Emotion Models: A Review

Article *in* International Journal of Control Theory and Applications · January 2017

2 authors:

SREEJA P S
Vellore Institute of Technology Chennai

Mahalakshmi G S
Anna University, Chennai

I J C T A, 10(8), 2017, pp. 651-657 ISSN: 0974-5572

Emotion Models: A Review

Sreeja P.S.* and G.S. Mahalakshmi**

ABSTRACT

Affective Computing (AC) contributes in new ways to improve communication between sensitive human and computers which are unemotional. Emotion recognition from the text is an evolving area of research in Natural Language Processing. Emotions influence the human behavior to a great extent. Sometimes actions are based emotions felt by us. Many researchers and Psychologists have provided answers to questions such as how do we have emotions and what causes us to have these emotions. They have proposed different theories to explain why human have emotions and suggest computational models to describe how to classify the emotions. In this paper, we discuss the various emotion theories and computational models of emotion and describe briefly, the different emotion models. Also, we propose a navarasa-based emotion model[ ] to identify emotions from poems.

***Index Terms*:** Emotion Models, Emotion theories, Categorical Model, Dimensional Model, Navarasa.

1. INTRODUCTION

In psychology, the emotion may be defined as a state of belief that results in psychological changes, which in turn results in physical changes that reflect one's thoughts and conduct during that state. Emotionality includes personality, character, temper and inspiration as the main psychological parameters that drive the human emotions. According to David G. Meyers[1], human emotion involves "...physiological arousal, expressive behaviors, and conscious experience."

A text depicts the emotional state of writer and invokes the emotions in the reader. The emotion of text can be interpreted in different ways using various computational models. Affective computing researchers either use a categorical model or dimensional model to recognize emotions. There is a rapid growth in emotion recognition research in all types of communication such as speech, text, and gestures.

Emotions and sentimental states are unescapable in the various all types of communication. It is important to understand the complete meaning conveyed by a message as well as the feeling of the reader. Since the current technology is towards more text-based communication such as emails, blogs, and news, headlines, etc., research is in this direction to utilize computer-based language processing techniques that include emotion models. Researchers have studied emotions since Darwin [2], and different schools of psychology have produced many theories representing the ways of understanding affective state. Recently, computer technologists have also started contributing to this research.

The main theories of emotion can be grouped into three main categories: physiological (James-Lange Theory of Emotion[3], Cannon-Bard Theory of Emotion[4]), neurological (Facial-Feedback Theory of Emotion), and Cognitive (Cognitive Appraisal Theory[5]). Physiological theories [6][7][8] propose that answers within the human body are responsible for emotions. Neurological theories [9][10][11] suggest that action within the brain lead to emotional reactions. Lastly, cognitive theories[12] argue that thoughts and other mental activity play an important role in forming emotions.

AC scientists have developed computational systems that identify and react to theAffective states of the user [13]. Affect-sensitive user interfaces are available in some domains including gaming, mental

*,** Deoartment of Computer Science, Anna University, Chennai, India, *Emails: srj_ps@yahoo.com, gsmaha@annauniv.edu*

health, and learning technologies. The basic principle in most of the AC systems is that they automatically identify and react to a user's emotional states while interacting with the computer. This makes the communication more usable, enjoyable, and effective.

There are two unique models for signifying emotions: the Categorical model and the Dimensional model. In the former, a topic is usually mandatory to select one emotion out of a set of emotions that denotes the best feeling conveyed. In this model, emotions are labeled. In the dimensional model, the representation is based on a set of quantitative measures using multidimensional scaling. Each model helps to convey a specific feature of human emotion, and both of them suggest perception as to how emotions are represented and interpreted by the human mind. These models assess the real emotional statuses of a person. The dimensional model exploits rating scales for each dimension by using tools like the Self-Assessment Manikin (SAM)[14] or Feeltrace [15]. SAM contains pictures of manikins, to evaluate the static degree of a dimension (e.g.,.) at a fixed moment. In contrast, Feeltrace studies information related to emotions continuously over time.

2. CATEGORICAL EMOTION MODELS

Emotions are recognized with the help of words denoting emotions or class tags. The categorical model either makes use of six basic emotion classes namely *anger*, *disgust*, *fear*, *joy*, *sadness*, and *surprise* [16] or uses domain-specific expressive classes such as boredom, confusion. There are both significant and unrelated emotions in this model. Each emotion has a specific set of features that express provoking circumstances or reactions. Most research in affective computing has concentrated on the aforementioned six basic emotions. However, many researchers have indicated that a varied set of emotions may be required for various fields, for example, in the area of instruction and education [17]. They proposed five categories (boredom, confusion, joy, flow, and frustration) for describing affect states in the student system dialogue. Students hardly feel fear or disgust, whereas they typically experience boredom or delight which is an argument for the need for domain-specific classes.

2.1. Pros and Cons of Categorical Emotion Models

The categorical model has the advantage that it represents human emotions automatically with easy to understand emotion labels. For instance, the emotional categories consist of distinct elements and a great variety of emotions within each discrete category.

All the emotions are not included as they are grouped together by one category. Furthermore, the same emotional states can be expressed using different emotional categories owing to cultural, environmental,

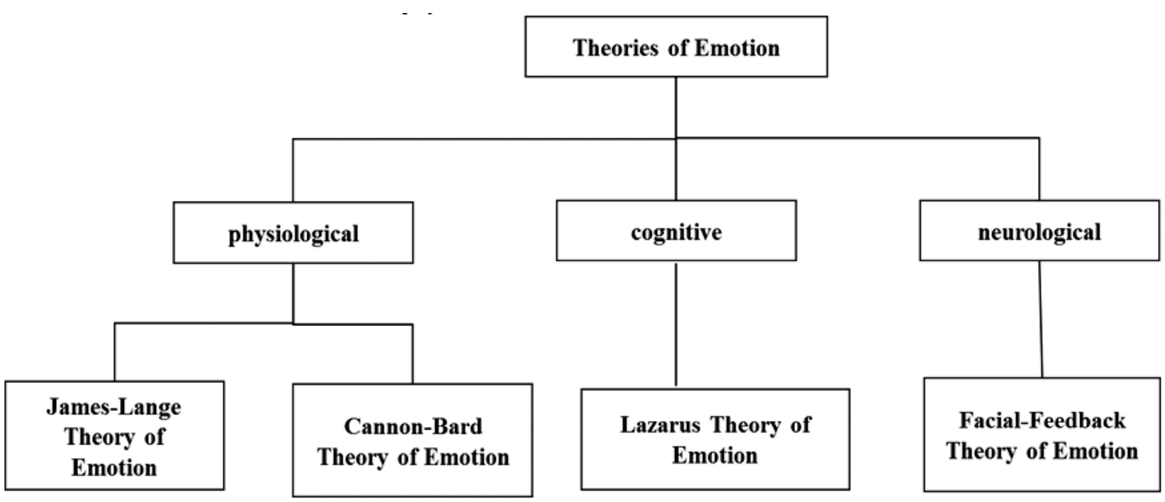

Figure 1: Theory of Emotions

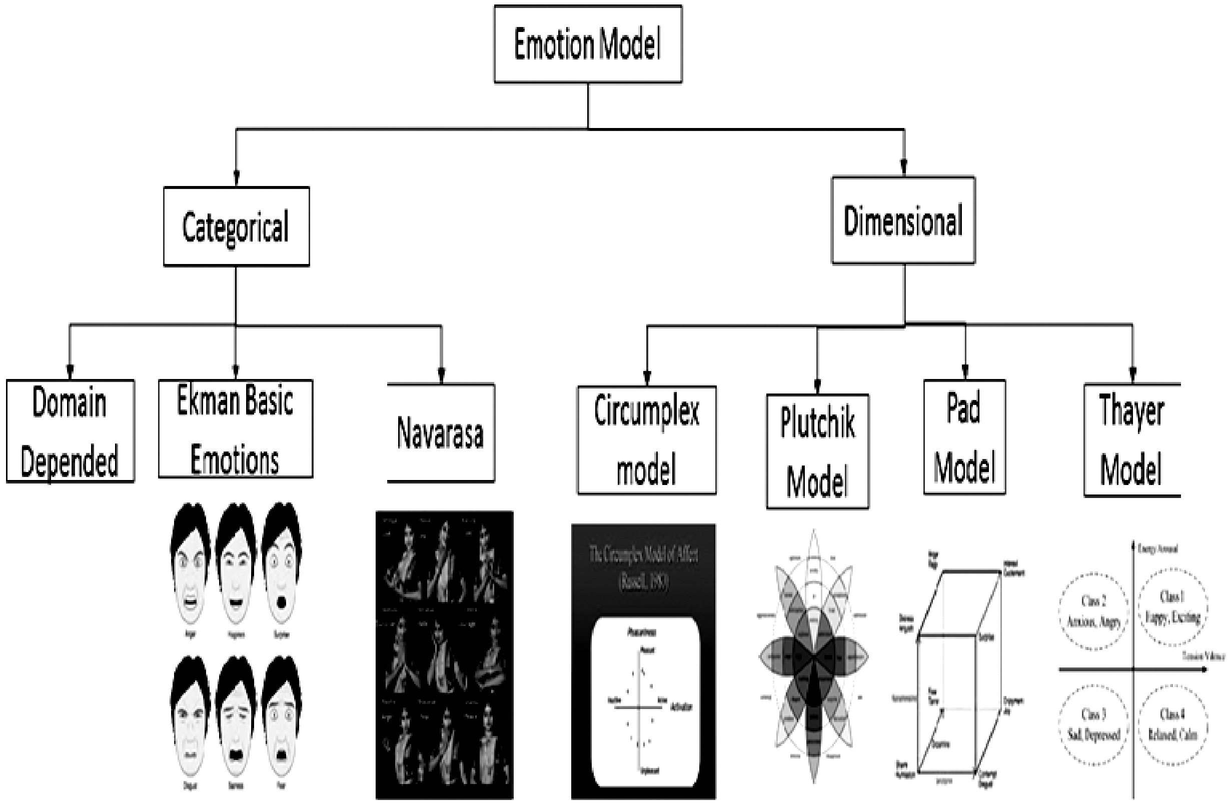

Figure 2: Emotion Models

linguistic or personality differences, which lead to difficulty in fixing the actual emotional category to which it belongs. These findings indicate that emotional categories may not represent different emotional states although the set of emotion categories is defined. Also, this problematic conceptualization may result in non-optimal or incompetent emotion-detection. It can lead to a mandatory choice identification problem, which is that subjects are likely to distinguish among presented categories rather than to identify an emotion label themselves. This method can force the subjects to choose a separate category. The second difficulty is more thoughtful and associated to the former one. It is occasionally not possible for topics to select an appropriate class since it does not occur in the label set. Thus, a categorical model has the boundaries of an identification task in attempting to distinguish the exact emotional states perceived by masses. For example, studies cannot help choosing one of the basic emotions (e.g. Anger, disgust, fear, joy, sorrow, and surprise) even though they feel neutral and want to pick out that category. However, the categorical model has been prevalent, and there are many variations of the model due to its ease and casualness. The only manner that the categorical models might deviate regards how many classes they are listing.

2.2. Navarasa-Based Model

Having read the various related work for emotion recognition using categorical model, and their limitations regarding emotion classes, especially for poems, we introduce a novel categorical model based on 'Navarasa' descriptions in 'Natyashastra'[29] to add value to emotion which a rarity in emotion detection. The basic emotions ('Navarasa') defined in 'Rasa Theory' description in 'Natyshstra' written 'Bharatha Muni'. These basic emotions are Shringara (Love), Roudra (Anger), Veera (Courage), Bhayanakam (Fear), Bhibatsa (Hate), Hasya (Joy), Shantha (Peace), Karuna (Sad) and Adbhutha (Surprise). There are many datasets available for emotion recognition research. But limited to our knowledge, we haven't find emotion corpus in above said nine basic emotions. Our previous work on Navarasa-based emotions [30] [31] [32] reveal the additional emotions such as Love, Hate, Courage are not traced by the existing categorical models.

This model has been depicted in fig. 2 among the other models. Furthermore, as future work we intend to improve the model to provide more accuracy in emotion intensity so as to resolve the existing ambiguity in emotions.

Table 1
Survey of Categorical Emotion Model

Papers	*Categories*
Alm et al. [18]	Anger, Disgust, Fear, Happiness, Sadness, Positively Surprise, Negatively Surprise
Strapparava et al. [19]	Anger, Disgust, Fear, Joy, Sadness, Surprise
Gill et al. [20]	Anger, Fear, Surprise, Joy, Anticipation, Acceptance, Sadness, Disgust
Balahur et al. [21]	Anger, Disgust, Fear, Guilt, Joy, Sadness, Shame
Balabantaray et al. [22]	Anger, Disgust, Fear, Happiness, Sadness, Surprise
Roberts et al.[23]	Anger, Disgust, Fear, Joy, Sadness, Surprise, Love
Agrawal et al. [24]	Anger, Disgust, Fear, Happiness, Sadness, Surprise
Sykora et al. [25]	Anger, Disgust, Happiness, Sadness, Shame, Surprise, Confusion, Fear
Wang et al. [26]	Anger, Disgust, Fear, Guilt, Joy, Sadness, Shame
Suttles et al. [27]	Anger, Disgust, Fear, Happiness, Surprise, Trust, Anticipation, Sadness
Calvo et al. [28]	Anger-Disgust, Fear, Joy, Sadness
Sreeja P.S et al. [29]	Anger, Courage, Fear, Hate, Joy, Love, Peace, Sad, Surprise (Navarasa Based)
Sreeja P.S et al. [30]	Anger, Courage, Fear, Hate, Joy, Love, Peace, Sad, Surprise (Navarasa Based)
Sreeja P.S et al. [31]	Anger, Courage, Fear, Hate, Joy, Love, Peace, Sad, Surprise (Navarasa Based)

3. DIMENTIONAL EMOTION MODELS

A second method for recognizing emotions is a dimensional model. It denotes affects in a dimensional form. A common set of dimensions link the various emotional states in this model. They are defined in a two(valence and arousal) or three (valence, arousal, and power) dimensional space. Each emotion occupies a position in this space. The valence dimension defines the positivity or negativity of emotion and ranges from unpleasant feelings to pleasant feeling (sense of happiness). The arousal dimension denotes the level of excitement that the emotion depicts, and it ranges from sleepiness or boredom to wild excitement. The influence dimension denotes the degree of power such as a sense of control over the emotion.

A range of dimensional models has been considered, and we will review each model in brief. Russell's model of affect is presented [33][34][35]. Emotion-related terms are organized in a circumplex shape which enables a subject to choose a position anywhere between two discrete emotion-related terms. Numerical data are obtained from the corresponding location of the points in the two dimensions (valence-arousal).

Thayer [36] utilizes the two dimensions of energy and stress.In the energy-stress design, contentment is positioned in low energy/low stress, exuberance in high energy/low stress, anxious/frantic in a high energy, high stress, and depression in low energy/high stress correspondingly.

Plutchik [37] and Whissell [38] have presented an affect model located in an activation-evaluation space. Even so, each model receives a wholly different approach to interpreting the position of emotion. Whissell proposed two numerical values to show how emotions can be related to activation and evaluation. On the other hand, Plutchik used angles on the emotion circle. The model is called the "emotion wheel," which is shown in Fig 1.2.

The closeness of two emotion classes in the circumplex represents conceptual similarity of the two classes. Mehrabian's model uses a three-dimensional PAD (Pleasure-Arousal-Dominance) representation

[39]. In this model, the dominance dimension is used to decide whether the subject feels in control of the state or not. The pleasure dimension resembles the valence of Russell's model.

3.1. Dimensional Emotion Model-An Overview

The description of emotional states by way of emotion dimensions has some advantages. However, the dimensional models have the advantage of not having to associate a certain emotional state (e.g. *anger* or *joy*). Here, scores are used to identify the emotions in two or three dimensions. These emotion dimensions can capture fine emotion concepts that differ only to a small extent as compared to broad emotion categories. Also, dimensions give a unique identification and a wide range of the emotion concepts. In particular, a dimensional description is a favorable approach to measuring the distinct emotional states. Also, emotional states are related to each other in a dimensional space, which is a significantly different approach from the categorical model. A dimensional model provides a means for measuring the degree of comparison between emotion categories. Adjacent classes in the space are very similar, while different categories are distinctly different from each other. In summary, a dimensional emotion model is a useful representation capturing all relevant emotions and provides a means for measuring the similarity between emotional states. It suggests that each emotion can be defined as a combination of arousal and pleasantness. This model is not useful for distinct categories.

Table 2
Survey of Dimensional Emotion Model

Papers	*Categories*
Lee et al. [40]	negative and non-negative emotions
Shin [41]	pleasure-displeasure and arousal-sleep dimensions
Kleinsmith et al. [42]	Valence, arousal, potency, and avoidance
Glowinski et al. [43]	Four emotions: high arousal (anger and joy) and low arousal (relief and sadness)
Vogt et al. [44]	positive-active, negative-active, positive-passive negative-passive mapped on the emotions of joy, satisfaction, anger, frustration
Khan et al. [45]	points from images positive, neutral, and negative emotion categories
Martin et al. [46]	emotional activation of a whole video
Calvo et al. [28]	Anger-Disgust, Fear, Joy, Sadness
Hasan et al. [47]	Happy-Active, Happy-Inactive, Unhappy-Active, Unhappy-Inactive

4. CONCLUSION

Emotion recognition includes text as a conventional approach. Herein, emotion detection from text usually finds the particular emotion by studying the input text. In this paper, a survey of prior work in this field is performed. We provide an overview of research on computational models of emotion that explain the common uses of the models and the machine learning techniques, pattern recognition and assumptions based on which these models are formed. Our goals here is to enable researchers interested in this field to study of emotions in general and to facilitate an understanding of this evolving field. So far most research has concentrated on categorical models of emotion, and not on systematic comparisons of the two models. We present a Navarasa-based emotion model described in 'Natyashasthra'. We do not know of a categorisation model based on natyasashtra which is our unique approach for emotion recognition in poems. Future work includes evaluation of Navarasa-based model proposed earlier to incorporate dimensions as well.

REFERENCES

[1] D.G. Myers, "Theories of emotion," Psychology: Seventh Edition, New York, NY: Worth Publishers, 500,(2004).

[2] C. Darwin, The expression of the emotions in man and animals, 1872.

[3] W. James, “What is an emotion,” Mind, vol. 9, no.34 pp. 188-205, 1884.

[4] W.B. Cannon, “The James-Lange theory of emotions: A critical examination and an alternative theory,” The American journal of psychology, vol.39, no.1/4, pp.106-124, 1927.

[5] R.S. Lazarus, J.R. Averill, and E.M. Opton, “Towards a cognitive theory of emotion,” Feelings and emotions, pp. 207-232, 1970.

[6] G. Chanel, K. Ansari-Asl, and T. Pun, “Valence-arousal evaluation using physiological signals in an emotion recall paradigm,” In 2007 IEEE International Conference on Systems, Man and Cybernetics, pp. 2662-2667, 2007.

[7] J. Kim, “Bimodal Emotion recognition using speech and physiological changes,” INTECH Open Access Publisher, 2007.

[8] J. Wagner, J. Kim, and E. André, “From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification,” In 2005 IEEE International Conference on Multimedia and Expo, pp. 940-943, 2005.

[9] G. Caridakis, K. Karpouzis, and S. Kollias, “User and context adaptive neural networks for emotion recognition,” Neurocomputing, vol.71. no.13, pp.2553-2562, 2008.

[10] A. Haag, S. Goronzy, P. Schaich, and J. Williams, “ Emotion recognition using bio-sensors: First steps towards an automatic system,” In Tutorial and Research Workshop on affective dialogue systems, pp. 36-48, 2004.

[11] K. Karpouzis, G. Caridakis, L. Kessous, N.Amir, A. Raouzaiou, L. Malatesta, and S. Kollias, “Modeling naturalistic affective states via facial, vocal, and bodily expressions recognition,” In Artifical intelligence for human computing, pp. 91-112, 2007.

[12] D. Kulic, E.A. Croft, “Affective state estimation for human–robot interaction,” IEEE Transactions on Robotics, vol.23. no.5, pp.991-1000, 2007.

[13] R.A. Calvo, S. D’Mello, “Affect Detection: An Interdisciplinary review of models, methods, and their applications,” IEEE Transactions on Affective Computing, vol.1, no.1, pp.18-37, 2010.

[14] P.J. Lang, “Behavioral treatment and bio-behavioral assessment: Computer applications,” Technology in mental health care delivery systems, pp.119-137, 1980.

[15] R. Cowie, E. Douglas-Cowie, S. Savvidou*, E. McMahon, M.Sawey, and M. Schröder, “ ‘FEELTRACE’: An instrument for recording perceived emotion in real time,” In ISCA tutorial and research workshop (ITRW) on speech and emotion, pp. 19-24, 2000.

[16] P. Ekman, “An argument for basic emotions,” Cognition & emotion, vol.6. no.3-4, pp.169-200, 1992.

[17] S. D’mello, A. Graesser, “ Mind and body: Dialogue and posture for affect detection in learning environments,” Frontiers in Artificial Intelligence and Applications, vol.158, 161-168, 2007.

[18] C. O. Alm, D. Roth, and R. Sproat, “Emotions from text: machine learning for text-based emotion prediction,” In Proceedings of the conference on human language technology and empirical methods in natural language processing, Association for Computational Linguistics, pp. 579-586, 2005.

[19] C. Strapparava, R. Mihalcea, “Learning to identify emotions in text,” In Proceedings of the 2008 ACM symposium on Applied computing, ACM, pp. 1556-1560, 2008.

[20] A. Gill, R.M. French, D.Gergle, and J.Oberlander, “ Identifying emotional characteristics from short blog texts,” In Proc. 30th Ann. Conf. Cognitive Science Soc., BC Love, K. McRae, and VM Sloutsky, eds, pp. 2237-2242, 2008.

[21] A. Balahur, J. M. Hermida, and A. Montoyo, “ Detecting implicit expressions of sentiment in text based on commonsense knowledge,” In Proceedings of the 2nd Workshop on Computational Approaches to Subjectivity and Sentiment Analysis, Association for Computational Linguistics, pp. 53-60, 2011.

[22] R. C. Balabantaray, M. Mohammad, and N. Sharma, “Multi-class twitter emotion classification: A new approach,” International Journal of Applied Information Systems, vol.4,no.1, pp. 48-53,2012.

[23] K. Roberts, M. A. Roach, J. Johnson, J. Guthrie, and S. M. Harabagiu, “EmpaTweet: Annotating and Detecting Emotions on Twitter,” In LREC pp. 3806-3813,2012.

[24] A. Agrawal, and A. An, “ Unsupervised emotion detection from text using semantic and syntactic relations,” In Web Intelligence and Intelligent Agent Technology (WI-IAT), 2012 IEEE/WIC/ACM International Conferences on Vol. 1, pp. 346-353,2012.

[25] M.D. Sykora, T. Jackson, A. O’Brien, and S. Elayan, “ Emotive ontology: Extracting fine-grained emotions from terse, informal messages,” IADIS International Journal on Computer Science and Information Systems, vol. 8, no. 2, pp. 106-118, 2013.

[26] X. Wang, and Q. Zheng, “Text Emotion Classification Research Based on Improved Latent Semantic Analysis Algorithm,” In Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE 2013), pp. 210-213, 2013.

[27] J. Suttles, and N. Ide, "Distant supervision for emotion classification with discrete binary values," In International Conference on Intelligent Text Processing and Computational Linguistics, pp. 121-136, 2013.

[28] R.A. Calvo, and S. Mac Kim, "Emotions in text: dimensional and categorical models," Computational Intelligence, vol. 29, no. 3, pp. 527-543, 2013.

[29] A. Rangacharya, Bharatha,The Natyashastra, Munshiram Manoharlal, 1996.

[30] P.S. Sreeja, and G.S. Mahalaksmi, "Applying vector space model for poetic emotion recognition," Advances in Natural and Applied Sciences, vol.9, no.6 SE, pp. 486-491, 2015.

[31] P.S. Sreeja, and G.S. Mahalakshmi, "Comparison of Probabilistic Corpus-Based Method and Vector Space Model for Emotion Recognition from Poems," Asian Journal of Information Technology, vol. 15, no. 5, pp. 908-915, 2016.

[32] P.S. Sreeja, and G.S. Mahalakshmi, " Emotion Recognition from Poems by Maximum Posterior Probability," Special Issue International Journal of Computer Science and Information Security (IJCSIS),vol. 16, no.CIC 2016, pp. 36-43, 2016.

[33] J. A. Russell, "Affective space is bipolar," Journal of personality and social psychology, vol. 37, no. 3, pp. 345-356, 1979.

[34] J. A. Russell, "A circumplex model of affect", Journal of Personality and Social Psychology vol. 39, no. 6, pp. 1161-1178, 1980.

[35] J. A. Russell, M. Lewicka, and T. Niit, " A Cross-Cultural Study of a Circumplex Model of Affect," Journal of Personality and Social Psychology, vol. 57, no.5, pp. 848-856, 1989.

[36] R. E. Thayer, "The biopsychology of mood and arousal," Oxford University Press. 1990.

[37] R. Plutchik, Emotion: A psycho-evolutionary synthesis, Harpercollins College Division, 1980.

[38] C. Whissell, "The dictionary of affect in language. Emotion: Theory, research, and experience," Measurement of Emotions, vol. 4, pp. 113-131, 1989.

[39] A. Mehrabian, "Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament," Current Psychology, vol. 14, no. 4, pp. 261-292, 1996.

[40] C.M. Lee, and S.S. Narayanan, " Toward detecting emotions in spoken dialogs", IEEE transactions on speech and audio processing, vol. 13, no. 2, pp. 293-303, 2005.

[41] Y.S.Shin, "Facial expression recognition based on emotion dimensions on different learning," In International Conference on Computational Science, Springer Berlin Heidelberg. pp. 81-88, 2007.

[42] A. Kleinsmith, and N. Bianchi-Berthouze, "Recognizing affective dimensions from body posture," In International Conference on Affective Computing and Intelligent Interaction, Springer Berlin Heidelberg, pp. 48-58, 2007.

[43] D. Glowinski, A. Camurri, G. Volpe, N. Dael, and K. Scherer, "Technique for automatic emotion recognition by body gesture analysis," In Computer Vision and Pattern Recognition Workshops, CVPRW'08. IEEE Computer Society Conference on, pp. 1-6, 2008.

[44] T. Vogt, E. André, and N. Bee, " EmoVoice—A framework for online recognition of emotions from voice," In International Tutorial and Research Workshop on Perception and Interactive Technologies for Speech-Based Systems, Springer Berlin Heidelberg, pp. 188-199, 2008.

[45] M.M Khan, R.D Ward, and M. Ingleby, "Classifying pretended and evoked facial expressions of positive and negative affective states using the infrared measurement of skin temperature," ACM Transactions on Applied Perception (TAP), vol. 6, no. 1, pp. 6.2-6.21, 2009.

[46] J.C. Martin, G. Caridakis, L. Devillers, K. Karpouzis, and S. Abrilian, "Manual annotation and automatic image processing of multimodal emotional behaviors: validating the annotation of TV interviews," Personal and Ubiquitous Computing, vol.13, no.1, pp.69-76, 2009.

[47] M. Hasan, E.Rundensteiner, & E. Agu, "Emotex: Detecting emotions in Twitter messages," In ASE BIGDATA / SOCIALCOM / CYBERSECURITY Conference, pp. 27–31, 2014.