

Effective Analysis of Emotiveness in Utterances Based on Features of Lexical and Non-Lexical Layer of Speech.

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Abstract:

We propose a highly effective method of analysis of emotiveness in utterances, which clearly outperforms present ones. The method is based on analysis of emotive features of the lexical layer of user's utterances and is supported by analysis of non-lexical emotive features conveyed in text. The system based on this method acquired 93% of accuracy in recognizing emotiveness of user's utterances and was able to propose emotive value and extract specific emotion on a level comparable to human evaluators.

Keywords: Emotiveness, analysis of emotiveness.

1. Introduction

Scientists have been fascinated by emotions for centuries. There are remarkable works trying to describe emotions, such as the ones by Darwin [1], or many others [2, 3, 4]. However, for a long time emotions were treated rather as an idol to worship, worthy attention of thinkers, but not material or tangible enough to be accurately described in detail, or processed by machines. Recent years brought research on emotions into the focus of Computer Science, and Artificial Intelligence, and its sub-fields like Natural Language Processing [5, 6]. Subjectivity of feelings though, driving researchers into a corner of ambiguity, often becomes a blockade for research in this field. However, as we assume, analysis of emotions, narrowed to specified borders, should give results comparable to those of humans.

2. Narrowed approach to affect analysis

There are different dimensions on which emotions can be analyzed, such as psychological, visual, vocal, linguistic, social, neurobiological, etc. Unfortunately, although it would be desirable to combine these fields for creating a multidimensional emotive analyzer, the development of research in each of these fields is still not sophisticated enough. Therefore, to create a firm ground for similar research in the future, we decided to narrow the approach towards emotions to textual surface of speech analysis, since it is the language, which makes human emotions so context-dependent and thus difficult to process only by its visual or phonetic manifestation.

Many attempts to analyze emotiveness in text either end in a failure, like the one by Read [7] (accuracy of 33%¹), or Alm et al. [8] (69%) or run into a problem of ambiguity of emotional rules, like in Wu, et al. [9] (81%).

Therefore we made the following assumptions to specify and narrow the affect analysis. Firstly, the research will be conducted on the basis of textual utterances. This releases us from analyzing relevant, but ambiguous and difficult to process mechanically – features such as vocal, visual and other dimensions of expressing emotions, giving a green light for concentrating on emotiveness in the textual surface of an utterance. Secondly, the analysis will be conducted on dialogue-like utterances appearing usually in speech. This limits appearance of utterances realizing descriptive or poetic function of language, such as literature and poetry. This approach relates to the future goal, which is to implement the system into conversation systems like Higuchi's [10] to make their utterance recognition and producing more natural. Finally, we will focus on the emotiveness of the utterances.

3. Emotiveness - linguistic approach

In language there are elements informing that emotions have been conveyed in the utterance, but do not have to express specified feelings or, more precisely, can express different feelings depending on the context of the sentence. Such elements, conveying emotive meaning in the sentence, make up the feature of language called emotiveness [26, 29], and are described by emotive function of language.

The emotive function of language [24, 25], is realized verbally through such parts of speech as exclamations, hypocoristics (endearments), vulgar language, mimetic expressions (*gitaigo*²), and so on [26]. A key role in expressing emotions is also played by the lexicon of words describing states of emotions [19]. On the borderline between verbality and nonverbality we can talk about elements of language such as intonation, voice modulation or tone of voice. In the written text

¹ All results rounded off to the nearest whole 1%.

² In this paper we use italic for Japanese expressions.

these are usually represented symbolically by exclamation marks, multiple usage of question marks, and so on. Nonverbal elements realizing emotive language are body language, with all its components, like gestures, face expressions, eye contact, or pose [1, 11, 21]. However in conversation systems like chat-bots the communication channel is limited to transmission of signals encoded in lines of letters, punctuation marks, symbols, etc. Therefore for analysis of emotiveness in conversation systems we need to agree to a compromise of restrictions in the communication channel and focus the analysis on its linguistic manifestations.

4. Emotive Elements Analysis Module (ML-Ask)

The analysis of emotiveness in the proposed system is based on Ptaszynski's idea of finding emotive elements in the text [12, 13, 20]. In an utterance made by the user emotive elements will be examined using the top-down determined databases of emotive elements in speech. We gathered these databases of each emotive elements appearing in conversation in Japanese, basing on different researches. The databases are divided into interjections [19, 23, 27, 28], emotive mimetics (*gitaigo*) [1, 28], endearments [26], vulgar vocabulary [17], which belong to lexical layer of speech, and symbols representing emotive elements from non-lexical layer of speech [26], like exclamation marks, syllable prolongation marks, etc. As a part of emotive symbols database, we also added an algorithm recognizing emoticons, as symbols already widespread and commonly used in everyday Internet communication tools. A few simple examples of sentences without emotive value (A, B), and those colored with emotions (A', B') are given below. The parts of each sentence that constitute its emotiveness were written in bold letters.

A: 今日はいい天気です。

Kyō wa ii tenki desu.

It is a good weather today.

A': ああ、今日はええ天気だな！ (^o^)

Aa, kyō wa ee tenki dana! (^o^)

Wow, now today is a fine weather! :D

B: 彼女は、大きいかさをもってきて、信之介を強く殴った。

Kanojo wa, ookii kasa wo mottekite, Shinnosuke wo tsuyoku nagutta.

She brought a large umbrella and strongly hit Shinnosuke.

B': あいつあ でっけーかさをもってきやがって、シンちゃんをひでーポコポコに しちまった！

Aitsaa dekkē kasa wo mottekiyagatte, Shin-chan wo hidē bokoboko ni shichimatta!

That slut lugged a huge umbrella with her and beat the crap out of Shin-chan.

After analyzing every utterance this way, the system returns a verdict

whether the utterance is emotive and what emotive elements were found in the utterance. On this basis the system proposes its emotive value of the sentence. The value is placed on a scale of 0 to 5. We checked two methods for emotive value calculation. The first one gives 0 for the lack of emotive element in the utterance and 1 point for appearance of every type of it. The second one counts 1 point for every piece of emotive element found in the sentence (but with maximum value of 5). We compared those two methods to choose latter as it gave results closer to human evaluators. In the next step, in the utterances determined as emotive, the system determines whether the emotiveness of the utterance is positive or negative and searches for specified feelings conveyed.

5. ML-Ask Evaluation Experiment

To verify how accurate the analysis of emotiveness in ML-Ask module is we performed an evaluation experiment.

5.1 Survey

We asked ten people (2 females and 8 males in the age from 20 to 34) to write three non-emotive sentences and three with similar meaning, but colored with emotions. This survey gave us a set of sixty sentences - thirty non-emotive and thirty emotive.

5.2 Experiment

The sentences gathered in the survey mentioned above were next analyzed by the system. For each sentence the system was supposed to determine whether the sentence was emotive and, if so, what were the emotive elements found and what the proposed emotive value of the utterance is. Next, the system was to determine what feeling exactly is conducted in the utterance and from that - whether the emotiveness is of positive or negative character. For classification of emotions we used Nakamura's [19] as the most appropriate classification of emotions in Japanese known today.

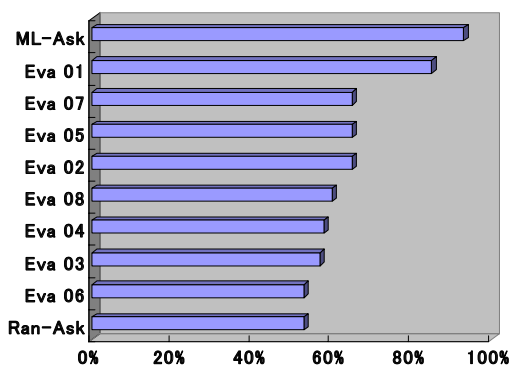
5.3 Evaluation

As it was mentioned above, the sense of emotiveness might differ among people. Therefore we also performed an evaluation of the gathered sentences. In the evaluation we asked eight people (2 females and 6 males in the age from 20 to 30) to determine whether the sixty sentences are emotive or not and how much (we decided to use the same scale as for the system, that is 0-5). The results given by the system and the results of evaluation were compared to the authors of the sentences classification of emotiveness and to each other. We also created another system - competing with ML-Ask - determining emotiveness and emotive value randomly without any linguistic knowledge and compared the results.

5.4 Results

5.4.1 Emotiveness - system and evaluators vs. authors

The beta version of the system used in former research [22] determined emotiveness in an accuracy rate of 88%, which was already higher than results of other systems attempting to compute emotiveness today. However after debugging and upgrading databases the final accuracy rose to 93% outperforming other systems. Accuracy of human evaluators in recognizing emotiveness of the sentences was established between 53% and 85%. The system determining emotiveness randomly (Ran-Ask) occurred ineffective achieving only 53% of accuracy.



	Ran-Ask	Eva 06	Eva 03	Eva 04	Eva 08	Eva 02	Eva 05	Eva 07	Eva 01	ML-Ask
results	53%	53%	57%	58%	60%	65%	65%	65%	85%	93%

Table 1 Results of determining emotiveness by ML-Ask, Ran-Ask and evaluators (Eva01~Eva08) – basing on the preset classification by authors of the utterances.

5.4.2 Emotive value - System vs. evaluators

After adding up the results of emotiveness recognition, we checked the unanimity of determining emotive value between ML-Ask and evaluators. For this step we used only utterances where at least 7 for 8 people guessed whether the sentence is emotive or not. The unanimity of ML-Ask with human evaluators was set at a range of 50% to 88%. Although the bracket is wide, we consider this result as satisfactory, since emotional intensity recognition is highly subjective among people. For the comparison, the approximate of unanimity among the evaluators themselves about the emotive value of the sentences was set at a level of 37% for the perfect match and 74% for the almost perfect match (a case when emotive value differ among evaluators by 1 emotive point).

5.4.3 Identification of emotions types

For evaluation of specified emotion recognition by the system we performed another survey. We asked twelve different people (2 females,

10 males) about emotions conveyed in emotive utterances (with a possibility of specifying more than one feeling). In many cases the results differed significantly and there were sentences with emotions unidentifiable by some evaluators. For such conditions the following assumptions were made. If ML-Ask guessed at least one of the emotion types classified by all evaluators per sentence, or the systems' classification coincided with the majority, the result was positive. In final results ML-Ask achieved an accuracy of 45% of the human level in recognizing the specific types of emotions. Some of the examples of successful emotion recognition are showed in the Table 1 below.

The result is satisfactory and encouraging, although is not perfect, which arises from lacks in appropriate databases created on Nakamura's collection [19]. However, we have already started to retrieve new entries from the Internet by using keywords from his collection to update the database, what clearly prognosticates the improvement.

Table 1 Two examples of successful recognizing of emotion types.

utterance / reading / meaning in English	ML-Ask	human evaluators
あなたの事が好きなんです。 /Anata no koto ga suki nan desu. / I love you.	好 [liking, fondness]	好 [liking, fondness] (7), 怖 [fear] (3), 喜 [joy] (2), 恥 [shame, shyness, bashfulness] (1), 昂 [excitement] (1)
この本さー、すげーやばかつ たよ。まじ怖すぎ。 / Kono hon saa, sugee yabakatta yo. Maji kowa sugi. / That book, ya know, it was a killer. It was just too scary.	怖 [fear]	怖 [fear] (6), 驚 [surprise] (2), 昂 [excitement] (2), 喜 [joy] (1), 無 [nothing] (1)

5.5 Description of errors

There were several errors found during the experiments. Although the evaluation given by the system about emotiveness was higher than we expected, a few lacks in databases of emotive elements were found, especially in the cases of using by authors highly informal language difficult to process by today tools for morphological analysis of the Japanese [14, 18]. However, such errors are can be reduced by designing an algorithm of recognizing Japanese informal speech, which we plan to propose in the next step of the project.

6. Conclusions

The analysis of emotiveness experiment confirmed that emotiveness is not incomputable on lexical level. Moreover, computer system designed in a specified way can determine emotiveness of a sentence with higher

accuracy than people, in specified borders described in this paper. Although there were still problems not solvable yet for a machine, the general results were very encouraging and thus we will continue the works on this project. It seems that with 93% of accuracy in determining emotiveness system proposed by us clearly outperforms the present ones of the kind.

7. Future work.

We set ourselves a number of targets to be achieved in the future. We will continue working on this project to eliminate the lacks in the databases mentioned above. We also plan to add a highly efficient algorithm for recognizing face marks (emoticons) in the near future. The code of the system will be upgraded to eliminate appearance of potential bugs. Implementing the algorithm to a conversation system will help to gather a large database of sentences. This will be helpful in finding emotiveness of specified words by their appearance in either emotive or non-emotive sentences. The system is already being actively implemented in two other projects – dynamic memory management system based on forgetting-recalling algorithm [12, 13], and Japanese Puns Generating system PUNDA [15, 16]. ML-Ask seems also to be perfect for filling the lacks in systems of recognizing emotions from facial expressions and voice or speech.

References:

- [1] C. R. Darwin, *The Expression of the Emotions in Man and Animals*, Oxford University Press, New York (1998)
- [2] N. H. Frijda, *The Emotions*, Cambridge University Press, Cambridge (1987)
- [3] Ortony, G. L. Clore, A. Collins, *The Cognitive Structure of Emotions*, Cambridge University Press, Cambridge (1988)
- [4] E. Izard, *Human Emotions*, Springer (1977)
- [5] N. Nakayama, K. Eguchi, N. Kando, *A Proposal for Extraction of Emotional Expression*, (in: IEICE Technical Report, vol. 104, no. 416, (2004), pp.13-18)
- [6] R. W. Picard, *Affective Computing*, The MIT Press, Cambridge (1997)
- [7] J. Read, *Recognizing Affect in Text using Pointwise-Mutual Information*, University of Sussex, Sussex (2004)
- [8] C. O. Alm, D. Roth, R. Sproat, *Emotions from text: machine learning for text based emotion prediction*, HLT/EMNLP, Vancouver (2005)
- [9] C. H. Wu, Z. J. Chuang, Y. C. Lin, *Emotion Recognition from Text Using Semantic Labels and Separable Mixture Models*, ACM Transactions on Asian Language Information Processing (2006)
- [10] S. Higuchi, R. Rzepka, K. Araki, *Web ni yoru tango kyōki hindo oyobi modarithi wo mochiūta zatsudan shisutemu* (Chat systems based on occurrence frequency of words of in the Web and modality), 2007 Electric and Information Sciences Associations Paper Competition in Hokkaido, Sapporo (2007)
- [11] E. T. Hall, *The Hidden Dimension*, Double Day New York (1966)
- [12] M. Ptaszynski, K. Sayama, *The idea of dynamic memory management system based on a forgetting-recalling algorithm with emotive analysis*. (in: Language Acquisition and Understanding (LAU) Technical Report, Hokkaido University, Sapporo (2007), pp. 12-16)
- [13] M. Ptaszynski, K. Sayama, R. Rzepka, K. Araki, *A dynamic memory management system based on forgetting and recalling*. 2007 Electric and Information Sciences Associations Paper Competition in Hokkaido, Sapporo (2007)
- [14] T. Kudo., *MeCab: Yet Another Part-of-Speech and Morphological Analyzer*, (2001) <http://mecab.sourceforge.net/> (2008.01.27)
- [15] P. Dybala, R. Rzepka, K. Araki, *PUNDA Project – a Design For A Japanese Puns Generating system* (in: Language Acquisition and Understanding (LAU) Technical Report, Hokkaido University, Sapporo (2007), pp. 6-11)
- [16] P. Dybala, R. Rzepka, K. Araki, *Dajare Types and Individualised Sense of Humour - A Prelude to PUNDA Project*, 2007 Electric and Information Sciences Associations Paper Competition in Hokkaido, Sapporo (2007)
- [17] J. Sjöbergh, *Vulgarieties are fucking funny, or at least make things a little bit funnier*, KTH CSC, Stockholm (2006)
- [18] Y. Matsumoto, A. Kitauchi, T. Yamashita, Y. Hirano, H. Matsuda, K. Takaoka, M. Asahara. *Japanese Morphological Analysis System ChaSen version 2.2.1*, Nara Institute of Science and Technology (2000)
- [19] Nakamura, *Kanjō hyōgen jiten* (Dictionary of Emotive Expressions), Tokyodo Publishing, Tokyo (2004)
- [20] M. Ptaszyński, *Moeru gengo - Intānetto kei-jiban no ue no nihongo kaiwa ni okeru kanjōhyōgen no kōzō to kigōrontekikinō no bunseki - "2channeru" denshikeijiban o rei toshite* –(Boisterous language. Analysis of structures and semiotic functions of emotive expressions in conversation on Japanese Internet bulletin board forum - 2channel -), UAM, Poznań (2006)
- [21] M. Argyle, *The psychology of interpersonal behavior*, Penguin, Baltimore (1967)
- [22] M. Ptaszynski, P. Dybala, W. H. Shi, R. Rzepka, K. Araki, *Lexical Analysis of Emotiveness in Utterances for Automatic Joke Generation*, ITE Technical Report Vol.32, No.47, pp. 39-42 (2007)
- [23] N. Tsuchiya, *Taiwa ni okeru kandōshi, iiyodomi no tōgoteki seishitsu ni tsuite no kōsatsu* (Observations of exclamations and fillers in conversation), Jinkō Chin Kenshi (Artificial Intel- igence Research Papers), SIG-SLUD-9903-11 (1999)
- [24] K. Bühler, *Sprachtheorie. Die Darstellungsfunktion der Sprache* (Theory of Language. Representative Function of Language), Ullstein, Frankfurt a.M., Berlin, Wien (1978)
- [25] R. Jakobson, *Closing Statement: Linguistics and Poetics* (in T. A. Sebeok (Ed.) *Style in Language*, The Massachusetts Institute of Technology Press, Massachusetts (1966))
- [26] T. Kamei, R. Kouno, E. Chino, *Gengogaku Daijiten* (Great Dictionary of Linguistics), Sansendo, Tokyo (1996)
- [27] Y. Oshima-Takane, B. MacWhinney (Ed.), H. Shirai, S. Miyata, N. Naka (Rev.), *CHILDES Manual for Japanese*, McGill University, The JCHAT Project (1995-1998)
- [28] T. Itoh, N. Minematsu, S. Nakagawa, *Analysis of filled pauses and their use in a dialogue system*, The Journal of the Acoustical Society of Japan, Vol.55 (1999)
- [29] C. L. Stevenson, *Facts and Values -- Studies in Ethical Analysis*, Yale University Press (1963)