Towards Fully Automatic Emoticon Analysis System (^o^)

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Abstract

In this paper we present CAO - a system for emotion estimation of emoticons - sets of symbols widely used to convey emotions in text-based online communication. The system first determines specific emotions expressed by emoticons with a predetermined database created by collecting emoticons from numerous dictionaries of face marks and online jargon. The emoticons, for which specific emotion type could not be determined with only the database, are analyzed basing on extraction of semantic areas of an emoticon, such as representations of "mouth" or "eyes". The semantic areas are automatically annotated based on co-occurrence statistics and the theory of kinesics, and provide hints about the potential groups of expressed emotions. The primary evaluation of the system showed its capability to analyze any new emoticon generated creatively by Internet users and to sufficiently estimate potential emotion types expressed. The system is also capable of sufficient extraction of new emoticons from sentences appearing on the Internet. Experiments with this system are presented and numerous applications are proposed.

Keywords:　Affect Analysis, Emoticon, Theory of Kinesics;

1. Introduction

On IJCAI 2009 Ptaszynski et al [1] presented a prototype method capable of specifying user emotions in a more sophisticated way than simple valence classification. The method is based on a ten type-classification of emotions in the Japanese language proposed by Nakamura [2]. Moreover, it does not only specify what type of emotion was expressed, but also determines whether the emotion is appropriate for the context it appears in. However, one of the problems in the method included lacks in affect analysis procedure. To improve the affect analysis we decided to create a system for affect analysis of emoticons as are often used in online communication.

The affect analysis is a sub-field of AI, focusing on classifying users' expressions of emotions. It takes as an object the human user and aims to estimate his/her emotional states, such as anger, excitement, joy, etc. There have been several approaches to either analyze emotive information conveyed by emoticons or use such information to generate emoticons automatically. For example, Tanaka et al [3] used kernel methods to classify emoticons. Yamada et al [4] on the other hand used statistics of n-grams for the same goal. Nakamura et al [5], on the other hand, used machine learning to generate emoticons for the use in a dialogue system. However, none of them presented research on a large number of emoticons analyzed automatically. Also, all of the above systems strictly depend on the number of emoticons in the database and therefore are highly vulnerable to user's creativity in generating new emoticons.

This paper presents a research aiming to create a system analyzing emoticons in fully automatic manner. One of the main steps to fulfill this goal was creating a coherent database of emoticons. To do that we first gather emoticons from Internet web sites that contain emoticon dictionaries. However, these dictionaries, although robust and rich in emoticon expressions, are usually grouped according to subjective naming criteria. To unify the naming we filtered the numerous categories form the online dictionaries with a previously developed affect analysis system based on linguistically underpinned classification of emotions. After the filtering, all emoticons were extracted from the groups with naming coherent with the scientific classification of emotions and regrouped, according to the classification. Next, we apply the theory of kinesics to divide the extracted emoticons into semantic areas (*kinemes*), such as representations of mouths and eyes. Finally the emotive affiliations of the semantic areas are automatically determined using co-occurrence statistics.

The system created on this database is evaluated with a comparison to other systems. The evaluation is based on training set and test set. As the training set we use the system's database. As the test set we use a corpus of over three hundred million sentences extracted from Internet Blogs. The system's performance is evaluated in such areas like emoticon detection in a sentence; emoticon extraction from a sentence; division of emoticon into semantic areas; emotion classification of emoticons. Finally, a number of applications of this system is proposed. One of the applications is the use of this system in sentence-based affect analysis. A primary experiment in this matter is performed to show our system's improving influence on baseline affect analysis system.

Table 1. Examples of emoticons with different numbers of sets of semantic areas; [M] - mouth; [E_L], [E_R] – eyes; [B_1], [B_2] - emoticon borders; [S_1] - [S_4] - additional areas;

No. of sets	Emoticon	S_1	B_1	S_2	E_L	M	E_R	S_3	B_2	S_4	...
1	ヾ(。･ω･)ﾉ	ヾ	(	。	･	ω	･	N/A	)	ﾉ	
1	(——;)	N/A	(	N/A	—	N/A	—	;	)	N/A	
						SET 01					SET 02
2	(^^)人(^^)	N/A	(	N/A	^	N/A	^	N/A	)	人	(^^)
2	☆- (●≧ ▿)人(▿ ≦ ●)- ☆	☆-	(	●	≧	▿	N/A	N/A	)	人	(▿ ≦ ●)- ☆
					SET 01		SET 02	SET 03		SET 04	
4	(∇ ´○)Ⅲ´★)ω´☆)∀ ´●)				(∇ ´○)		Ⅲ´★)	ω´☆)		∀ ´●)	

3. Definition of Emoticon

Emoticons have been used in online communication for many years and number of them has been developed, depending on the language of use, letter input system, the kind of community they are used in, etc. However, they can be roughly divided into three types: **a)** Western one-line type; **b)** Eastern one-line type; and **c)** Multi-line ASCII art type.

Western emoticons are characteristic as rotated by 90 degrees, such as ":-)" (smiling face), or ":-D" (laughing face). They are the simplest of the three as they are usually made of two to four characters and are of relatively small number. Therefore, we excluded them from our research as not being challenging enough to be a part of language processing. Moreover, our research focuses on the use of emoticons by Japanese users and this type of emoticons is rarely used in Japanese online communities. However, as the western-type emoticons can be gathered in a list of about fifty, such a list can be simply added to our system on the end in a simple sub-procedure.

Multi-line ASCII art type emoticons, on the other hand, consist of number of characters written in several up to even several dozens of lines, which, when look at from a distance make up a picture, often representing a face or several faces. Their multi-line structure makes their analysis to be considered more as a task for image processing than language processing, since this would be the only way for the computer to obtain an impression of the emoticon from the point of view similar to a user looking at the computer screen. Because of the above we do not include multi-liners in our research.

Table 2. Ratio of unique emoticons to the all extracted ones and their distribution in the database according to emotion types.

joy, delight	anger	sadness, gloom	fear	shame, shyness, bashfulness	liking, fondness	dislike	excite-ment	relief	surprise, amazement	Over- all	
3128	1238	1203	179	526	1988	704	1124	99	1227	**11416**	All extracted emoticons
1972	1221	1169	179	511	1972	698	1120	99	1196	**10137**	No. of unique emoticons
63%	99%	97%	100%	97%	99%	99%	100%	100%	97%	**89%**	Ratio

Finally, eastern emoticons, comparing to the western ones, are usually unrotated and present faces, gestures or postures from the point of view easy to read for the reader. Some examples are: "^o^" (laughing face), "(^_^)" (smiling face), "(ToT)" (crying face). They arose in Japan, where they are called *kaomoji*, in 1980s and since then have been developed on a number of online communities. They are made of three to over twenty characters written in one line and consist of a representation of at least one face or posture, up to a number of different face-marks. In the research described in this paper we focused mainly on this type of emoticons, as they have a large variation of appearance and are sophisticated enough to express different meanings.

Therefore, for the need of this research we define "emoticon" as a one-line string of symbols containing at least one set of semantic areas, which we classify as: "mouth" [M], "eyes" [E_L], [E_R], "emoticon borders" [B_1], [B_2], and "additional areas" [S_1] - [S_4] placed between the above. Each area can include from one to many characters. We also allowed part of the set to be of empty value. The minimal emoticon set considered in this research contains of only two eyes (a set represented as "E_L,E_R"), mouth and an eye ("E_L,M" or "M,E_R"), or mouth/eye with one element of the additional areas ("S_1/S_2,E_L/M" or "M/E_R,S_3/S_4"). See Table 1 for details.

Emoticons defined this way can be considered as representations of body language in text based conversation, where communication channel is limited to transmission of letters and punctuation marks. Therefore we based our approach to analysis of emoticons on assumptions similar to the ones from the research on body language. In particular we apply the theory of kinesics to define semantic areas as separate *kinemes* and then automatically assign to them emotional affiliation.

4. Theory of Kinesics

The word *kinesics*, as defined by Vargas [6], refers to all non-verbal behavior related to movement, such as postures, gestures and facial expressions and functions today as a term for body language in anthropology. It is studied as an important part of nonverbal (or "iconic") communication along with paralanguage (e.g. voice modulation) and proxemics (e.g. social distance). The term was first used by Birdwhistell in 1952 [7], who founded the theory of kinesics in the fifties and developed it further till seventies [8]. The theory assumes that non-verbal behavior is used in everyday communication systematically and can be studied similarly to language. A minimal part distinguished in kinesics is a *kineme* - the smallest set of body moves containing a certain meaning, e.g. raising eyebrows, or moving eyes upward in face movements. Birdwhistell developed a complex system of *kinegraphs* to annotate kinemes in the research on body language.

4.1 Emoticons in the View of Kinesics

One of the current applications of kinesics is in annotation of affect display in psychology to determine which emotion is represented by which body movement or facial expression. Emoticons can be considered as representations of body language in online text-based communication. Using this reasoning we based our analysis of emotive information conveyed in emoticons on annotations of the particular semantic areas grouped in an automatically constructed emoticon database.

5. Database of Emoticons

Developing a coherent database of emoticons classified according to emotions they represent was the first step in creation of CAO - the system for analysis of emoticons. The database development was done in several steps. Firstly, we collected emoticons from seven Internet online emoticon dictionaries. Then, the naming of emotion classes was unified with the linguistic classification of emotions in Japanese. Next, we applied the idea of kinemes form the theory of kinesics to divide the extracted emoticons into semantic areas. Finally emotive affiliations of the semantic areas were determined statistically by calculating their co-occurrence in the database.

5.1 Resource Collection

To create a coherent database of emoticons and its semantic areas we first needed a raw collection of emoticons. These were extracted from seven online emoticon dictionaries available on seven popular Web pages dedicated to emoticons: Face-mark Party, Kaomojiya, Kaomoji-toshokan, Kaomoji-café, Kaomoji Paradise, Kaomojisyo and Kaomoji Station[1]. All of those dictionaries are easily accessible from the Internet and provide a large collection of popular emoticons.

5.2 Database Naming Unification

The data in every dictionary is divided into numerous categories, such as "greetings", "affirmations", "actions", "hobby", "expressing emotions", etc. The number of categories however and their nomenclature is far from unification. Every dictionary provides its own category number and naming. To solve this problem we processed all category names with an affect analysis system ML-Ask developed by Ptaszynski [9]. The data in every dictionary is divided into numerous categories, such as "greetings", "affirmations", "actions", "hobby", "expressing emotions", etc. The number of categories however and their nomenclature is far from unification. Every dictionary provides its own category number and naming. To solve this problem we processed all category names with an affect analysis system ML-Ask developed by Ptaszynski [9]. One of the procedures in this system is to classify the words according to what emotion type they express. The system uses a coherent classification of emotions based on Nakamura's emotive expressions dictionary developed after a long time study on words describing emotional states in Japanese [2]. The names of categories from all online emoticon collections which revealed some emotional characterization were selected and grouped according to Nakamura's classification of emotions. Finally the emoticons from those collections were extracted from the Web pages. This way we extracted a large number of 11,416 emoticons. However, since some emoticons could appear in more than one collection form the seven, we performed a filtering to extract only the unique ones. The number of emoticons after the filtering was 10,137 (89%). This means that most of emoticons appearing in all seven collections were unique. For all emotion types, except "joy" almost all of the emoticons were unique. The emotion types for which the number of extracted emoticons was the highest were in order: joy, fondness, anger, surprise, gloom, and excitement. This means that Internet users express these emotion types more often than the rest. The ratio of unique emoticons to the all extracted ones and their distribution across the emotion types is shown in Table 2.

5.3 Extraction of Semantic Areas

After collecting the sufficient database of emoticons divided according to emotion types coherent with linguistic classification of emotions in Japanese, we performed an extraction of all semantic areas appearing in the unique emoticons. The extraction was done according to the definition of an emoticon presented above.

[1] Respectively: http://www.facemark.jp/facemark.htm, http://kaomojiya.com/, http://www.kaomoji.com/kao/text/, http://kaomoji-cafe.jp/, http://rsmz.net/kaopara/, http://matsucon.net/material/dic/, http://kaosute.net/jisyo/kanjou.shtml

Firstly, we defined the possible emoticon borders and extracted all unique triplets of semantic areas for combined eyes and mouth together (E_LME_R). From those triplets we extracted mouths (M) and pairs of eyes (E_L,E_R). Finally, having extracted the triplets E_LME_R and defined the emoticon borders we extracted all existing additional areas (S_1,…,S_4).

5.4 Annotation of Semantic Areas

Having the emoticons divided into semantic areas, occurrence frequency of the area in the emotion type database was calculated for every triplet, eye pair and mouth. All unique areas were summarized in order according to their occurrence rate in the database for each emotion type. This way every eye-mouth-eye triplet and all separate areas were automatically annotated according to the probability of which emotion they tend to express.

6. Database Statistics

The number of unique combined areas of E_LME_R triplets was 6,185. The number of unique areas representing pairs of eyes (E_L,E_R) was 1,920. The number of unique mouth areas (M) was 1,654. The number of unique additional areas was respectively $S_1 = 5{,}169$, $S_2 = 2{,}986$, $S_3 = 3{,}192$, $S_4 = 8{,}837$ (Overall 20,184).

6.1 Database Coverage

In the hitherto research on analysis of emoticons one of the most popular approaches was the one assuming that every emoticon is a separate entity, therefore is not divided into separate areas or characters [9]. However, this approach depends strongly on the number of emoticons in the database and is heavily vulnerable to user's creativity in generating new emoticons. The approach presented here assumes that emoticons can be analyzed more efficiently when divided into systematic parts. To confirm the above we calculated the coverage of the database of raw emoticons. The database of raw emoticons contains 10,137 unique emoticon specimens and 6,185 unique E_LME_R triplets. The database of semantic areas generated as described above contains 1,920 unique pairs of eyes E_L,E_R and 1,654 of unique mouths M. Therefore the number of all possible combinations of triplets $E_L,E_R \times M$, even excluding the additional areas is equal to 3,175,680 (over three millions of combinations). Comparing this to the number of raw emoticons, the somewhat large number of 10,137 unique specimens and 6,185 unique triplets the coverage of database of only raw emoticons does not exceed 0.3% and 0.2% respectively. Therefore a method based only on raw database would lose 97% of possible coverage. In our approach if an emoticon provided by the user does not appear in the database of raw specimens, the emoticons are divided into semantic areas, which are analyzed separately. This way the 97% of coverage is not lost.

7. System for Affect Analysis of Emoticons - CAO

The database of emoticons describes above, including the databases of semantic areas, was applied in CAO - a system for emotiCon Analysis and decOding of affective information. The system performs several procedures. Firstly, it detects whether there are any emoticons in the input. Secondly, if emoticon was detected, the system extracts all emoticons form the input. Thirdly, the system looks up in the database of raw emoticons which emotion type the extracted sample is used most often to express. If there is no raw emoticon matched with the input, the system separates the emoticon into semantic areas and tries to match an emoticon consisting of a triplet E_LME_R and additional characters. This procedure is assumed to be capable of analysis of most of the emoticons generated by the user. However, in case when the system could not find a matching triplet, it looks separately for the pair-of-eye area and the mouth area.

7.1 Emoticon Detection in Input

The first procedure of the system after obtaining an input is responsible for detecting whether there are any emoticons in the input. The presence of an emoticon is sensed when in a row appeared at least three symbols used usually in emoticons. A set of 1139 of those symbols was selected as being the most frequent symbols appearing in emoticons as analyzed by Ptaszynski [10].

Input: ･ﾟ･(ﾉД`;)･ﾟ･
Find match in raw emoticon database: ･ﾟ･(ﾉД`;)･ﾟ･
    If no match, localize E_LME_R triplet in the E_LME_R triplet database: ﾉД`
    If no triplet found, look for any E_LME_R combination;
    If no combination matched, find any E_LE_R or M from separate semantic area database: ﾉ;`, Д
Localize emoticon borders B_1,B_2 : (,)
Localize additional areas S_1,S_2,S_3,S_4 : ･ﾟ･,;,･ﾟ･
Determine the emoticon structure: **S_1**: ･ﾟ･, B_1:(, **S_2**:N/A, E_LE_R: ﾉ`, M: Д, **S_3**:;, B_2:), **S_4**: ･ﾟ･
Look for next emoticon;

Figure 1. The flow of the procedure for emoticon extraction form input.

Input: ･ﾟ･(ﾉД`;)･ﾟ･
Determine emotion types according to raw emoticon database:
･ﾟ･(ﾉД`;)･ﾟ･ : sorrow/sadness(3), excitement(2),
  If no match, determine emotion types for E_LME_R triplet:
  ﾉД`:excitement(14),anger(2),sorrow(1),fear(1),joy(1),fondness(1)
    If no emotion types for triplet found, find emotion types for separate semantic areas E_LE_R and M:
    ﾉ`:sorrow(3),shame(3),joy(2),fondness(2),fear(1),excitement(1),anger
    Д:sorrow(53),excitement(52),anger(42),surprise(37), joy(28
      fondness(25),dislike(22),fear(12),shame(9),
Determine emotion types for additional areas: ･ﾟ･:...,;:...,･ﾟ･:...
Proceed to next emoticon;

Figure 2. The flow of the procedure for affect analysis of emoticon.

7.2 Emoticon Extraction from Input

In the emoticon extraction procedure the system extracts all emoticons from input. It is done in three stages. First, the system is looking for a match with raw emoticons from the database. Secondly, if there is no perfect match, it is looking for any E_LME_R triplet form the triplet database. If a triplet is found the system matches the rest of the elements of the template $\mathbf{S_1}B_1\mathbf{S_2}E_LME_R\mathbf{S_3}B_2\mathbf{S_4}$ using all databases of additional areas and emoticon borders. Finally, in case the E_LME_R triplet was not found in the triplet database, the system searches firstly for any triplet match form all E_LME_R combinations. If no match was found either, the system looks for a match with any of the areas separately - eyes, mouth or additional. The flow of this procedure is shown on Figure 1.

Although the extraction procedure could function also as the detection procedure, it is time consuming. The differences in processing time are not visible for small number of inputs. However, we plan to use CAO to annotate large corpora including over several millions of entries. Therefore the detection procedure is added to shorten the processing time, as the system will skip the sentences with no suspicion of an emoticon.

7.3 Affect Analysis of Emoticons

In the affect analysis procedure the system estimates which emotion type is the most probable for an emoticon to express. This is done by matching the recognized emoticon to the databases with emotions types annotated on the database elements and their occurrence statistics. This procedure is performed as an extension to the extraction procedure. The system first checks which emotion types were annotated on raw emoticons. If no emotion was found, the system looks for emotion annotations for E_LME_R triplet. If no match was found, the semantic area databases for eyes E_LE_R and mouth M are considered separately and the matching emotion types are extracted. Finally, emotion type annotations for additional areas are determined. The flow of this procedure is shown on an example on Figure 2.

7.4 Output Calculation

Using the emotion annotations for emoticons and semantic areas we calculated the final emotion ranking output on three different ways to specify the most efficient one further in the process of evaluation.

7.4.1 Occurrence

Occurrence was the straight forward number of occurrences of an element (emoticon, a triplet or semantic area). The higher occurrence hit-rate an element had in the emotion type database the higher it scored. For more elements the final score for an emotion type was calculated as a sum of all occurrence scores for this emotion type. The final emotion scores were placed in descending order of the final sums of their occurrences.

7.4.2 Frequency

Frequency was the occurrence number of a matched element (emoticon or semantic area) divided by the number of all elements in the particular emotion type database. The higher the frequency rate there was for the matched element in the emotion type database the higher it scored. For more elements the final score for an emotion type was calculated as a sum of all frequency scores of the matched elements for this emotion type. The final scores for each emotion type were placed in descending order of the final sums of their frequencies.

7.4.3 Unique Frequency

Unique frequency is similar in calculation to the usual frequency. The difference is that denominator (division basis) is not the number of all elements in the particular emotion type database, but the number of all unique ones.

8. Evaluation of CAO

To fully verify the system's performance we carried out an evaluation. The evaluated areas were: emoticon extraction from input, and emotion classification of emoticons.

8.1 Training Set Evaluation

The training set for the evaluation included all 10137 unique emoticons form the database. However, to avoid perfect matching with the raw emoticon database (and therefore scoring 100% of accuracy) we made the system skip matching with this database and continue with further procedures (matching triplets or separate semantic areas and additional areas). The system's score was calculated as follows. If the system annotated the emoticon taken from a specific emotion type database with the database emotion type as the first one, it counted for 1 point. If the system annotated the emotion type, but it was not the name of the database from which the emoticon was taken, the score was calculated as the rank divided by the number of all emotions annotated. Therefore, if the system annotated 5 emotion types on an emoticon taken from the "joy" database and the "joy" annotation appeared on the second place, the system's score was 4/5 (0.8 point), and so on.

8.3 Results

8.3.1 Emoticon Extraction from Input

The system extracted overall number of 19,141 of emoticons form the database of original 10,137. The larger number of extracted emoticons on the output was caused by the fact that many emoticons contain more than one emoticons set (see example in Table 1). The verification showed that on average 82% of all extracted emoticons were extracted correctly according to the definition. The erroneously extracted samples contained usually only the additional areas. This problem however can be easily solved in the future by reattaching the additional areas to emoticons in a simple post-procedure.

8.3.2 Affect Analysis of Emoticons.

At first, we checked to how many of the extracted emoticons the system was able to annotate any emotions. This was done with an accuracy of 97.4% (18637 emoticons out of 19141). Here, the main problem were the emoticons extracted incorrectly previously in the extraction procedure. Therefore we can assume that solving the previous problem will positively influence accuracy on this stage as well. As for the three output calculations we compared, all of them were satisfyingly correct. The one with the highest overall score and most balanced one was Frequency. For details see Table 3.

Table 3. Results for emotion estimation of emoticons for each emotion type with all three score calculations.

Emotion type	Occurrence	Frequency	Unique Frequency
anger	0.810202	0.781187	**0.840650**
dislike	0.685650	**0.821890**	0.743040
excitement	0.777200	0.728500	**0.811650**
fear	0.454891	**0.932440**	0.616747
fondness	0.918113	0.796666	**0.929330**
joy	**0.940970**	0.774152	0.933418
relief	0.591000	**0.978200**	0.637200
shame	0.703205	**0.926970**	0.743172
sorrow	0.855965	**0.860180**	0.851917
surprise	0.843766	0.856036	**0.867340**
Overall	0.758097	**0.845621**	0.797447

9. Conclusions and Future Works

In this paper we presented a prototype system for automatic affect analysis of emoticons - CAO. The system is created on a database of emoticons containing over ten thousand of unique emoticons collected from the Internet. These emoticons are automatically distributed into emotion types with the use of previously developed affect analysis system. Finally, the emoticons are divided into semantic areas, like mouths or eyes and the hit-rate statistics of all their co-occurrence was calculated. The division of emoticons into semantic areas is based on Birdwhistell's [7,8] idea of kinemes as minimal meaningful elements in body language. As the database of CAO contains over ten thousand of emoticons and several thousands of elements for each unique semantic area, the system is capable to automatically annotate potential emotion types to any emoticon. There is finite number of semantic areas used by users in emoticons generated during online communication. CAO can match over three million of emoticon face triplets (eye-mouth-eye), which is sufficient enough to cover most of the possibilities.

The evaluation showed that the system could annotate emotions on 97% of all extracted samples. The three ways of calculating emotion rank score we compared showed that the highest and the most balanced one was based on occurrence frequency. The system is still not perfect. However, the analysis of errors showed that most of them can be easily solved by improving the extraction procedure, which we plan for the near future.

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