A study of the state of the art of Affective Computing in Ambient Intelligence environments

Idoia Cearreta, Juan Miguel López, Karmele López de Ipiña, Nestor Garay, Carmen Hernández, Manuel Graña

University of the Basque Country, Computer Science Faculty

Manuel Lardizabal 1, E-20018 Donostia

{idoia.cearreta, juanmi, karmele.ipina, nestor.garay, mamen.hernandez, manuel.grana} @ehu.es

Abstract

This paper reviews the research that is been made integrating two emerging areas: Affective Computing (AC) and Ambient Intelligence (AmI). A deep review about the state of the art integrating both research areas is explained. Then, a practical example is provided to check the viability of AC thinking in AmI environments, pointing out the difficulties this process has. Finally, some actual and future trends are mentioned in order to make clearer topics related to AC in AmI environments.

1. Introduction

Human beings are usually communicating, sometimes to make something known and sometimes to receive information from the external world. Human emotions are an influencing factor in the way we deal with and relate to objects and artefacts [35]. It is also relevant their importance in Human-Computer Interaction (HCI) as part of human-computer communication [9]. As an inherent part of human communication, study of emotions in HCI is important as the emotional states of the people interacting with computers or devices is relevant in order to provide better adaptation to people's particular skills.

This paper is centred in computer-based systems and technology, either software or either hardware. It has to be said that computer-bases systems may be entire computers or bare devices.

Generally speaking, computer-based communication can be decomposed in three types:

- Communication between user and computer,

- Using the computer-based systems to communicate two or more people (computer-mediated communication), and
- Using the computer-based systems to communicate user with the environment.

In order to make possible a more natural communication between computers and humans, recent years a great effort is devoted to Affective Computing (AC) [1, 39]. AC, a discipline that develops devices for detecting and responding to users' emotions, and affective mediation, computer-based technology that enables the communication between two or more people displaying their emotional states [17, 39], are growing research areas [44] that must join assistive technology research to improve the neglected area of Affective Communication in disabled people [18]. It is clear that this is an interdisciplinary area encompassing issues that come from Psychology, Artificial Intelligence, Sociology, Ergonomics, and so on.

While in initial steps AC has been centred in enhancing implicit communication between user and computer and even computer-mediated communication (via chats, electronic mails, etc.), later on it is also enhancing communication with the environment [29]. In this way, some environmental variables can be adapted to user's current emotional state in order to get a more comfortable interaction, for example, personalising environmental music, or lightening. The main idea is making user interfaces more intelligent and adaptive to users. In the particular case of communicating with the environment, several techniques that come from Ambient Intelligence (AmI) can be combined with AC topics in order to get a more natural interaction.

AmI refers to a specific vision of the Information Society Technologies Advisory Group (ISTAG) of the European Community according to which humans will be surrounded by intelligent interfaces supported by advanced technologies distributed everywhere and mainly embedded in everyday objects such as furniture, clothes, vehicles, roads and smart materials [33]. The same authors suggest that, on the practical side, AmI may be roughly described as the opposite of virtual reality: virtual reality puts people inside a computer-generated world; AmI puts the computer inside the world to help people [33]. [41] introduced a psychological definition of AmI, based on the experience of the user: "AmI is the effective and transparent support to the activity of the subject/s through the use of information and communication technologies".

Hence, some intelligent sensors are integrated within AmI systems. These sensors can be used in conjunction with emotional models in order to detect user's affective status. As one of the characteristics of Affective Communication is multimodality, multimodal integration is highly relevant to affect recognition given the multi-component nature of emotion [30]. It is known, for example, that emotions are closely related (if not associated) with cognition [27], that facial expressions can generate emotion physiology, and that facial expressions are associated with emotions [13].

Next section shows a review of the main theories and models related to emotions, and how they are applied in computer-based systems. Then, application of AC thinking in AmI is reviewed. A practical example about the viability of AC in AmI environments using Machine Learning (ML) techniques is provided next. Finally, some conclusions are given and future research topics are highlighted.

2. Related work

Emotion can be understood as "an impulse that induces the action", causing automatic reaction behaviours to the environmental stimulus. From the point of view of psychology, emotion is a feeling expressed by a physiologic function like facial reactions, cardiac pulse and behavioural reactions like aggression, crying, covering the face, etc.

This section surveys emotion models found in the literature and a review of certain computer-based affective applications.

2.1. Models of Emotions

One of the classic debates in emotion theory is whether emotions are innate or whether they are learned [9]. On the one hand, several theories, such as Darwin's theory, argue that all emotions are innate or biologic, as well as the expression of themselves and each one of emotions have evolved through time to address a specific environmental concern of our ancestors. According to [22], each emotion has a unique autonomic signature.

On the other hand, other theories, such as [37] and [42], argue that emotions are learned social constructs, with the exception of startle and innate affinity and disgust. The emotions are viewed as cognitive processes related to the architecture of the human mind (decision making, memory, attention, etc.) and also the animals (aggression, affection, sadness). In human emotions surroundings, the direct interaction with the outside, have influence, but also the emotional memory arisen from the experience of the individual and the cultural surroundings, which is denominated socialized emotion. The emotional answer often socialized does not correspond with the pure emotional answer and can get to mask the state of the organism.

Nevertheless, according to [9], another researchers believe in the existence of basic emotions and there is a small set of innate emotions. For example, authors such as [13] think that basic emotions are universal and shared by all humans, from which the rest of affective reactions are derived.

Emotion is a state of a system, induced by an external or internal event, that potentially affects its integrity or objective. In the biological systems the emotion indicates the existence of an excellent state with respect to the integrity of the individual or its species. In socialized species, the relevance extends to group integrity and in the cultural species, to the integrity of norms. This are denominated camouflage emotions. The emotional states involve a deviation of a normality rank or balance and produce an answer of normalization or preservation. The variables caused by the

impact of the event and the answer of the system contain information that is used by the internal and external components to optimise the preservation conduct. Emotional states in the human beings produce external signals that they contain information of the relevance of the event on all the planes of values of the individual (individual physical integrity or of the group and/or adjustment to the norm). This is the reason why biological signals (cardiac frequency, face, thermograph, skin resistance, so large pupil expression) contain ambiguous information on the emotional state, limiting them to express the intensity of the state.

Different models of emotions proposed in cognitive psychology should be taken into account as a useful starting point. Although several theoretical models of emotions exist, the most commonly used are the dimensional [25] and categorical [12, 43] models of emotions.

For practical reasons, categorical models of emotions have been more frequently used in AC. For example, [40] has implemented several algorithms that recognize eight categories of emotions based on facial expressions. [38] has developed algorithms for the production and recognition of five emotions based on speech parameters. Although the dimensional approach has been less followed, there also exist some AC applications based on this approach such as Feeltrace, a tool for recording perceived emotion in real time according to two dimensions: Arousal and Valence [10].

[25] proposed that three systems exist that would be implied in the expression of the emotions and that could serve like indicators to detect the emotion of the user:

- Subjective or verbal information: reports of perceived emotions described by users,
- Behavioural: facial and postural expressions and speech paralinguistic parameters,
- Psychophysiological responses: such as heart rate, galvanic skin response (GSR), and electroencephalographic (EEG) response.

The subjective, behavioural and physiological correlates of emotions should be taken into account when possible. The correlations between the three systems could help computers to interpret ambiguous emotions. For instance, a person with apraxia could have problems in the articulation of facial gestures, but subjective information written down with assistive technology, could be used by a computer to interpret his/her emotional state. In that sense, more specific models or theories which describe the components of each system of expression can be found in the literature and selected according to the particular case; for example, dictionary of emotional speech [8], acoustic correlates of speech [43], or facial expressions [12]. In any case, as [5] suggest, for vocal emotional expression it is necessary to increase the number and variety of emotions studied for each emotional expression modality, replicate the differences in recognition and expression accuracy between emotions and investigate cultural and language differences.

There are mainly two channels of human communication: the verbal or explicit channel (language) and the nonverbal or implicit channel [11, 24]. Moreover, there are times when people communicate directly, for example when talking to an audience that is beside the speaker, while there are times when people uses some devices to communicate, for example phone in telephonic conversations.

According to [19] p. 53, "although we tend to regard language as the main channel of communication, there is general agreement among experts in semiotics that anywhere from 80 to 90 percent of the information we receive is not only communicated nonverbally but occurs outside our awareness." Meanwhile, [32] affirms that 7% of the communication between two people is verbal, 38% vocal (tone, shades, etc.) and 55% is body language. Therefore, in terms of [32], unaided visually impaired and deaf people lose 55% and 38%, respectively, of the affective information that people without those sensorial impairments are able to process. Similarly, [29, p.1673] refer that "Important information in a conversational exchange comes from body language, voice prosody, facial expressions revealing emotional content, and facial displays connected with various aspects of discourse. Communication will become ambiguous when these are accounted for during HCI and computer-mediated communication". It is agreed that the study of multimodality in emotions is highly relevant to

perform more accurate emotion synthesis or recognition.

2.2. Applications of Models of Emotions in Computing Environments

As previously mentioned, the human interaction includes emotional information of the interlocutors, that is transmitted by the explicit channel through the language and by the implicit channel by the nonverbal communication. Nevertheless, it has been appraised that these concepts, that are also associated to the interpersonal relations, appear in the communication with the computers [39]. Therefore, the main objective of the Affective Computation is detect and process the emotional information with the purpose of improving the communication between the person and the computer-based system.

Distance learning, robotic and psychotherapy are some of the fields that could benefit from the affective computer. Furthermore, the Affective Computing research group of the Massachusetts Institute of Technology (MIT) has started up an investigation, with the objective to help in the field of the distance learning or also called "e-learning", and to determine the emotional needs of the students [1].

AC also is useful in the field of Telemedicine. According to [34], p.5, Tele-Home Health-Care (tele-HHC) provides communication between medical professionals and patients in cases where hands-on care is not required, but regular monitoring is necessary. For example tele-HHC interventions are currently used to collect vital sign data remotely (e.g., ECG, blood pressure, oxygen saturation, heart rates, and respiration), verify compliance with medicine and/or diet regimes, and assess aspects of mental or emotional status.

Another application is "Driving Safety" [34]. Taking into account that the inability to manage one's emotions while driving is identified as one of the major causes for accidents, when the system recognizes the driver is in a state of anger, for example, the system could change the music [23], or suggest a relaxation technique [26], depending on the driver's preferred style.

[39] proposes an aid for the autistic people. This problem affects around 1.5 and 2 people in each 1,000. The autism is a developmental disorder which persists during all the life. This illness affects in different degrees the ability as far as the communication to the understanding of the language, the social coexistence and the capacity of the imagination. Some autistic people are incredible memorizing and can learn to recognize facial expressions, but the majority has difficulties with the compression of the emotions, and hence they lack emotional intelligence. According to [39], a way to help these people is to rehearse with them different situations repeatedly and this way, they will be able to learn to react of natural form. The idea is to design computers which had the capacity to teach to these people different social scenes.

[30] article collects a listing of different applications from automatic recognition of facial expression. For example, user coaching, distance learning/tele-teaching assistant, automobile driver alertness/drowsiness monitor, stress detector, entertainment and computer games, health and family planning, etc.

All these applications provide several affective skills, among them the capacity to recognize, to express and to have emotions. Some of the applications are simple engineering problems, but others are more complicated, because they depend on existing affective abilities in the human beings. The main aim is to design affective systems to be able to combine them with other systems and to create really intelligent and personal systems [39].

2.3. Affective Computing in Ambient Intelligence

AmI is a new multidisciplinary paradigm rooted in Norman's ideas about Ubiquitous Computing [35]. In AmI, technologies are deployed to make computers disappear in the background, while the human user moves into the foreground in complete control of the augmented environment. AmI fosters novel anthropomorphic human–machine models of interaction; as AmI is a user-centric paradigm, it supports a variety of artificial intelligence methods and works pervasively, no intrusively, and transparently to aid the user. It supports and promotes interdisciplinary research encompassing the technological, scientific and

artistic fields creating a virtual support for embedded and distributed intelligence.

AmI builds on three recent key technologies [2]: Ubiquitous Computing, Ubiquitous Communication and Intelligent User Interfaces. Some of these concepts are barely a decade old and this reflects on the focus of current implementations of AmI. Ubiquitous Computing means integration of microprocessors into everyday objects like furniture, clothing, white goods, toys, even paintings. Ubiquitous Communication enables these objects to communicate with each other and the user by means of ad-hoc and wireless networking. Finally, an Intelligent User Interface enables the inhabitants of the AmI environment to control and interact with the environment in a natural (voice, gestures) and personalised way (preferences, context).

It seems interesting including AC paradigm within AmI. User gestures (both facial and corporal), speeches, words, etc., can be used to detect people's emotional state by reading multimodal sources.

Current research in these areas, however, is generally limited to passive inference, mostly affect-insensitive, and in a static domain [28]. Efficiency in user-state inference is usually not considered and the utility of an action does not usually vary over time. In the affective-state assessment for user modelling and assistance, the information from sensory modalities is not sufficient and must be integrated with high-level models of the user and the environment.

Multimodality can be achieved by means of a set of sensors such as cameras, microphones and/or psychophysiological parameters. Some of them may be obtained in a non-obstrusive way (mainly images and speeches) while others may be intrusive (mainly physiological ones). Anyway, the miniaturization of computer-based devices is making possible the development of wearable computers that can help in recording psychophysiological parameters, without causing any disturb to people.

Given the relative novelty of both AC and AmI, little work has been performed taking both paradigms into account. Some of the most remarkable ones are commented next.

In [28] a new probabilistic framework based on the Dynamic Bayesian Networks (DBNs) is introduced to dynamically model and recognize user's affective states and to provide the appropriate assistance in order to keep user in a productive state. They incorporate an active sensing mechanism into the DBN framework to perform purposive and sufficing information integration in order to infer user's affective state and to provide correct assistance in a timely and efficient manner. Experiments performed involving both synthetic and real data demonstrated the feasibility of the proposed framework as well as the effectiveness of the proposed active sensing strategy, but it must be mentioned it was performed with a small set of emotional states (three in this case) and for short periods of time.

MOUE (a Model Of User's Emotions) is a system developed which builds a model of user's emotions by first observing the user (e.g. patient) via multi-sensory devices: camera, mouse, keyboard, microphone and wearable computer [7]. MOUE system has been applied for tele-HHC applications, which includes: developing a system architecture for monitoring and responding to human multimodal affect and emotions via multimedia and empathetic avatars; mapping of physiological signals to emotions and synthesizing the patient's affective information for the health-care provider. Results using a wireless non-invasive wearable computer to collect physiological signals and mapping these to emotional states have shown the validity of this approach.

In [20], an Affect and Belief Adaptive Interface System (ABAIS) designed to compensate for performance biases caused by users' affective states and active beliefs is described. The ABAIS architecture implements an adaptive methodology consisting of four steps: sensing/inferring user affective state and performance-relevant beliefs; identifying their potential impact on performance; selecting a compensatory strategy; and implementing this strategy in terms of specific GUI adaptations. ABAIS provides a generic adaptive framework for integrating a variety of user assessment methods (e.g. knowledge-based, self-reports, diagnostic tasks, physiological sensing), and GUI adaptation strategies (e.g. content- and format-based).The ABAIS performance bias prediction is based on empirical findings from emotion research

combined with detailed knowledge of the task context. The initial ABAIS prototype was demonstrated in the context of an Air Force combat task, used a knowledge-based approach to assess the pilot's anxiety level, and adapted to the pilot's anxiety and belief states by modifying selected cockpit instrument displays in response to detected changes in these states.
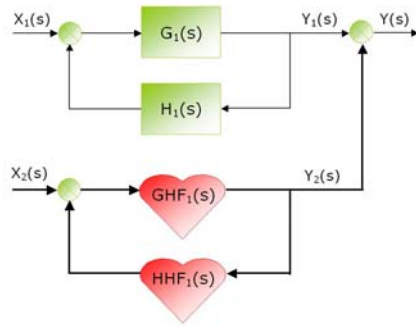

Figure 1. Automatic system regulation taking into account both human and non-human components.

A better approach of automatic system regulations may be achieved taking into account both human and non-human components, as it can be seen in Figure 1. Thus the classic automation tries to regulate the system G1 (s) and inputs X1(s) by means of automatic regulators H1 (s) to obtain a suitable response Y(s). The influence in the system of humans (human factors) GHF1(s) and their emotions are obviated in spite of being one of its important parts. The possible regulation of human factors as emotions by means of appropriate regulators HHF1(s) would help to protect undoubtedly humans and to take advantage better of their capacities. Therefore first step is to obtain appropriate human modelling and measurement of both perceptible and not perceptible emotions.

It is also remarkable that NASA is also working in human automation in projects related to Airspace Systems and Complex environments, etc. [21].

3. Testing Human Emotion Complexity

It is not easy detecting emotions in AmI environments, as the emotion expression is multimodal. Moreover, parameters are usually obtained in obtrusive ways.

In this section, a study related to a modality that can be obtained in a non-intrusive way is presented, as an example of the complexity of human emotion detection by using different ML techniques. This is to remark that an AmI system coping with multimodality will be very complex when trying to extract relevant parameters of any modality and trying to synchronize in real time all of them to make emotion estimations.

Using a bilingual affective database, different speech parameters have been calculated for each audio recording. Studying the validity of automatic emotion recognition in speech is important for AmI environments as speech is an important emotion expression modality for human beings. As most existing affective databases are created using recording performed by professional actors, it must be pointed out that this can lead to problems when recognizing emotions with amateur people as their acting skills are not as remarkable as professionals'.

It must be taken into account that affective databases used to train affective systems are usually based on recordings performed by professional actors. RekEmozio database [31] is a multimodal bilingual database for Spanish and Basque. The scope of RekEmozio database is summarized in Table 1. For audio recordings, professional and non-professional actors were asked to speak both semantically meaningful and non-semantically meaningful sentences in a concrete given emotion (154 sentences for professional actors and 28 sentences for non-professional actors). Recordings in RekEmozio database were used to perform an audio parameter extraction process, and this information was stored in the database [4]. This way, each recording was parameterized and values of these parameters can be used as an input for the different ML techniques used. On the other hand, categorical classification of emotions was used. Seven emotions were used: the six basic emotions described by [14], that is, Sadness, Fear, Joy, Anger, Surprise and Disgust; and also Neutral emotion.

Table 1.   Summary of RekEmozio database scope

Language	Basque	Spanish	Women	Men	Total
Professionals	7	10	8	9	17
Non-professionals	2	10	5	7	12
Sentences	1134	1820	1372	1582	2954

Several methods have been applied (MLE [3]; MDM [6], FISHER [15], KNN [45], SVM [16]) over different train and test sets with professionals and non-professionals in order to analyze the complexity of recognition and clustering of Human Emotions. It was intended to compare the emotion recognition performance in speech comparing results for professionals and non-professionals. Training was built with %70 of the samples of the analyzed set.

Next subsections show two different kind of analyses have been carried out to test:

3.1. Differences between learned and natural emotions

Table 2 shows the results with several methods and kind of training and test. Train columns reflect recognition results achieved expressed in percentiles with the methods when training material is used whereas Test columns reflect results without using training material (that is, independent test). Independent test for professionals and non-professionals shows the great difference between both behaviours. Best performance is obtained for Support Vector Machine (SVM) algorithm when this is trained and tested with both professionals and non-professionals. In any case, best results for independent test are quite low (58.38%).

Table 2.   Summary of experiment to test differences between learned and natural emotions

ALGR	Professionals		Non-Professionals		All Actors	
	Train	Test	Train	Test	Train	Test
MLE	56.75	32.00	99.44	19.74	51.21	43.05
MDM	18.18	18.30	20.79	17.22	18.76	17.89
FISHER	42.92	33.77	48.50	26.05	39.70	40.87
KNN	65.01	23.68	67.98	16.36	62.73	44.44
SVM	99.39	14.48	94.94	14.44	97.69	58.38

3.2. Emotion clustering

Table 3 shows the results in percentiles with several methods (C4.5, Bayesian Network –BN–, K-Nearest Neighbour –KNN–, Core Vector Regression –CVR–, and Multilayer Perceptron – MLP–) with professionals and non-professionals, for standard emotion clustering [19] (STD_EMT) and clustering obtained by KNN method for 7, 15 and 20 emotions (KNN-7,15,20). Best performances are obtained for emotion clusters building by KNN algorithm. Clustering reaches up to 98.33%, that is a very good result.

Table 3.   Summary of experiment to test emotion clustering

	C.45	BN	KNN	CVR	MLP
STD-EMT	30,3	31,20	31,91	38,4	38,08
KNN-7EMT	89,30	77.8	98,53	92,41	97,20
KNN-15EMT	91,25	73,04	92,77	93,44	96.03
KNN-20EMT	92,28	73,85	92,59	93.02	96.70

4. Conclusions

This paper shows a review about the work made in AC and in AmI. These two emerging areas are working together very recently. After presenting theories and models related to emotions, several topics related to the application of AC issues in AmI environments are described.

ML Paradigms have proven to be useful in affective state detection in HCI, and is also useful for such purposes in AmI environments when there is interaction with users [28]. In this paper, an application of these paradigms is shown when applied to speech parameters. The achieved results are far from 100%, but they should be compared with human recognition rate. We plan to do that comparison in the future. Multimodality will also have to be taken into account. Moreover, usability studies also have to be taken into account to make possible proactive approach in new systems.

As [28] mentioned, further research is ongoing to integrate multiple and heterogeneous models to improve the robustness and performance of user state detection and assistance decision (due to the variability of individual personality and especially the strict requirement of accuracy on such assistance systems).

New advances related to advances in technology allow to anticipate that AmI applications will be including more AC related work in near future, with increasing number of functionalities and incorporating better models. Anyway, ethics and security are two topics that

have to be taken into account in such applications, specially in the case of vulnerable groups like the elderly and people with disabilities.

References

[1] Affecting Computing (n.d.). Retrieved March 30, 2007, from http://affect.media.mit.edu/

[2] Alcañiz, M. and Rey, B. (2005). New Technologies for Ambient Intelligence. In Ambient Intelligence: The evolution of technology, communication and cognition towards the future of the human-computer interaction. G. Riva, , F. Vatalaro, F. Davide, M. Alcañiz (Eds.) IOS Press, pp. 3-15. ISBN: 1-58603-490-1

[3] Aldrich, J. (1997). R. A. Fisher and the making of maximum likelihood 1912-1922. Statistical Science, Vol. 12(3), pp. 162-176.

[4] Álvarez, A., Cearreta, I., López, J.M., Arruti, A., Lazkano, E., Sierra, B., Garay, N. (2006). Feature Subset Selection based on Evolutionary Algorithms for automatic emotion recognition in spoken Spanish and Standard Basque languages. In P. Sojka, I. Kopecek and K. Pala: Text, Speech and Dialog. LNAI 4188, Springer, pp. 565-572

[5] Banse, R., & Scherer, K. R. (1996). Acoustic profiles in vocal emotion expression. Journal of Personality and Social Psychology, Vol. 70 (3), pp. 614-636.

[6] Beran, R. and Millar, W. (1994). Minimum distance estimation in random coefficient regression models. Ann. Statist. 22, 1976-1992.

[7] Bianchi, N. & Lisetti, C. L. (2002). Modeling Multimodal Expression of User's Affective Subjective Experience. In User Modeling and User Adapted Interaction, 12(1), pp. 49-84.

[8] Bradley, M.M., Lang, P.J., Cuthbert, N.B., (1997). Affective Norms for English Words (ANEW). NIMH Center for the Study of Emotion and Attention, University of Florida.

[9] Brave, S. & Nass, C. (2003). Emotion in Human-Computer Interaction. In The Human-Computer Interaction Handbook: Fundamentals, Evolving Technologies and Emerging Applications, Jacko, Julie A. and Sears, Andrew, Eds., Lawrence Erlbaum Assoc.

[10] Cowie, R., Douglas-Cowie, E., Savvidou, S., McMahon, E., Sawey, M. & Schröder, M. (2000). 'Feeltrace': An Instrument For Recording Perceived Emotion In Real Time. In: ISCA Workshop on Speech & Emotion. Northern Ireland, pp. 19-24.

[11] Cowie, R., Douglas-Cowie, E., Tsapatsoulis, N., Votsis, G., Kollias, S., Fellenz, W., & Taylor, J. G. (2001). Emotion recognition in human-computer interaction. In IEEE Signal Processing Magazine, 18(1), pp. 32–80.

[12] Ekman P. (1984). Expression and nature of emotion. In: K. Scherer & P. Ekman (Eds.): Approaches to emotion. Hillsdale, Nueva Jersey: Erlbaum.

[13] Ekman, P. & Friesen, W. (1975). Unmasking the Face: A Guide to Recognizing Emotions from Facial Expresssions. Englewood Cliffs, NJ: Prentice Hall.

[14] Ekman, P. & Friesen, W. (1976). Pictures of facial affect. Consulting Psychologist Press, Palo Alto, CA.

[15] Fisher, D.H. (1987). Knowledge acquisition via incremental conceptual clustering. Machine Learning, Vol. 2, No. 2, pp.139-172.

[16] Fradkin, D. & Muchnik, I. (2006). Support Vector Machines for Classification. In J. Abello and G. Carmode (Eds) "Discrete Methods in Epidemiology", DIMACS Series in Discrete Mathematics and Theoretical Computer Science, Vol. 70, pp. 13-20.

[17] Garay, N., Abascal, J., & Gardeazabal, L. (2002). Mediación emocional en sistemas de Comunicación Aumentativa y Alternativa. Revista Iberoamericana de Inteligencia Artificial, 16, pp. 65–70.

[18] Garay N., Cearreta I., López J. M., & Fajardo I. (2006). Assistive Technology and Affective Mediation. Human Technology. Special Issue on "Human Technologies for Special Needs" (Guest editor: José Juan Cañas). Vol. 2, No. 1. Pp. 55-83.

[19] Hall, E. T. (1998). The Power of Hidden Differences. In M. J. Bennett (Ed.), Basic Concepts of Intercultural Communication: Selected Readings (pp. 53-67). Yarmouth, ME: Intercultural Press, Inc.

[20] Hudlicka, E. & McNeese, M. D. (2002). Assessment of User Affective and Belief States for Interface Adaptation: Application to an Air Force Pilot Task. User Model. User-Adapt. Interact. 12(1), pp. 1-47.

[21] Human Automation Integration research branch (n.d.). Retrieved from http://human-factors.arc.nasa.gov/ihi/.

[22] James, W. (1884). What is an emotion? Mind, 9, pp. 188-205.

[23] James, L. (2000). Road Rage and Aggressive Driving. Amherst, NY: Prometheus Books.

[24] Knapp, M. L. (1980). Essentials of nonverbal communication. New York: Holt, Rhinehart & Winston.

[25] Lang, P. J. (1979). A bio-informational theory of emotional imagery. Psychophysiology, Vol. 16, pp. 495-512.

[26] Larson, J. & Rodriguez, C. (1999). Road Rage to Road-Wise. Tom Doherty Associates, Inc. New York, NY.

[27] Leventhal , H. & Scherer, K. (1987). The relationship of emotion to cognition: A functional approach to a semantic controversy. Cognition and Emotion 1 (1), pp. 3-28.

[28] Li, X., & Ji, Q. (2005). Active Affective State Detection and User Assistance With Dynamic Bayesian Networks. IEEE transactions on systems, man, and cybernetics-part a: systems and humans, Vol. 35, No. 1.

[29] Lisetti, C., & Nasoz, F. (2004). Using Non-invasive Wearable Computers to Recognize Human Emotions from Physiological Signals. In EURASIP Journal on Applied Signal Processing - Special Issue on Multimedia Human-Computer Interface, Vol. 2004 (11).

[30] Lisetti, C. L., & Schiano, D. J. (2000). Automatic Facial Expression Interpretation: Where Human-Computer Interaction. In Artificial Intelligence and Cognitive Science Intersect. Pragmatics and Cognition (Special Issue on Facial Information Processing: A Multidisciplinary Perspective), 8(1): 185-235

[31] López J. M., Cearreta I., Garay N., López de Ipiña K., Beristain A. (2006) Creación de una base de datos emocional bilingüe y multimodal. VII Congreso de Interacción Persona-Ordenador (Interacción 2006), Puertollano (Es). Pp. 57-66

[32] Mehrabian, A. (1971). Silent Messages. Belmont (California), USA: Wadsworth Publishing Co.

[33] Morganti, F., & Riva, G. (2005). Ambient Intelligence for Rehabilitation. In Ambient Intelligence: The evolution of technology, communication and cognition towards the future of the human-computer interaction. G. Riva, , F. Vatalaro, F. Davide, M. Alcañiz (Eds.). IOS Press, pp. 283-295. ISBN: 1-58603-490-1.

[34] Nasoz, F., Alvarez, K., Lisetti, C. L., & Finkelstein, N. (2003). Emotion Recognition from Physiological Signals for Presence Technologies. International Journal of Cognition, Technology, and Work – Special Issue on Presence, Vol. 6(1).

[35] Norman, D. (2003). Emotional Design. Why we love (or hate) everyday things. Basic Books. ISBN: 0465051359.

[36] Noyes, J. M., & Frankish, C. R. (1992). Speech recognition technology for individuals with disabilities. Augmentative & Alternative Communication, 8, pp. 297-303.

[37] Ortony, A., & Turner, T. J. (1990). What's basic about emotions. Psychological Review, 97(3), pp. 315-331.

[38] Oudeyer, P-Y., (2003). The production and recognition of emotions in speech: features and algorithms. International Journal of Human-Computer Studies, Vol. 59 (1-2), pp. 157–183.

[39] Picard, R. W. (1997). Affective computing. Cambridge, MA: MIT Press.

[40] Picard R. W. (1998). Towards Agents that Recognize Emotion. In: Acts Proceedings IMAGINA (Monaco), pp. 153-165.

[41] Riva, G. (2005). The psychology of Ambient Intelligence: Activity, situation and presence. In, Ambient Intelligence: The evolution of technology, communication and cognition towards the future of the human-computer interaction. Riva G., Davide F., Vatalaro F. and Alcañiz M. (Eds.) IOS Press, pp. 17-33. ISBN: 1-58603-490-1.

[42] Roseman, I. J., Antoniou, A. A., & Jose, P. E. (1996). Appraisal determinants of emotions: Constructing a more accurate and comprehensive theory. Cognition and Emotion, 10(3), pp. 241-277.

[43] Scherer, K. R. (1986). Vocal affect expression: A review and a model for future research. Psychological Bulletin, Vol. 99, pp. 143-165.

[44] Tao, J., & Tan, T. (2005). Affective computing: A review. In J. Tao, T. Tan, & R. W. Picard (Eds.), Proceedings of the First

International Conference on Affective Computing & Intelligent Interaction (ACII'05; pp. 981–995). Beijing, China: Springer.

[45] Ting, K.M. (1995). Common issues in Instance-Based and Naive-Bayesian classifiers, Ph.D. Thesis, Basser Department of Computer Science. The Univesity of Sidney, Australia.