A Computational Approach for Analyzing and Detecting Emotions in Arabic Text

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ABSTRACT

The field of Affective Computing (AC) expects to narrow the communicative gap between the highly emotional human and the emotionally challenged computer by developing computational systems that recognize and respond to the affective states of the user. Affect-sensitive interfaces are being developed in number of domains, including gaming, mental health, and learning technologies. Emotions are part of human life. Recently, interest has been growing among researchers to find ways of detecting subjective information used in blogs and other online social media. This paper concerned with the automatic detection of emotions in Arabic text. This construction is based on a moderate sized Arabic emotion lexicon used to annotate Arabic children stories for the six basic emotions: Joy, Fear, Sadness, Anger, Disgust, and Surprise. Our approach achieves 65% accuracy for emotion detection in Arabic text.

Keywords - Emotion recognition, affective computing, human- machine interaction, emotional Arabic lexicon, text analysis.

1. INTRODUCTION

Human Computer Interaction (HCI) is defined as "a discipline concerned with the design, evaluation and implementation of interactive computing systems for human use and with the study of major phenomena surrounding them". It is an interdisciplinary field which arises from the overlapped roots in computer science, software engineering, image processing, human factors, cognitive science, psychology. One of the primary aims in human- computer interaction research is to develop an ability to recognize affective state of a user, thereby making a computer interface more usable, enjoyable, and effective [1]. Effective design of Affective computing systems relies on cross-disciplinary theories of emotion with the practical engineering goal of developing affect-sensitive interfaces. Affect detection is a very challenging problem because emotions are constructs with fuzzy boundaries and with substantial individual difference variations in expression and experience [2].

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Emotion detection researches have investigated emotion detection in prosody, changes in physiological state, facial expressions and text. There is a little of researches in emotion detection from text in comparison to the other areas of emotion detection [4].

Text based emotion detection can be used in business, education, psychology and any other field where there is paramount need to understand and interpret emotions.

Emotion detection in text aims to infer the underlying emotions influencing the author/writer by studying their input texts. This is based on the fact that if a person is happy, it influences them to use positive words. And, if a person is sad, frustrated or angry, the kind of words they use can signify their underlying negative emotion. Emotion detection in text has a number of important applications. In the area of business development, emotion detection can help marketers to develop strategies for customer satisfaction, new product development and service delivery. Psychologists can benefit from being able to infer people's emotions based on the text that they write which they can use to predict their state of mind. In the field of education, the ability of computers to automatically track attitudes and feelings with a degree of human intuition has contributed to the development of Text-to-Speech systems and Intelligent Tutoring Systems (ITS). Web communication can be facilitated through video, voice recordings, images and text [4], [5], [6]. In the absence of face-to-face contact to detect facial expressions and intonations in voice, the alternative option is to infer emotions from text in online forums. Work in emotion detection can be classified into: that which looks for specific emotion denoting words, that which determines tendency of terms to co-occur with seed words whose emotions are known, that which uses hand coded rules, and that which uses machine learning techniques. An emotion lexicon is a list of emotions and the words that are indicative of each word, and it is prerequisite to identify emotions in the text. As of now, highquality, high-coverage emotion lexicons do not exist for any language. Few lexicons for some language are available such as the WordNet Affect lexicon (WAL) for six basic emotions, for English words and the General Inquirer (GI) which categorizes words into a number of categories, including positive and negative semantic orientation [7].

In this paper, a computational approach for analyzing and tracking of emotions from Arabic children stories is proposed. Along with a construction of a moderate-sized Arabic lexicon to identify the emotional expressions at word, sentence and document level. The VSM model is used for the classification of stories according to the six basic emotion categories. The proposed architecture is tested by Arabic textual dataset to find the results and discuss the preliminary findings [8].

The paper is organized as follows: Section 2 reviews related work that covers emotions models used to capture the affective states of a text, information retrieval as a tool for emotion detection, and computational approaches for emotion detection. Section 3 describes the emotion architecture that has been proposed and validated. Section 4 explains the experimental setup that is used and discusses the results. The paper is concluded by discussing the findings, and proposing areas to be considered in future research in Section 5.

2. RELATED WORK

2.1 Computational approaches for emotion detection

Emotions can be represented by two different models. One popular approach involves the use of a categorical representation, in which emotions consists of labels such as boredom, frustration, and anger. An alternative approach emphasizes the importance of the fundamental dimensions of valence and arousal in understanding emotional experience. Dimensional approaches have long been studied by emotion theorists and they suggest the existence of at least two fundamental dimensions: valence (pleasure/displeasure) and arousal (activation/deactivation). Other researchers have found 'dominance' a third dimension important to represent emotional phenomena. A categorical model is adopted for most emotion recognition in text and video, while dimensional representation is suitable in the case of speech. [9]

Three approaches currently dominate the emotion detection task are: keyword based, learning based and hybrid based approach. These make use of features selected from syntactic (n-grams, pos tags, phrase patterns) and semantic (synonym sets) data to detect emotions.

2.1.1 Keyword Spotting approach

This approach depends on the presence of keywords and may involve pre-processing with a parser and emotion dictionary. It is easy to implement, intuitive and straight forward since it involves identifying words to search for in text.

2.1.2 Learning based approach

This approach uses a trained classifier to categorize input text into emotion classes by using keywords as features. It is easier and faster to adapt to domain changes since it can quickly learn new features from corpora by supplying a large training set to a machine learning algorithm for building a classification model. However, acquiring large corpora may not always be feasible. The major drawback of this approach is that it leads to inexact boundaries between emotion classes and a lack of context analysis.

2.1.3 Hybrid based approach

This approach consists of a combination of the keyword based implementation and learning based implementation. The main advantage of this approach is that it can yield higher accuracy results from training a combination of classifiers and adding knowledge-rich linguistic information from dictionaries and thesauri. The advantage of this is that it will offset the high cost involved in using human indexers for information retrieval tasks and minimize complexities encountered while integrating different lexical resources. [10]

2.2 Emotions in Text

The research on detecting emotional content in text refers to written language and transcriptions of oral communication. Early research to link text and emotions aimed at understanding how people express emotions through text, or how text triggers different emotions, was conducted by Osgood.

Osgood [11] used multidimensional scaling (MDS) to create visualizations of affective words based on similarity ratings of the words provided to subjects from different cultures. The words can be thought of as points in a multidimensional space, and the similarity ratings represent the distances between these words. The emergent dimensions found by Osgood were "evaluation," "potency," and "activity." Evaluation quantifies how a word refers to an event that is pleasant or unpleasant, potency quantifies how a word is associated to an intensity level, and activity refers to whether a word is active or passive.

Lutz [12] has found similar dimensions but differences in the similarity matrices produced by people of different cultures. Samsonovich and Ascoli [13] used English and French dictionaries to generate "conceptual value maps," a type of "cognitive map" similar to Osgood's, and found the same set of underlying dimensions. Other researches [14], [15], [16] involve a lexical analysis of the text in order to identify words that are predictive of the affective states of writers or speakers.

Several of these approaches rely on the Linguistic Inquiry and Word Count (LIWC) [17], a validated computer tool that analyzes bodies of text using dictionary-based categorization. LIWC-based affect detection methods attempt to identify particular words that are expected to reveal the affective content in the text [18]. Other researchers have used corpora-based approaches that assume that people using the same language would have similar conceptions for different discrete emotions and used thesauri of emotional terms. For example, Wordnet is a lexical database of English terms and is widely used in computational linguistics research [19]. Strapparava and Valituti [20] extended Wordnet with information on affective terms.

The Affective Norm for English Words (ANEWs) (Bradley and Lang, 1999, Stevenson, Mikels and James, 2007) [21], [22] is one of several projects to develop sets of normative emotional ratings for collections of emotion elicitation objects, in this case English words. International Affective Picture System (IAPS) (Lang, Greenwald, Bradley and Hamm, 1993), a collection of photographs. These collections provide values for valence, arousal, and dominance for each item, averaged over a large number of subjects who rated the items using the Self-Assessment Manikin (SAM) introduced by Lang and colleagues. Finally, affective norms for English Text (ANET) [23] provide a set of normative emotional ratings for a large number of brief texts in the English language.

There are also some text-based affect detection systems that rely on a semantic analysis of the text. For example, Gill et al. (2008) [24] analyzed 200 blogs and reported that texts judged by humans as expressing fear and joy were semantically similar to emotional concept words (phobia, terror for fear and delight, and bliss for joy). They used Latent Semantic Analysis (LSA) (Landauer, McNamara, Dennis and Kintsch, 2007) [25] and the Hyperspace Analogue to Language (HAL) (Lund and Burgess, 1996) [26] to automatically compute the semantic similarity between the texts and emotion keywords. Although this method of semantically aligning text to emotional concept words showed some promise for fear and joy texts, it failed for texts conveying six other emotions, such as anger, disgust, and sadness. So, it is an open question whether semantic alignment of texts to emotional concept terms is a useful method for emotion detection.

The most complex approach to textual affect sensing involves systems that construct affective models from large corpora of world knowledge and applying these models to identify the affective words in texts (Akkaya, Wiebe and Mihalcea, 2009, Breck, Choi and Cardie, 2007, Liu, Lieberman and Selker, 2003, Pang and lee, 2008, Shaikh, Prendinger and Ishizuka, 2008) [27], [28], [29]. This approach is called sentiment analysis, opinion extraction, or subjectivity analysis because it focuses on the valence of a textual sample (positive or negative, bad or good) rather than assigning the text to a particular emotion category (angry and sad) [30]. Supervised and unsupervised machine learning techniques have been used to automatically recognize emotion in text. Supervised techniques have the disadvantage that large annotated datasets are required for training. The emotional interpretations of a text can be highly subjective, so more than one annotator is needed, and this makes the process of the annotation very time consuming and expensive. Thus, unsupervised methods are preferred in the field of Natural Language Processing (NLP) and emotions. Strapparava and Mihalcea compared a supervised (Naïve Bayes) and four unsupervised techniques (combinations of LSA with Wordnet Affect) for recognizing six basic emotions (Strapparava and Mihalcea, 2008).

D'Mello and colleagues (D'Mello, Craig, Witherspoon, McDaniel and Graesser, 2010) [31] used LSA but for detecting utterance types and affect in students' dialogue within an Intelligent Tutoring System. As it is required in a categorical model of emotions, D'Mello proposed a set of categories for describing the affect states in student system dialogue. Kort (2001) combined the two emotion models, placing categories in a valence arousal plane. To date, most affective computing researchers have utilized and evaluated supervised methods based on the categorical emotion model. Most of the works mentioned above carried out for English.

2.3 Information retrieval as a tool for emotion detection

Information retrieval is the acquiring of specific information about a topic and is usually based on a query [32]. Text classification consists of categorizing text at the document, sentence or token level (document classification, opinion recognition, word sense disambiguation) [33]. Classification is an information retrieval task used for analyzing the content of unstructured data expressed in natural language on the web (email, scientific documents and government reports) [34].

Text classification is currently the main method for emotion detection in text [35]. Nevertheless, the highly subjective nature of emotion, this method faces many challenges. The major challenge identified is the inclusion of subjectivity detection mechanisms. Kao et al. [36] have specifically identified three issues associated with keyword spotting techniques. They are: "ambiguity in keyword definitions", "incapability of recognizing sentences without keywords" and "lack of linguistic information" [37].

3. ARCHITECTURE FOR EMOTION DETECTION

The focus of this study is on sentence emotion based on emotion words using a dataset composed of children's stories. The dataset consists of 100 documents containing 2,514 sentences. Sentences are the basic units for emotional expression, so they are used as basic level for emotion annotation. Each document is decomposed into non-overlapping and sequential sentences. Stories consist of words that are written by with the intension to evoke emotions and to attract the children's attention are suitable for this experiment because stories tended to evoke emotions that attract the reader's attention.

The problem of classifying the emotional orientation of sentences in the domain of children's stories can be decomposed into two subproblems:

- **Annotating a dataset**

A dataset of 65 documents is annotated on sentence level with eight emotion categories, the basic six emotions (سعادة, حزن, خوف, غضب, اشمئزاز, مفاجأة), in addition to the (neural category) in case of the sentence does not contain any emotion words, and the (mixed category) when the sentence contains emotional words belongs to more than one emotion category. The documents have been annotated by two annotators independently to measure agreement on the annotation of this dataset. The annotators were asked to select the appropriate emotions for each sentence based on the presence of words with emotional content, and also the overall feeling invoked by the sentence. The agreement between two annotators is calculated by finding observed and expected agreement. Observed agreement (A_o) calculates how much two annotators agreed on the individual annotations that each annotator made. Expected agreement (A_e) calculates how much the annotators are expected to agree if they each randomly assigned emotions to the sentences. Kappa value is calculated with the following equation: $K = (A_o - A_e) / (1 - A_e)$
A Kappa value of 1.0 is total agreement and 0.0 is complete random labeling.

For our dataset the Observed agreement (A_o) is (0.16), and the Expected agreement (A_e) is (0.55). The Kappa value is (0.46) that suggesting moderate agreement. This result is due to the nature of emotion, that is inherently ambiguous both in terms of the emotion classes and the natural language words that representing them. Many instances a sentence may be found to exhibit more than one emotion (the word "صرخ" can relate to three categories ("سعاده، حزن، غضب"), more than one emotion can be assigned to one sentence, that the terms in the anger category tend to share disgust terms and also fear and sadness terms, a sentence also could not be attributed to any determined categories. Cohen's kappa is used to measure the agreement in classifying items into determined categories.

Based on the annotated dataset, the emotion lexicon for the six basic emotions is constructed. To the best of our knowledge, at present, there are no large Arabic emotion lexicons. The developed Arabic lexicon is an affective lexical repository of words referring to emotional states relevant to the six basic emotion categories extracted from the annotated dataset and with direct translation of English emotional lexicons. This lexicon contains emotional words for direct and indirect affective words. The direct emotional words refer directly emotional states. While indirect emotional words have indirect reference that depends on the context. Testing dataset is selected from this dataset randomly, includes 35 documents, this allows to measure how well our process marks the sentences from which we have obtained our Arabic lexicon.

- **Automatic Emotion Detection**

In the first step in the procedure the text goes through preprocessing steps which are: stopwords removal and word stemming. These steps help the significant linguistic components of text to be focused and considered by removing unimportant data.

Starting with the motion words lexicon, which contain six lists of affective words with both direct and indirect emotion words for each category, the Vector Space Model (VSM) is used to compute the similarities between sentences and the basic six emotion lexicon. With the emotional word intensity values and term frequency, the emotion weight matrix can be measured. An emotional word is represented as a vector to record its intensity of the six basic emotional classes. The matrix *l*, whose entire *l (i, j)* are the emotion weight of the term *i* in sentence *j*. Terms are encoded as vectors in a matrix, whose components are co-occurrence frequencies of words in the sentences for each documents corresponding to the six emotional categories. The matrix element means the importance of the term in representing the emotional meaning of the sentence. Sentences in our categorical approach are converted to a vector whose components are co-occurrence frequencies of emotional words in sentences, for example a sentence vector is represented as vector values corresponding to the basic six emotions:
$\vec{s} = (0.0, 0.4, 0.7, 0.0, 0.0, 0,0)$

Both the sentences and emotional categories are represented in a common vector space as in fig.1.

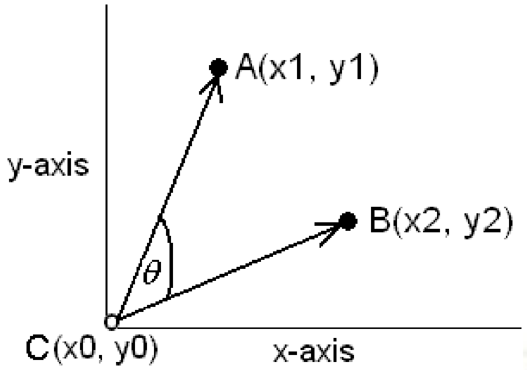

Fig.1 sentences and emotion categories are represented as vectors in the vector space model

Distances between the sentences and emotional categories can then be measured by using the cosine angle between the input sentence and an emotional vector as a similarity measure to label each sentence with the closest category using (1). If the cosine similarity does not exceed a threshold, the input sentence is labeled as "neutral", the absence of emotion. Otherwise it is labeled with one emotion associated with the closest emotional vector having the highest similarity value. A predetermined threshold is (0.6) is used for the purpose of validating a strong emotional relation between two vectors. The values produced by this technique are to be used for the classification task that converts each sentence into predefined categories. The classification consists of finding the closest emotion category to the sentence. One class with the maximum score is selected as the final emotion class.

$$\mathrm{Sim}(A, B) = \text{cosine}\ \theta = \frac{A \bullet B}{|A||B|} = \frac{x1^{*}x2 + y1^{*}y2}{(x1^2 + y1^2)^{1/2}\ (x2^2 + y2^2)^{1/2}}$$

(1)

After that, each document can be represented by summing up the normalized vectors of all the sentences contained in it. The similarity between each document and the emotional categories is computed also using the cosine similarity and assign a document a category with the highest value.

Fig.3 the results of measuring the similarity between the normalized documents' vectors in our dataset with the emotional categories to determine which category each document belongs to. Each document has different values with respect to each emotion from the six basic emotions; a document is labeled with the emotion with the highest value which indicate the closest vector to that document.

10.docx

Frequency						Normalization						Weight %					
1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
44	9	51	2	3	0	0.65	0.13	0.75	0.03	0.04	0.00	40.37	8.26	46.79	1.83	2.75	0.00
33	3	10	2	2	0	0.95	0.09	0.29	0.06	0.06	0.00	66.00	6.00	20.00	4.00	4.00	0.00
0	6	41	0	1	0	0.00	0.14	0.99	0.00	0.02	0.00	0.00	12.50	85.42	0.00	2.08	0.00

11.doc

Frequency						Normalization						Weight %					
1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
8	1	0	0	0	0	0.99	0.12	0.00	0.00	0.00	0.00	88.89	11.11	0.00	0.00	0.00	0.00
6	1	0	0	0	0	0.99	0.16	0.00	0.00	0.00	0.00	85.71	14.29	0.00	0.00	0.00	0.00
0	0	0	0	0	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

12.docx

Frequency						Normalization						Weight %					
1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
65	10	48	5	1	0	0.80	0.12	0.59	0.06	0.01	0.00	50.39	7.75	37.21	3.88	0.78	0.00
46	3	4	4	1	0	0.99	0.06	0.09	0.09	0.02	0.00	79.31	5.17	6.90	6.90	1.72	0.00
0	7	44	1	0	0	0.00	0.16	0.99	0.02	0.00	0.00	0.00	13.46	84.62	1.92	0.00	0.00

Fig.2. similarity values for various documents

After that, K-mean method is used in the classification of the documents, which propose clusters for the six emotional categories. In the first step random vectors have been assigned arbitrary to 10 classes, then compute the similarity between these classes and the normalized vectors of the documents. The documents will be clustered in different classes. For each class a new class value will be computed getting the average of the vectors for all the documents containing in it. Repeat the above steps with the new vector values for the categories until no change occur in the values of the classes vectors. Each category contains some of the documents that are related to this category. This will facilitate the information retrieval processes that making queries for specific documents easier.

Fig.2 shows the results of applying the K-means method on the test dataset using the three emotional words (all, direct, and indirect) in this case the majority class is "السعادة", in the three emotional words. This is due to the sentences in the children stories tending to have more happy emotional terms.

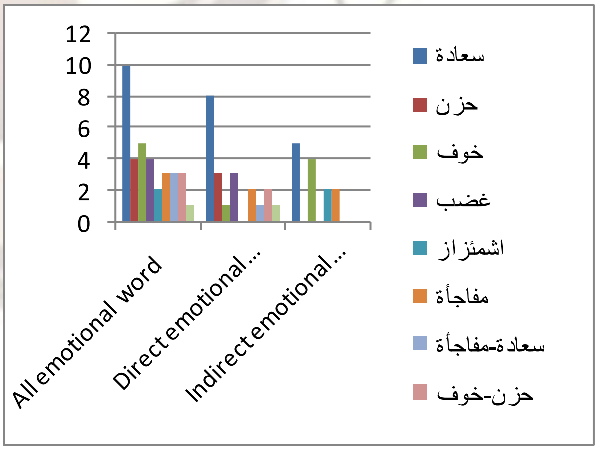

Fig.2 no of documents within different emotional categories

The goal of affect detection is to predict a single emotional label to a given input sentence. In this dataset of stories the majority class is happiness.

Classification accuracy is usually measured in terms of precision, recall, and F-measure.

$$\text{Precision} = \frac{TP}{TP+FP}, \qquad \text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

Precision is the number of correctly labeled sentences retrieved by the algorithm divided by all the sentences retrieved by the algorithm.
Recall is the number of correctly labeled sentences retrieved by the given algorithm divided by the sentences annotated as correct. After precision and recall are calculated, the values are used to calculate the f-score, the harmonic mean of precision and recall that functions as a weighted average equation.

$$f - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3)$$

Table 1 Overall average results for the three datasets using precicion, recall, and f-scors

Emotions	Precision	Recall	F – measure
السعادة	0.794	0.771	0.782
الحزن	0.675	0.612	0.642
الخوف	0.714	0.585	0.643
الغضب	0.6	0.6	0.6
الإشمئزاز	0.4	0.333	0.363
المفاجأة	0.867	0.8	0.828

Table1 shows the results of measuring the accuracy of our approach to automatic emotion detection with the test dataset. Our method obtained average 65% f-measure for recognizing the six basic emotions for Arabic emotion sentences. This showed promising results compared with the existing classification methods used with other languages.
From the above results, it has been found that the emotions computed by our method are in agreement with the emotion annotated by annotators.

4. CONCLUSION

Emotions recognition on text has wide applications. This study investigates a computational approach for analyzing and tracking emotions in Arabic children stories based on emotion words. This implies a development of Arabic lexicon used for determining emotional words in the input text. Arabic differs from European languages morphologically, syntactically, and semantically. The Arabic language is difficult to deal with due to its orthographic variations and its complex morphological structure. The Vector Space Model (VSM) is used to compute the similarities between sentences and the basic six emotion lexicon, the input sentence is labeled with the closest category. K-mean method is used in the classification of the documents, which propose clusters for the six emotional categories. Each category contains some of the documents that are related to this category. The results show that the majority class is "السعادة". Detecting emotions in Arabic texts is useful for a number of purposes including: identifying blogs that express specific emotions towards the topic of interest, identifying what emotions a newspaper headline evoke, and create automatic dialogue systems that respond automatically and appropriately to different emotional states of the user. The resulting document level emotion tagger can be used in an emotion based information retrieval system. The experiments show that emotional words and sentences play important role for emotion recognition, but more linguistic expressions such as negative word, conjunctions, and punctuations should be considered for more accurate recognition. That the affective meaning is not simply expressed by the lexicon used as the model assumes, it is also an effect of the linguistic structure.

5. FUTURE WORK

Research efforts will be directed towards applying machine learning techniques that work with unlabeled data, rather than annotating data which is time consuming and also susceptible to error.
Integrate the in-depth semantic analysis of the text, the affective lexicon used need to be enhanced that it should include the entire emotional adjective, nouns, verbs, and adverbs, emoticons, and abbreviations to handle abbreviated language.
The emotions of a text can be affected by many factors: emotion words, negative words, conjunctions, modifiers, punctuations, contexts in this study not all of these factors are included, in future research it is useful to include the impact of the function words in changing the emotional values of the text.

REFERENCES

[1] W. Peter, M. Roger, F. Petra, C. Marc and W. Yorick, *Emotion in Human-Agent Interfaces* (January 2006).
[2] S. Turkle, The Second Self: *Computers and the Human Spirit* (Simon & Schuster, 1984).
[3] S. Mingli , Y. Mingyu, L.Na, Ch. Chun, *A robust multimodal approach for emotion recognition* (College of Computer Science, Zhejiang University, China, 2008).
[4] P. Ekman. "Are there basic emotions?", *Psychological Review*, *99*, pp. 550-553.
[5] N. Frijda, "Emotion, Cognitive Structure, and Action Tendency," Cognition and Emotion, vol. 1, pp. 115-143, 1987.
[6] O. Zeljko , G. Nestor , L. Miguel , F.Inmaculada , C.Idoia, *An Ontology for Description of Emotional Cues*, (Computer Science Faculty; University of the Basque Country, 2005).

[7] B. Nadia, C. Paul, C. Anna, J. Charlene, and K. Woong. *On posture as a modality for expressing and recognizing emotions.* UCLIC, University College London, Remax House, Alfred Place, London WC1E 7DP, UK.

[8] C. Elizabeth, N. Shami, P. Christian, *Let's get emotional: Emotion research in human computer interaction*, (California, USA, April 2007).

[9] S. Mingli , Y. Mingyu, L.Na, Ch. Chun, *A robust multimodal approach for emotion recognition* (College of Computer Science, Zhejiang University, China, 2008).

[10] Shiv Naresh Shivhare, Saritha Khethawat, "Emotion Detection from Text", *CS & IT 05*, 2012, pp.371-377.

[11] C.E. Osgood,W.H. May, and M.S. Miron, Cross-Cultural Universals of Affective Meaning (Univ. of Illinois Press, 1975).

[12] C. Lutz and G. White, "The Anthropology of Emotions," *Ann. Rev. Anthropology, vol. 15*, pp. 405-436, 1986.

[13] A.V. Samsonovich and G.A. Ascoli, Cognitive Map Dimensions of the Human Value System Extracted from Natural Language, *Proc. AGI Workshop Advances in Artificial General Intelligence: Concepts, Architectures and Algorithms*, pp. 111-124, 2006.

[14] M.A. Cohn, M.R. Mehl, and J.W. Pennebaker, "Linguistic Markers of Psychological Change Surrounding September 11, 2001", *Psychological Science, vol. 15*, pp. 687-693, Oct. 2004.

[15] J. Pennebaker, M. Mehl, and K. Niederhoffer, "Psychological Aspects of Natural Language Use: Our Words, Our Selves," *Ann. Rev. Psychology, vol. 54*, pp. 547-577, 2003.

[16] J. Kahn, R. Tobin, A. Massey, and J. Anderson, "Measuring Emotional Expression with the Linguistic Inquiry and Word Count," Am. J. *Psychology, vol. 120*, pp. 263-286, Summer 2007.

[17] J. Pennebaker, M. Francis, and R. Booth, Linguistic Inquiry and Word Count (LIWC): A Computerized Text Analysis Program. Erlbaum Publishers, 2001.

[18] J. Hancock, C. Landrigan, and C. Silver, Expressing Emotion inText-Based Communication, *Proc. SIGCHI*, 2007.

[19] G. Miller, R. Beckwith, C. Fellbaum, D. Gross, and K. Miller, "Introduction to Wordnet: An On-Line Lexical Database", *J. Lexicography, vol. 3*, pp. 235-244, 1990.

[20] C. Strapparava and A. Valitutti, "WordNet-Affect: An Affective Extension of WordNet," *Proc. Int'l Conf. Language Resources and Evaluation*, vol. 4, pp. 1083-1086, 2004.

[21] M.M. Bradley and P.J. Lang, "Affective Norms for English Words (ANEW): Instruction Manual and Affective Ratings," Technical Report C1, *The Center for Research in Psychophysiology*, Univ. of Florida, 1999.

[22] R.A. Stevenson, J.A. Mikels, and T.W. James, "Characterization of the Affective Norms for English Words by Discrete Emotional Categories," *Behavior Research Methods, vol. 39*, pp. 1020-1024, 2007

[23] .M.M. Bradley and P.J. Lang, "Affective Norms for English Text (ANET): Affective Ratings of Text and Instruction Manual,"Technical Report No. D-1, Univ. of Florida, 2007.

[24] Gill, R. French, D. Gergle, and J. Oberlander, "Identifying Emotional Characteristics from Short Blog Texts," *Proc. 30th Ann. Conf. Cognitive Science Soc.*, B.C.Love,K.McRae,and V.M. Sloutsky, eds., pp. 2237-2242, 2008.

[25] T. Landauer, D. McNamara, S. Dennis, and W. Kintsch, Handbook of Latent Semantic Analysis. Erlbaum, 2007.

[26] K. Lund and C. Burgess, "Producing High-Dimensional Semantic Spaces from Lexical Co-Occurrence", *Behavior Research Methods Instruments and Computers, vol. 28*, pp. 203-208, 1996.

[27] E. Breck, Y. Choi, and C. Cardie, "Identifying Expressions of Opinion in Context," *Proc. 20th Int'l Joint Conf.* Artificial Intelligence, 2007.

[28] H. Liu, H. Lieberman, and S. Selker, "A Model of Textual Affect Sensing Using Real-World Knowledge," *Proc. Eighth Int'l Conf.* Intelligent User Interfaces, pp. 125-132, 2003.

[29] M. Shaikh, H. Prendinger, and M. Ishizuka, "Sentiment Assessment of Text by Analyzing Linguistic Features and Contextual Valence Assignment", *Applied Artificial Intelligence, vol. 22*, pp. 558-601, 2008.

[30] B. Pang and L. Lee, "Opinion Mining and Sentiment Analysis," *Foundations and Trends in Information Retrieval, vol. 2*, pp. 1-135, 2008.

[31] S. D'Mello and A. Graesser, "Multimodal Semi- Automated Affect Detection from Conversational Cues, Gross Body Language, and Facial Features," *User Modeling and User-Adapted Interaction, vol. 10*, pp. 147-187, 2010.

[32] H. H. Binali, V. Potdar, and C. Wu, "A State Of The Art Opinion Mining And Its

Application Domains," *in IEEE ICIT09*, Gippsland, Victoria, Australia, 2009.

[33] H. Cunningham, D. Maynard, K. Bontcheva, V. Tablan, C. Ursu, M. Dimitrov, M. Dowman, N. Aswani, I. Roberts, Y. Li, A. Sha, and A. Funk, "Developing Language Processing Components with GATE Version 5 (a User Guide)," 2009.

[34] F. Sebastiani, "Machine Learning in Automated Text Categorization," *ACM Computing Surveys*, *vol. 34*, No.1, pp. 1-47, 2002.

[35] J. Read, *"Recognising Affect in Text using Pointwise-Mutual Information "*: Master of Science, University of Sussex, 2004.

[36] E. C.-C. Kao, L. Chun-Chieh, Y. Ting-Hao, H. Chang-Tai, and S. Von-Wun, "Towards Text-based Emotion Detection," *in International Conference on Information Management and Engineering*, 2009, pp. 70-74.

[37] Pang Bo, and Lillian Lee. 2008. *Foundations and Trends in Information Retrieval 2, vol. 1-2*, pp. 1–135.