Emotion Recognition from Textual Modality Using a Situational Personalized Emotion Model

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Abstract

To understand the other person's emotion, we should know the situations in which the person is surrounded and the personality of the person. In most previous studies, however, these important characteristics don't be considered, and emotion recognition has been considered as a problem of classifying texts. In this paper, we attempt to novel approaches to utilize situational information and personality of emotional subject. We propose the method extracting situational information, and the personalized emotion model for reflecting personality of emotional subject. To extract and utilize situational information, we propose situation model using lexical and syntactic information. In addition, To reflect personality of emotional subject, we propose personalized emotion model using KBANN(Knowledge-based Artificial Neural Network). Experimental results show that the proposed system can recognize emotions more accurately and intelligently than previous text-based emotion recognition systems.

Keywords: emotion, recognition, situation, personality, text

1. Introduction

Human emotion recognition is an essential research field in human-computer interaction research. Emotion recognition can be subdivided according to the modality such as voice, facial expressions, brain signals and text. The text is a very informative modality because it can handle intelligent emotional features that another modality cannot handle. A number of computer science researchers in the field of emotion recognition have steadily researched text-based emotion recognition. They have treated emotion recognition problem as a kind of classifying problem that has been widely used in information retrieval, NLP, machine learning and so on. However, we think that such previous attempts have limitations to recognize emotion, because emotion is very complicated, and it must be considered surrounding situation and personalized judgments about the situation [1].

To reflect surrounding situational information, we extract situational information from natural language text, and construct the situation model. For this we use emotion lexicon dictionary and dependency parser. One more thing to consider is that created emotions may be different for each person even if the same situation is given. To realize this idea, we propose personalized emotion model that is built for each emotional subject.

Experimental results show that the proposed system can recognize emotions more accurately and intelligently than previous text-based emotion recognition systems. In

particular, in case that input sentences have no emotional keyword, significant improved result is shown.

2. Related Works

Most of the text-based emotion recognition is based on a keyword-spotting algorithm [2, 3]. Keyword-spotting method is relatively easy to process, because it only handles word-level vocabulary information. So, much of linguistic information is lost. In addition, processing ironic or negative expression is almost impossible because it only handles surface information of sentence. Because of these limitations, we think a keyword-spotting algorithm is not suitable in the area needed high accuracy or intelligent language processing.

Some researcher who felt the limitations of keyword-spotting method have tried to utilize syntactic information, semantic information, pragmatic information or other linguistic information [4, 5]. However, previous researches don't consider surrounding situation and personality for emotional subject. In this paper, we attempt human-like intelligent emotion recognition using these characteristics.

3. Implementation

In general, text-based emotion recognition researches handle two to eight emotions. However, we chose both sixteen emotions proposed by Lazarus and six emotions proposed by Ekman as candidate, and we selected nine emotions (anger, fear, sadness, happiness, disgust, surprise, love gratitude, and anxiety) as target for recognition based on the conditions which have a relatively high occurrence rate and are easy to recognize.

We assume that emotion recognition process is "To recognize a given situation from text, and to find emotions by matching the situation with emotion creation rules that consider personalized emotion model". To implement this idea, given situation and personalized emotion model should be defined and modeled. The situation described in this paper is stimuli or input data to generate emotion. We extract the situation information from natural language text, and use it as input data for emotion recognition and as situation knowledge.

We extract the situation knowledge from natural language text in English, and utilize it in the course of subsequent processing. We define the situation knowledge as entity-relationship structure, and call it as the situation model. We use to weighted graph data structure to represent the strength of relations. Following figure illustrates an example of the simple situation model.
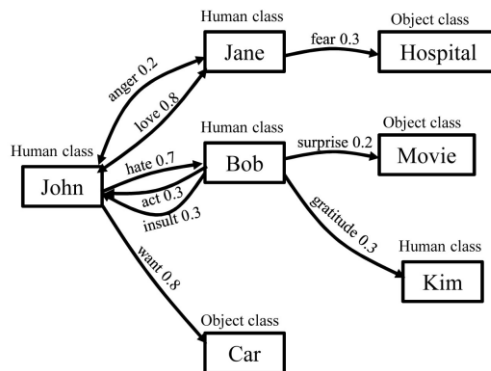

Figure 1. An Example of Situation Model

Each class (node) can be subdivided into human classes and object classes. A human class indicates human that own emotion. An object class indicates the objects that can relate to the human. Each class is connected by the relation. The relation only can be expressed as predefined emotional language vocabulary. Every natural language sentence is mapped to emotional lexicon through emotional lexicon dictionary.

Human class and object class should be identified by natural language processing from input text sentence. For this, we parse input text by the Stanford dependency parser [6]. In the result of dependency parsing, most sentences have nominal subject dependency (has *nsubj* tag in parsing result of the Stanford dependency parser) except special exception (omitting subject, etc). In the nominal subject dependency relation, the governor could be a main verb and the determiner could be a subject. In the case that the main verb is the copular verb (has *cop* tag), the subject and the main verb could be found in copula dependency. We could also find the subject in case that subject is noun phrase by tracking determiner of the nominal subject dependency relation. The object could be found by the dependency including the main verb. It can be the target object of the relation. The relation name is assigned as the mapped word with the main verb in the emotion lexicon dictionary. Situation knowledge can be expanded by iterating the process described above for an input sentences.

Emotion lexicon is determined as the lexicon used at the emotion creation rules. Emotion lexicon dictionary is automatically constructed by expanding 25 initial seed words into k-depth synonyms and antonyms. In addition, whenever a new lexicon appear in an input sentence in learning process and test process, the user can determine the emotion category and add the lexicon into the emotion lexicon dictionary.

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

We have to find subject from input sentence in order to build personalized emotion model. The subject of an input sentence is already found in the process for extracting situation knowledge. If this subject is human then determine it as emotional subject. We determine the subject as human subject if the subject is subject of emotional relation (such as like, fear).

We employ the KBANN (Knowledge Based Artificial Neural Network) [7] as data structure for emotion model. When domain-knowledge exists, the KBANN can expect better performance though having sparse training data. We use domain-knowledge such as emotion creation rule and it is difficult to get 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 25-cell flag array corresponding 25 representative emotion lexicons (which are used in the emotion creation rule). Each element of the array has 1 if corresponded emotional lexicon exists or 0 if corresponded emotional lexicon not exists.

We roughly show the process of design KBANN with an example for Anger emotion creation rule. For more detail about design KBANN with domain-knowledge, refer the papers for KBANN [7]. According to psychological theory [1], Anger is created when emotional subject suffer from insulting words or actions. We can make it creation rule as Anger $\rightarrow$ anger $\vee$ (insult $\wedge$ (verbal $\vee$ act)). Then network can be built by Network changing rule in

the paper proposing KBANN. As the same way, nine networks can be built by nine emotion creation rules. The training corpus is constructed with sentences including abundant emotional expressions. The corpus consists of about 3000 sentences. Each sentence tagged with nine target emotions and neutral emotion. Once a input sentence goes to the the system, dependency parsing, extracting situation information, selecting KBANN corresponding to emotional subject, inputting 25 flag array of emotion structure into the KBANN, and refining weight parameters of the KBANN through back-propagation algorithm are performed respectively. The proposed emotion recognition system is shown in Figure 2.
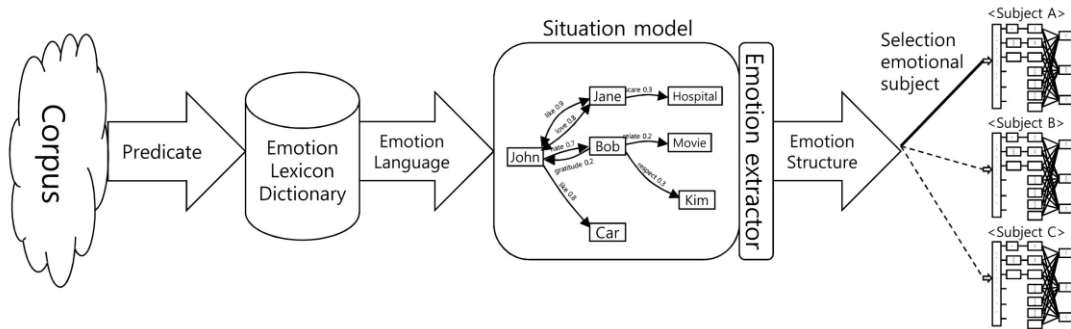

Figure 2. System Overview

4. Experiment

There is no standard corpus for experiment in emotion recognition field yet. Therefore, we decided to build the corpus including abundant emotional information. About 3000 sentences are included in the corpus. About 49 percent of the sentences include emotional information directly or indirectly. We evaluated accuracy of proposed emotion recognition system by comparing emotions predicted by the system with tagged emotions in the test corpus. Ten-fold cross validation method is used. 2970 sentences in the corpus are used for the test. The evaluation result is in Table 1.

Table 1. Accuracy of Emotion Recognition

Scenario	Correct	# of sentences	Accuracy (%)
Anger	95	154	61.69
Disgust	79	150	52.67
Fear	134	178	75.28
Love	96	189	50.79
Sadness	102	129	79.07
Surprise	128	181	70.72
Gratitude	76	157	48.41
Unrest	87	144	60.42
Happiness	107	153	69.93
Neutral	1189	1535	77.46
Total	2093	2970	70.47

In addition, we implemented a keyword-based emotion recognition system 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. About 50 percent of sentences in the corpus have emotional keywords. Figure 3 shows the accuracy of emotion recognition using the proposed system with and without an emotional keyword.
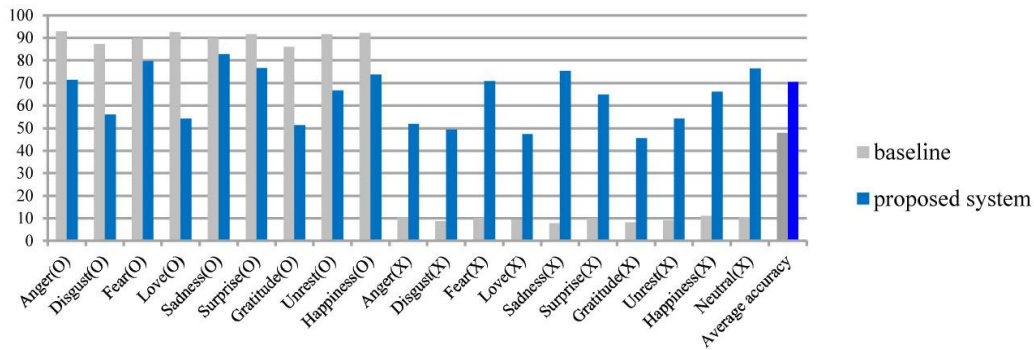
Figure 3. Accuracy of Emotion Recognition with an Emotional Keyword (O) and without an Emotional Keyword (X)

Baseline system using keyword-spotting method showed about 90% of accuracy in case of having emotional keywords. In the case of having no emotional keyword, the accuracy was approximately 10%. On the other hand, proposed system almost uniformly showed approximately 70% of accuracy in both cases. Average accuracy of proposed system was 70.47%, and average accuracy of baseline system was 48%. This experiment showed that proposed method is beneficial in the case that input sentence has no emotional keyword and the case that situation information and personality are needed to recognizing emotion.

5. Conclusion

In this paper, we attempt to recognize emotion using situational information and personalized emotion model. We extract situational information by using dependency parser and the emotion lexicon dictionary, and construct the situation model. The proposed system could also recognize emotions in case having no emotional keyword in input sentences, because it uses situational information. In addition, the system is designed to reflect the characteristic, that each emotional subject may get different emotion in same situation. For this, we constructed and utilized the personalized emotion model using KBANN.

Though proposed system can do human-like intelligent emotion recognition, which traditional text-based emotion recognition system cannot, included characteristic of keyword-spotting algorithm and improve the recognition accuracy. Like these, we attempt novel approaches considering the characteristic of emotion. As a result, we showed that intelligent emotion recognition considering surrounding situation and personality of emotional subject is possible.

However still most difficult point to recognize emotion from text modality is natural language processing. To utilize our study in various application areas, complex sentence, embedded sentence, substitute, irony, omission, ambiguity and a number of remained natural language processing issues should be solved in advance.

In emotion recognition area, until now, voice and vision modality have core position. However text modality could play an important role in human-like intelligent emotion recognition as showed in this paper.

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