer adaptable emotion structure (called OCC model). They structured emotions according to event variable, agent variable, and object variable. They assumed emotion is created to adapt to the conditions described by these variables. However, this model has the disadvantage that psychological views are damaged by the computational views when implementing a computer program. Dyer et al. [9] considered emotions between people to describe the slots of goal state, expectations and positive-negative status. However, their approach only handles fragmentary emotion. Lazarus et al. [1] insist that emotion is created by six factors, the fate of personal goals, self or ego, appraisals, personal meanings, provocations, and action tendencies. Their theory is too abstract and unrealizable to computerize, since it is purely psychological. However, through their theory, we verified that our assumption of 'human emotion is created through a given situation and personal judgments' makes sense.

3. Implementation

3.1 Target Emotions for Recognition

In general, text-based emotion recognition research considers from two to eight emotions. As more kinds of emotion are considered, recognition accuracy decreases. For this reason, most researchers select about six kinds of emotions to recognize. Psychologists have made many attempts to classify emotion; however, because there are so many types of emotions, some of which are very difficult to recognize, many emotion recognition researchers use Ekman's universal emotions [10] (anger, fear, sadness, happiness, disgust,

and surprise) as target emotions. These universal emotions have been recognized as the standard in the field of emotion recognition using visual modalities. We used both the 16 emotions proposed by Lazarus and the six emotions proposed by Ekman as candidates. Among them, we selected nine emotions (anger, fear, sadness, happiness, disgust, surprise, love, gratitude, and unrest) as targets for recognition based on conditions which have a relatively high occurrence rate and are easy to recognize.

3.2 The Emotion Recognition Process

We assume that the aim of the emotion recognition process is to recognize a given situation from the text and to identify emotions by matching the situation with emotion occurrence rules that consider a personalized emotion model. To implement this idea, a situational and personalized emotion model should be defined and generated. In general, "situation" is a very inclusive and abstract concept. It may be described as the surrounding environment, past memories, relationship, culture, recent changes in position, and complex and diverse environmental factors. However, the situation described in this paper is stimuli or input data to generate emotion. We extracted situational information from natural language text and used it as input data for emotion recognition and as situation knowledge.

3.3 Situation Model

We extracted situation knowledge from natural language text in English and utilized it in the course of subsequent processing. We define situation knowledge as an entity-relationship model and call it the situation model.

3.3.1 Data Structure of the Situation Model

The situation model should be able to freely add and search situation knowledge. As a suitable model for these properties, we used a graph data structure. More precisely, we used a weighted graph to represent the strength of the relations. Figure 1 illustrates an example of a simple situation model.

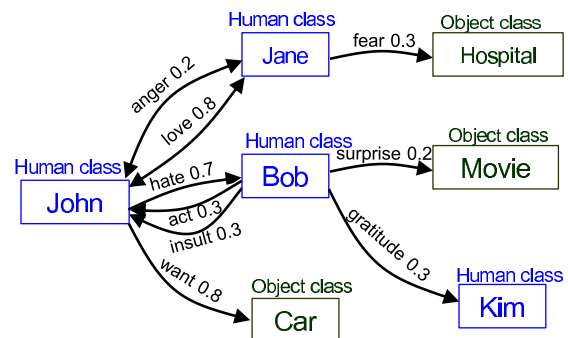Each class (node) can be subdivided into human classes

Fig. 1 An example of a situation model.

and object classes. A human class includes humans that have emotions. An object class includes objects that are related to humans. In other words, the object class refers to all classes except the human class. Each class is connected by a relation, and the relation can only be expressed according to a predefined emotional language vocabulary (explained in Sect. 3.4). Every natural language sentence is mapped to an emotional lexicon using the emotional lexicon dictionary. The subject is determined to be in the human class only if he or she is the subject of an emotional relation (expressed by an emotional word such as fear).

3.3.2 Identifying the Emotional Subject, Object and Relation

In the situation model, the relation is expressed as an emotional lexicon in the emotional lexicon dictionary. However, the human class and object class should be identified by natural language processing from the input text sentence. For this, we parsed the input text using the Stanford dependency parser [11]. As a result of dependency parsing, most sentences have nominal subject dependency (*nsubj* tag in the Stanford dependency parser) except special exceptions (e.g., omitting the subject). In the nominal subject dependency relation, the governor is mostly a main verb, and the determiner is mostly a subject. In the case where the main verb is a copular verb (*cop* tag), the subject and the main verb could be found in copular dependency. We could also find the subject when the subject is a noun phrase by tracking the determiner of the nominal subject dependency relation. The object can be found based on this dependency, including the main verb, and it can be the target object of the relation.

We tested the accuracy of the proposed method in identifying the emotional subject, object and predicate using a simple sentence corpus containing 952 sentences. The results are shown in Table 1.

The relation name is assigned as the mapped word with the main verb in the emotion lexicon dictionary. If there is no mapped word in the dictionary, we consider it to have no situational information, and the input sentence is discarded. In all cases with ambiguity in terms of finding the subject, object, and main verb, the input sentence is also discarded for reducing noise knowledge. The situation knowledge can be expanded by iterating the process described above for input sentences.

3.3.3 Expression of Decreasing Emotion

We use a weighted graph data structure to express the char-

acteristic by which emotion is attenuated gradually over time. Once an emotion is created, it is kept for an arbitrary duration but not permanently. In our application, the time concept is difficult to consider, because we only use textual data. Alternatively, we identified a sentence as a time unit by assuming that a sentence is written in proportion to the time.

The weight value in each relation is set to 1 when the relation is generated. Whenever an input sentence is processed, all the weight values of relations in the situation model are reformulated according to the emotion generated by the input sentence. The strength of emotion (the same as the weight value) in a relation is calculated using the following equation:

$$E' = (1 - \gamma)(\alpha E + \beta NE) + \gamma \qquad (1)$$

where E' is the value of the current amount of emotion and is the same as the weight value of the relation. E is the value of the previous emotion. NE is the value of the emotion created by the current input sentence. E', E and NE have a value from 0 to 1. α is the weight assigned to maintain the previous emotion, β is the weight to enlarge the influence of created emotion, and $\alpha + \beta = 1$. γ is the value to maintain the minimum amount of emotion. The property of decreasing emotion can be controlled by α, β, and γ.

3.4 Emotion Lexicon Dictionary(ELD)

An emotion lexicon is defined for reducing the problem space. In Wicken et al.'s human information processing model [12] and Atkinson et al.'s memory structure model [13], human thinking consists of an encoding process to conceptualize and simplify complex information. By mimicking the characteristics of the human thought process, the problem space for emotion recognition can be markedly reduced.

The emotion lexicon is determined to be the lexicon used by the emotion occurrence rules (explained in Sect. 3.7), and the lexicon's k-depth synonyms and antonyms. Other words not included in the emotion lexicon are omitted because we do not believe the words convey emotion. The emotion lexicon dictionary is automatically constructed by expanding 25 initial seed words into k-depth synonyms and antonyms (25 seed words are extracted from the emotion occurrence rules). In addition, whenever a new lexicon appears in an input sentence during the learning and testing process, the user can determine the emotion category and add the lexicon to the emotion lexicon dictionary. When the new lexicon is added to the dictionary, k-depth synonyms and antonyms are added automatically using Wordnet [14].

3.5 Situation Extractor

An emotion extractor module extracts the situational information from the constructed situation model. A situation is represented by [*Sobject-relation*(-*Tobject*)] in tuple form.

Table 1 Accuracy of identifying the emotional subject, object, and predicate.

	# sentences	# correct	# incorrect	Accuracy(%)
Subject	952	931	21	98
Object	952	867	85	91
Predicate	952	873	79	92
All	952	819	133	86

Only situations having Sobject as the human class can be extracted. The situation extractor module operates with one essential parameter (*Sobject*) and one optional parameter (*Tobject*). The essential parameter is an emotional subject (only human class is possible). The module searches all situations having *Sobject* as the parameter, and the optional parameter is the target object parameter, the additional condition. If the module has both parameters, the module searches all relations having the in-link object as the essential parameter and out-link objects as optional parameters. Otherwise, if the module has an essential parameter and no optional parameter, the module searches all relations having essential parameters (including [*Sobject-relation-NULL*]).

3.6 Personalized Emotion Model

After acquiring situation knowledge with the situation extractor, the way in which an emotional subject would interpret the extracted knowledge must be determined. To this end, the personalized emotion model is built in the training phase. In order to build a personalized emotion model, the emotional subject in an input sentence must be determined. The subject of an input sentence is found during the process for extracting situation knowledge (in Sect. 3.3.2). If this subject is a human class in the situation model, it is classified as an emotional subject.

We employ the KBANN (knowledge-based artificial neural network) as a data structure for the emotion model. The KBANN is proposed for overcoming the weaknesses of ANN (e.g., long training time, lack of a problem-independent network design method, and difficulty interpreting a trained network). When domain knowledge exists, the KBANN can yield better performance than other machine learning methods despite sparse training data. We use domain knowledge such as the emotion occurrence rule, which makes it difficult to obtain abundant training data. For these reasons, the KBANN is very useful for our emotion recognition system.

We define and use the emotion structure as input data for the KBANN. An emotion structure is a 25-cell flag array corresponding to 25 representative emotion lexicons, which are used in the emotion occurrence rule. Each element of the array is equal to 1 if a corresponding emotional lexicon exists or 0 if a corresponding emotional lexicon does not exist.

Lazarus' emotion creation plots [1] are used as domain knowledge for initializing the KBANN. We show the design process of KBANN with an example of an anger emotion occurrence rule. For more detail about designing KBANN with domain-knowledge, refer to a previous paper [15]. According to Lazarus, anger is created when a subject's emotional status suffers from insulting words or actions. We can create this rule to say "Anger → anger ∨ (insult ∧ (verbal ∨ act))." Then, a network can be built with KBANN using a network changing rule from [15] as shown below. In the same way, nine networks can be built using nine emotion occurrence rules. The unified KBANN for nine emotions is shown in Fig. 3.

The training corpus is constructed with sentences including abundant emotional expression. To minimize the influence of natural language processing accuracy for the entire emotion recognition system, the corpus is written with simple sentences and uses no substitutes. We use eight actors in the corpus to create and evaluate the personalized emotion model. In addition, the scenario is written to reveal the character of each person. The corpus consists of about 3,000 sentences. Each sentence is tagged with nine target emotions (anger, fear, sadness, happiness, disgust, surprise, love, gratitude, and unrest) and a neutral emotion. Once an input sentence goes into the system, dependency parsing, extracting situational information, KBANN selection according to the emotional subject, input of 25 flag arrays of the emotion structure into the KBANN, and refining weight parameters of the KBANN through the back-propagation algorithm are performed respectively.

3.7 Emotion Occurrence Rules

The predefined emotion occurrence rules are used as domain knowledge to indirectly reduce the hypothesis space. We extract essential factors (essential words) to develop an emotion occurrence rule based on abstract words in psychology [1]. We then write the emotion occurrence rule keeping the meaning of the words as an essential factor. At this time, a self-reference factor is added to the rule in order to include characteristics of the keyword-spotting algorithm. For example, below is the emotion occurrence rule for anger. The anger shown in bold is the self-reference factor.

$$Anger \rightarrow \textbf{anger} \vee (insult \wedge (verbal \vee act)) \qquad (2)$$

If the input sentence includes emotional keywords related to the anger emotion, ELD maps the keyword into the emotional lexicon of anger. Then, the situation model has

Ex) He was ***angry*** with the ***lovely*** dog

Fig. 2 An example of an emotion structure.

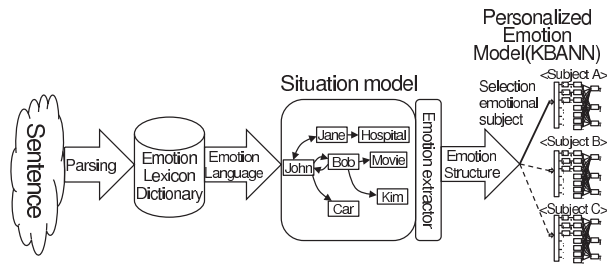**Fig. 3** The unified KBANN.

Fig. 4   System overview.

an anger relation for the emotional subject, and the situation extractor can extract situational information for anger from the situation model. Then, KBANN obtains anger information from the situation extractor and outputs the anger emotion.

3.8   System Overview

The proposed emotion recognition system is shown in Fig. 4.

4.   Experimental Results and Analysis

In this study, we tried entirely different techniques compared to those used in traditional text-based emotion recognition. We attempted to recognize situational information from natural language text, personalized emotions based on situational information, and emotions when emotional keywords do not appear. In addition, we dealt with nine emotions and a neutral state as target emotions, which is more than other text-based emotion recognition researchers have studied. Moreover, we considered the property of decreasing emotion over time.

To evaluate the attempts mentioned above, methods for evaluating each characteristic are needed. However, existing general-purpose corpora cannot be used for our experiments because there is no existing corpus that includes emotional information, situational information, personal character information, and emotional information for situations with decreasing emotion. Therefore, we designed and built our own corpus for the experiment. However, some evaluation difficulties remained. First of all, there is no research with which an objective comparison can be made because the proposed method has many distinctly different elements from traditional methods. It is very difficult to quantitatively evaluate the characteristics of a situation model, such as a personalized emotion model or decreasing emotion. Despite these difficulties, we attempted to evaluate the core elements of our proposed system with user testing, and we implemented a keyword-based emotion recognition system and tested it with our designed corpus as a baseline for comparison.

4.1   Corpus Construction

About 3,000 sentences were included in the corpus. About 49 percent of the sentences directly or indirectly included emotional information. The scenarios in the corpus are assumed to take place in kindergarten. The characters are six children and two teachers. Various situations under this environment are considered in the corpus. We uniformly distributed the appearance frequency of each character. Eight writers participated in building the corpus to generate diverse dialog. Each writer took charge of one character to maintain character consistency. The omission or substitution of subjects was prohibited. Each sentence in the corpus was annotated with the emotion, emotional subject and situational comments.

4.2   Evaluation Method and Result

We evaluated three aspects of the proposed system. First, we evaluated whether the situation model constructed with the given corpus reflects the real situation. Second, we evaluated whether the personalized emotion model reflects the corresponding person's characteristics. We were able to evaluate the results of the artificial neural network (General ANN cannot be evaluated) because we employed KBANN. Finally, we evaluated the emotion recognition accuracy of our emotion recognition system.

4.2.1   Situation Model

The tester verified the collected situation knowledge for each input sentence including emotional information. The results are shown in Table 2.

4.2.2   Personalized Emotion Model

Based on the predefined personalities of eight characters, a constructed personalized emotion model was evaluated by ten testers. Some examples of the trained KBANN for a hot-tempered character and a placid character in the experiment are shown in Fig. 5. We describe only the relevant parts in Fig. 5 because the size of the network is too large. As Figure 5 shows, the weight of the nodes associated with anger is greater than that of others in the network for a hot-tempered character. In contrast, the weight of the nodes associated with sadness is greater than others in the network for a placid character.
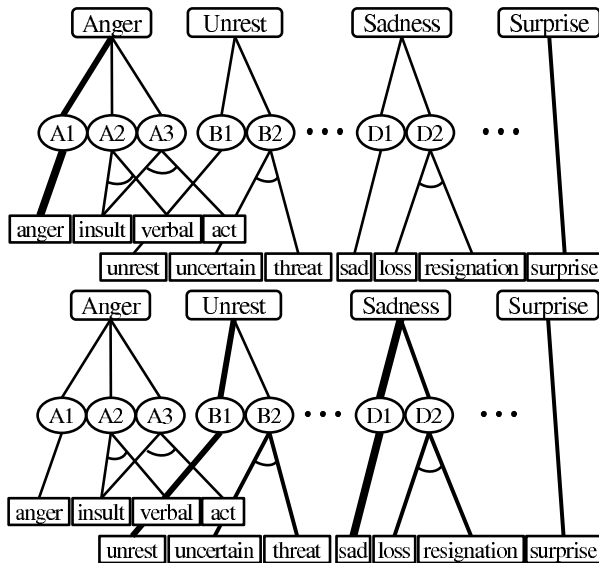
The testers subjectively compared the personalized KBANN to a corresponding predefined character's personality and gave a score according to evaluation guidelines. The guidelines are shown in Fig. 6. The results of the evaluation are shown in Table 3.

4.2.3   Emotion Recognition

We evaluated the accuracy of the proposed emotion recognition system by comparing emotions predicted by the system with tagged emotions in the test corpus. A ten-fold cross validation method was used. A total of 2,970 sentences in the corpus were used for the test. In addition, we implemented a keyword-based emotion recognition system

Table 2　Accuracy of the situation model.

Emotion	Correct	# of sentences	Accuracy(%)
Anger	109	154	70.78
Disgust	85	150	56.67
Fear	143	178	80.34
Love	99	189	52.38
Sadness	106	129	82.17
Surprise	132	181	72.93
Gratitude	79	157	50.32
Unrest	91	144	63.19
Happiness	111	153	72.55
Total	955	1435	66.55

Table 3　Average evaluation scores of the testers.

Character	Average evaluation scores of the testers
1	65.83
2	64.17
3	56.43
4	65.46
5	81.33
6	63.57
7	83.33
8	68.75
Total	68.61

Fig. 5　Examples of a personalized emotion model (hot-tempered character and placid character) trained by the experiment. A greater weight value is expressed as a thicker line in the figure.
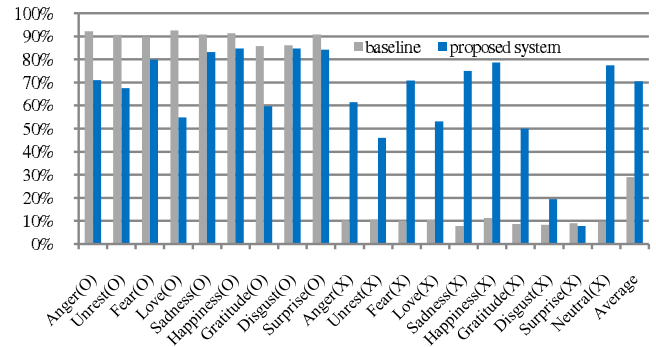
Fig. 7　Accuracy of emotion recognition with an emotional keyword (O) and without an emotional keyword (X).

Guidelines for evaluating personalized emotion model

Tester name :

1. (0~40) The highest weighted emotion is matched to corresponding character's personality?
2. (0~40) The weights of the opposite emotions with the character's personality are low?
3. (0~10) The weights of the similar type of emotions (positive, negative, aroused, depressed, and so on) with the character's personality are a little high?
4. (0~10) Are there the weights, which you cannot understand, with considering the character's personality?

TOTAL SCORE(0~100) :

Fig. 6　Guidelines for evaluating the personalized emotion model.

using a simple keyword-spotting algorithm as the baseline. The baseline system identifies emotional keywords by using an emotional keyword dictionary. If an input sentence had emotional keywords, the system output mapped the emotion in the emotional keyword dictionary. If an input sentence had more than two emotional keywords mapped to different emotions, then the more frequent emotion was selected. If two emotions appear with equal frequency, the first emotion

is selected. About 50 percent of sentences in the corpus have emotional keywords. Figure 7 shows the accuracy of emotion recognition using the proposed system with and without an emotional keyword.

The baseline system using a keyword-spotting method showed approximately 90% accuracy when an emotional keyword was included. With no emotional keyword, the accuracy was approximately 10%. On the other hand, the proposed system showed approximately 70% accuracy in both cases. The average accuracy of the proposed system was 68.4%, and the average accuracy of the baseline system was 48%. This experiment showed that the proposed method is beneficial when the input sentence has no emotional keyword or when situational information and personality are needed to recognize emotion.

4.2.4　Discussion

We conducted the experiment by evaluating situation model, personalized emotion model, and unified emotion recognition methods. As shown in advance, the proposed method shows better performance when emotional keywords are not included. This means that the proposed method using situational information and a personalized emotion model is useful for recognizing implicit emotional information. When emotional keyword is included, the proposed method showed slightly worse performance than baseline using a keyword-spotting algorithm, although the proposed method has the keyword-spotting characteristic in the KBANN. This may be because the keyword-spotting characteristic is weakened during training, and explicit information in natural lan-

guage sentences is lost due to precedence steps (emotion lexicon mapping; identifying the emotional subject, object and relation; situation extraction; and emotion decay) which are not 100% accurate.

All the sub-modules that make up the proposed method are essential to implement the proposed idea. Among the sub-modules, we think the most important module to recognize emotion is the personalized emotion model using KBANN. Natural language sentences can be divided into sentences explicitly including emotional keywords and others. In the former, the keyword-spotting characteristic reflected by KBANN design mainly affects the result. Also, in the latter, emotion occurrence rules reflected by KBANN design mainly affect the result.Therefore, for more advanced emotion recognition, it is needed to maintain the KBANN personalized emotion model and to improve the rest of the sub module in future research.

As mentioned at the beginning of Sect. 4, objective comparisons with existing studies are difficult. However, the experimental results show that the proposed method using situational information and the personalized emotion model are useful to recognize emotion from textual data which contains an implicitly expressed emotion.

5. Conclusion

In this study, we attempted to develop an emotion recognition system using situational information and a personalized emotion model. We extracted situational information using a dependency parser and an emotion lexicon dictionary and constructed a situation model. The proposed system can even recognize emotions with no emotional keyword in the input sentences because it uses situational information. In addition, the system is designed to reflect the fact that different people (subjects) may have different emotions in the same situation. We constructed and utilized the personalized emotion model with KBANN.

The proposed system can achieve human-like intelligent emotion recognition which a traditional text-based emotion recognition system cannot. We also include characteristic of keyword-spotting algorithm in the system. In addition, we reflect that the strength of emotion decreases over time. We attempted many new approaches based on the properties of a particular emotion. As a result, we found that intelligent emotion recognition considering the surrounding situation and personality of the subject is possible.

Recognizing emotion from text only using natural language processing is difficult. To utilize our study in various applications, complex sentences, embedded sentences, substitutes, irony, omission, ambiguity and a number of remaining natural language processing issues must be resolved. These are left for future research.

Until now, voice and vision modalities have created several problems for emotion recognition. However, text modality could play an important role in intelligent emotion recognition, as demonstrated in this paper. More advanced emotion recognition can be expected with a multi-modal recognition system that includes text modality.

References

[1] R.S. Lazarus, and B.N. Lazarus, Passion and reason: Making sense of our emotions, Oxford University Press, New York, 1994.

[2] C.H. Lee and S. Narayanan, "Toward detecting emotions in spoken dialogs," IEEE Trans. Speech Audio Process., vol.13, pp.293–303, 2005.

[3] C. Ma, A. Osherenko, H. Prendinger, and M. Ishizuka. "A chat system based on emotion estimation from text and embodied conversational messengers (preliminary report)," IEEE Int'l Conf on Activ. Medi. Tech. (AMT-05), pp.546–548, Takamatsu, Kagawa, Japan, May 2005.

[4] C.H. Wu and Y.J. Chen, "Multi-keyword spotting of telephone speech using fuzzy search algorithm and keyword-driven two-level CBSM," Speech Commun., vol.33, pp.197–212, 2001

[5] C.H. Wu, Z.J. Chuang, and Y.C. Lin. "Emotion recognition from text using semantic labels and separable mixture models," ACM Trans. Asian Lang. Inf. Proc., vol.5, no.2, pp.165–182, 2006.

[6] C. Lee and G.G. Lee "Emotion recognition for affective user interfaces using natural language dialogs," Proc. IEEE Int. Sympo. Robot & Human Interact. Commun., pp.798–801, Jeju, 2007.

[7] Y.S. Seol, D.J. Kim, and H.W. Kim, "Emotion recogniton from text using knowledge-based ANN," Int. Tech. Conf. Circuits/Systems, Computers & Commun., pp.1569–1572, 2008.

[8] A. Ortony, G.L. Clore, and A.M. Collins, The cognitive structure of emotions, Cambridge University Press, England, 1988.

[9] M.G. Dyer, "Emotions and their computations: Three computer models," Cognition and Emotion, vol.1, no.3, pp.323–347, 1987.

[10] P. Ekman, "Universial facial expressions in emotion," Studia Psychologica. vol.15, no.2, pp.140–147, 1973.

[11] The Stanford Natural Language Processing Group, http://nlp.stanford.edu/software/lex-parser.shtml

[12] C.D. Wickens, Engineering Psychology and Human Performance, 2nd ed., Harper Collins, NewYork, 1994.

[13] R.C. Atkinson and R.M. Shiffrin, "Human memory: A proposed system and its control processes," The Psychology of Learning and Motivation: II., Academic Press, Oxford, England, 1968.

[14] The WordNet homepage, http://wordnet.princeton.edu/

[15] G.G. Towell and J.W. Shavlik, "Knowledge-based artificial neural networks," Artifi, Intelli., vol.70, pp.119–165, 1994.

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