Proceedings of the 18th International Conference on Automation & Computing, Loughborough University, Leicestershire, UK, 8 September 2012

Emotion Recognition – Theory or Practicality

Michael Hurst, Thomas W Jackson & Mashhuda Glencross
Department of Information Science and Department of Computer Science, Loughborough University, UK
{M.A.Hurst, T.W.Jackson, M.Glencross}@lboro.ac.uk

***Abstract—* Emotion is something that every person experiences throughout his or her lifetime. It is intrinsic to life itself. However, emotion is still one of life's unknowns. The main issue is that emotion is entirely subjective. Each person experiences emotion in entirely different ways, which makes the art of recognising emotion a challenge. Due to the potential that accurate emotion recognition can yield, in regards to Human Computer Interaction, the challenge is one that many believe is worth solving. This state of the art review, explores how technological advancements and are paving the way in understanding the emotion a person is experiencing. The authors outline how their research aims to use technology as well as innovative techniques to achieve high classification accuracy. If achievable the technologies and techniques could achieve significant advancement within interaction as well as countless other application areas.**

Keywords - Affective Computing, Emotion Recognition, Application Areas, Technological Advancements, HCI

I. INTRODUCTION

The art of recognising the emotion and/or mood of a person has been one that has gained added prominence since the turn of the 21st century. Technological advances have meant that for the first time, the prospect of accurate emotion recognition is now real. The advancement of technology has already had a huge impact on fields such as communication and media. Now the time has come for the emotion recognition to benefit from technology.

Significant research is currently underway in attempting to use technology and a combination of both traditional techniques as well as newly formed methods to accurately classify the emotion that a person is exhibiting [1, 11]. Techniques/methods such as EEG, heart rate analysis, facial feature analysis, gesture analysis and speech analysis have all been used producing promising results. However, there are a number of issues that are arising that are proving difficult to overcome. The success of emotion recognition will always be measured on the accuracy of correctly classifying emotion and as a result these issues are having a significant negative impact on success.

For this state-of-the art review, the authors aim to display a full understanding into how the field of emotion recognition has developed into the entity it is today. In order to do this, the authors within this paper will firstly look at the theory behind emotions and what emotion is, where it comes from and how it can be classified. Once emotion can be defined, the authors will then determine how emotion has been recognised in both the pre and post computer era specifically looking at how technology is being used to recognise emotion. By analysing previous research the authors will outline potential areas that an emotion recognition environment can be applied upon. Finally, the authors will outline their proposed methods to developing an environment that can accurately recognise emotion.

This research was funded by the Loughborough University Graduate School

II. THEORY OF EMOTIONS

The emotion that a person exhibits has been a hotbed of discussion of thousands of years dating all the way back to the 4th century BC by Aristotle [1]. The history of this domain is not surprising. Emotion is something that is one of life's great unknowns. It is part of every one of us but for the majority of this time period, has been based on theories with no scientific backing. It is this lack of scientific backing that has led to countless debates and contrasting theories up until the present day.

A. The Science of Emotion

Since the turn of the 20th century, advances in medical research have led people to develop a greater understanding into what emotion actually is. Research now understands that all the communication between the brain and the body is by electrical signals and emotion is no different [2]. When someone experiences an emotion, the brain is essentially producing involuntary electrical signals that make a person feel the way they do [2]. This is referred to as the cognitive theory as it believes that the brain is the central to all emotion [3]. Furthermore, emotion is not just a mental process; it is physical also [2]. The arrival of goose bumps when afraid or a smile when happy is not coincidental. Evolution means that the brain has learnt to send electrical signals to parts of the body in response to certain emotions being exhibited.

These signals sent from the brain to the body can be explained by basing it on the human race's willingness to adapt in order to survive. For example, a new-born baby often displays emotions physically by smiling or crying although they have not learnt what smiling or crying is. Referred to as the Darwinian Theory, emotion selection is based entirely on nature [3]. It is this cue that has evolved into the biology of a person that is essential for that person to survive.

"Even the simulation of an emotion tends to rise it in our minds" – Charles Darwin [4]

Most research as outlined above is based on the premise that the displaying of emotion is a sub-product of electrical signals being sent from the brain. However, the Jameson Theory alternatively states that emotions arise as a result of physiological changes (i.e. a smile results in a happy emotion) [3]. Research has proven for example that someone who is told to smile will be happier than those who are not [5]. It is this reason that the Jameson theory cannot be discounted and why facial cues must be considered within any emotion research.

Based on traditional approaches, emotion or the effects of emotion are hardwired into our makeup and is essentially an involuntary action. However, it is possible with experience to go some way to masking these signals. More and more people now avoid appropriately showing their emotions for a number of reasons. Whether it is due to caring for someone or to gain an advantage over someone else, the masking of true emotions is now an everyday fact of life. So much so terms such as *'stoic'* and *'poker face'* [6] are now commonplace in society.

B. *Classifying Emotion*

Pre-dating the fundamental understanding of emotion, the study of classifying emotion has been one, which has seen a number of theorists exhibiting confounding views on the actual emotions a person exhibits.

Arguably the most commonly used classification system is that outlined by Paul Ekman in 1972 [7]. Ekman stated that emotions were not culturally sensitive and all humans had a set of six basic emotions based on their facial expressions. These were anger, disgust, fear, joy/happiness, sadness and surprise [7]. The widespread use of this system can be explained by its integration into the facial action coding system (hereby referred to as FACS), which allows researchers to determine what emotions are being expressed by deciphering certain points on the face [8].

Ekman's research specifically looked at emotions that were displayed using certain facial expressions. Emotion however, is considered to be based on electrical signals with facial expressions regarded as a sub-product of these impulses. Therefore some emotions may not exhibit facial expressions. As a result of this, an additional set of eleven emotions were proposed that may or not may be based on facial expressions [9]. These are amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure and shame [9].

To fully understand emotion, not only is work being done in distinct emotion classification but also in how each emotion fits together. Russell states "interrelationships can be represented by a spatial model in which affective concepts fall in a circle" [10]. Based on a simple 2-dimensional axis of valence and arousal, Russell provided 8 basic emotions that aligned in a circle [10]. This model referred to as the circumplex (or dimensional) model of affect uses opposite ends of the dimensions to represent opposite emotions and links emotions that are located close together. This was the first model that allowed for a statistical representation of each emotion both in terms of circular representation (where each emotion is located in the circle) and also in terms of dimensional representation (where each emotion is located on each axis) [10]. This has been the predominant reason why this emotion classification system has been used more than others in applied emotion recognition systems most notably in the development of the International Affective Picture System (hereby referred to as IAPS) and studies that use the IAPS dataset [11].

Other emotion classification systems have been developed based on the aspect of using multiple dimensions in emotion classification first used by Russell. Plutchik for example takes this idea one step further by introducing multiple levels of a similar emotion [12]. This is on top of placing similar emotions side-by-side and placing opposite emotions on opposite sides of one another. The addition of both colour and location help to rationalise the link between emotions. Closeness in location and colour symbolise the closeness between similar emotions and different levels of the same emotion [12].

Even though these three classification systems are the most common, there are other systems from other researchers in the field that base emotions around different ideologies. These include further work into multi-dimensionality as well as culturally sensitive classification systems.

III. Emotion Recognition

Although there has been a lack of scientific backing to theories presented, it has not limited the practice of emotion recognition in reality. Flourishing in the middle to latter parts of the 20th century, the reasons why emotion recognition is needed are diverse. Reasons include but are not limited to therapy, research and scientific curiosity.

Traditionally, the recognising of emotion is a skill that is practiced by many in the physical world on a daily basis. The reading of body language as well as the understanding of verbal communication achieves this. However, more and more communication is taking place in the virtual world through computers. As body language is a physical process, the skill of recognising emotion cannot currently be replicated in this virtual setting.

As emotions are difficult to understand in the virtual world, there has been some effort to experiment with different technologies and techniques in order to implement a computer based environment that can effectively recognise a user's emotion. This effort has seen the rise of the field titled 'affective computing' by Rosalind Picard [6]. Affective Computing brings together the fields of psychology, cognitive science and computer science in order to assist in emotion recognition in the virtual world [6].

A. *New Visible Input Techniques*

One of the approaches that researchers use within affective computing is using technology to implement traditional techniques. This is arguably the most common approach due to its ease in comparison as this approach deals with entirely physiological feedback that can be seen by the naked eye. Within this approach, the techniques have been refined over a large number of years leaving the majority of work involved in understanding how to map technology onto these techniques.

In regards to specific techniques, the majority of research is to understand how technology can be used to read body language [6]. Body language is a communication medium that the majority of people use to express their emotions without verbalising them. In order to read one's body language requires observation of one or a combination of the face, the body, the eyes and the voice.

1) Face

The most obvious and common form of body language is facial expressions. There are a large amount of facial expressions that a person can exhibit and each of the facial expressions in the majority of occasions conforms to a certain emotion being exhibited (i.e. a smile means that someone is happy). However certain limitation apply when analysing facial expressions such as the ease of masking certain facial expressions and that different people exhibit emotions in different ways.

Ekman's model of six basic emotions was created specifically based on facial expressions [7] and whilst working on this model, he went on to create a way to distinctively map certain expressions based on the movement of certain muscles in the face referred to as the facial action coding system [8]. Ekman coded a selection of 44 different muscle movements (referred to as action units) such as a nose wrinkle (AU=9) and a lip stretcher (AU=20). Then a combination of these action units was mapped to each of the six emotions based on his classification system. To understand AU's, takes 100 hours of training and considerable more time to implement onto a video as each frame has to be analysed independently. To assist, numerous research projects have produced good results in using a wide range of algorithms such as support vector machines to automate this process [13, 14] based on the initial FACS framework.

2) Gestures

Just like facial expressions, gestures are an equally important form of body language. Within this research, it is important to distinguish between the two due to the varying techniques needed to automate them. For this reason, we distinguish gestures as any expressive body movements except for any facial movements (not including head movements).

Even though the reasoning behind displaying gestures and facial expressions are effectively the same, the difference arises when understanding proximities. Whereas facial expressions are used to convey feelings and ideas within one's personal space, gestures are used to convey feelings across greater distances usually within one's social space [15]. It is proximity that means that research into gesture analysis is at a far higher level than that of its counterpart. As gestures are needed to carry over a greater distance, it is far more elaborate and obvious and as a result easier to analyse.

Gesture analysis has been a hotly debated research topic in a wide range of fields due to its potential in terms of interaction specifically gameplay. Its power is proven by the commercial success of the Microsoft Kinect motion sensing device which is at time of publication the fastest selling consumer electronics device[1] which has gesture analysis at its core. Most research into gestures has used the Microsoft Kinect system due to its ability to handle 3D modelling and representations. Gestures analysis have produced promising results (average 66% across 8 emotions) even though this research typically uses forced gestures as opposed to natural gestures [16].

3) Voice

When contributing in vocal communication, it is normal for someone to understand the feeling that his or her counterpart is experiencing through the understanding of the communication itself. However, for a variety of reasons, people lie. Therefore, many researchers within the field of emotion and affective computing often discount verbal communication on its own in studies looking into emotion recognition.

It is important to note that these brain-controlled actions can easily be affected by the biological make up itself. For example, if a person is intoxicated, the electrical signals can be distorted which results in incorrect actions being attributed. It is this reason why tone, pitch and speed are all attributes that can be analysed to understand emotion.

There are two ways to detect emotions whilst looking at vocal attributes, 1) mapping changes and 2) comparing the changes the communication itself. For example, when someone is fearful, his or her vocal chords tremble due to the presence of adrenaline. This can be used independently to understand an emotion or to discount an emotion that is being communicated.

Just like gesture and facial expressions, vocal analysis can be performed automatically by a selection of real time data analysis algorithms. As the algorithms that are used are essentially very similar, research studies into emotion recognition often take a multi-modal approach across both voice and either/or facial expressions and body language.

[1] http://www.bbc.co.uk/news/business-12697975

4) Eyes

Out of the traditional techniques listed, the analysis of eye movements is arguably the least researched of the four in regards to the automation within affective computing. To understand the link between the eyes and emotion, we can look at either/or 1) proximity and/or 2) velocity. Proximity can be used to tell if someone is comfortable at looking at stimuli or not (i.e. people may look away when distressed). Alternatively, velocity can be used to distinguish high arousal emotions as these emotions often mean that a person is more alert.

Eye tracking technology has seen drastic improvements over the past decade and is now common in a whole host of fields. There are numerous commercial examples of eye tracking technology such as the Tobii eye-tracking product suite[2] and more recently as a feature of the Samsung Galaxy SIII (S3)[3]. So much of the technological advancements, an open source project titled Opengazer[4] now means that eye tracking can now be used on most traditional webcam hardware.

B. New Invisible Input Techniques

Technological advancements within computing mean that computers can now gather data that humans cannot mainly down to these sources being located under the skin. This is where computers can gain a significant advantage against their human counterparts. Technology can be used to look at the direct sub-products of the messages from the brain as well as the brain itself. Referred to as biological responses, research specialises in looking at these mainly as they do not possess the same limitations as physical responses (i.e. can't be masked).

1) Brainwaves

As outlined in the cognitive model, the brain is central to all emotions [3]. Technological advances and the launch of numerous commercial Electroencephalography (EEG) devices (EPOC Emotiv[5], Neurosky Mindset[6]) now give researchers the opportunity to analyse brainwaves for a wide range of reasons not limited to analysing seizures [17], artificial intelligence [18] and specifically for this research, psychology [19-21].

EEG due to its nature is included within most affective computing research. However, classification accuracy (using data to understand correct emotions) within this affective computing has seen disappointing results. Based on five emotions, results see an improvement of roughly 20-25% on chance once pre-processing has occurred [19, 20]. The main reasons for this are unique biological makeup, rogue brainwave electrical activity such as environmental noise and other muscle movements such as blinking [19, 20, 22]. Pre-processing usually consists of artefact removal, noise removal and then using a mix of classifiers such as naive Bayes classifier, fisher discriminant analysis, neural networks and support vector machines in order to interpret what emotion is being exhibited.

To combat low classification accuracy, more and more innovative methods have been used such as only using extreme high/low values, which specifically look at only emotions that are being strongly elicited. The trade-off of discounting the majority of data (7 out of 10 samples) comes by an increased classification accuracy increasing significantly to 70%-80% based on 5 emotions [20].

[2] http://www.tobii.com/
[3] http://www.samsung.com/
[4] http://www.inference.phy.cam.ac.uk/opengazer/
[5] http://www.emotiv.com/
[6] http://www.neurosky.com/

2) *Brain Oxygenation Levels*

Whereas brainwaves can be monitored to understand activity, brain oxygenation levels can be monitored to understand stimulation. Devices that specialise in this type of monitoring are referred to as fNIR devices that are based on a headset that uses infra-red to scan the brain's pre-frontal cortex [23]. The infrared sensor monitors differing levels of oxygenation within this region. As the pre-frontal cortex is responsible for cognitive tasks, differing oxygenation levels here can show those that are more aroused either with high, neutral or low valence [23].

3) *Heart Rate / Blood Flow*

A sub-product of certain emotions specifically those emotions on the high end of the arousal scale (distressed/aroused/excited) is high heart rate. Referred to as tachycardia, it is common when one is exhibiting these emotions that a persons heart rate jumps from 50-100 bps to 100+ bps as a result of the presence of adrenaline. Therefore, a device can be used to monitor heart rate to understand someone who is experiencing high arousal [24]. As well as heart rate monitors, blood flow monitors work in a similar way. This less obtrusive monitor (located on fingertips) can also understand high arousal in a similar way.

4) *Muscle Contraction*

All muscles in the human body use electrical signals to communicate between itself and the brain. Therefore, just as with brainwaves, we can also look at electrical activity within muscle contractions to understand emotion. For example an Electromyography (EMG) sensor can be used for large muscle contractions such as running as well as small large muscle contractions such as clenching ones jaw [25]. EMG is not only easier to automate physical movements due to the simpler data stream but also can detect smaller contractions, which are not picked up by the naked eye. However, there are numerous limitations of EMG devices that have limited its use. These include cost, electrical artefacts/noise and obtrusiveness.

5) *Skin Conductance*

One of these biological responses that can occur as a result of a brain sending electrical signals is differing perspiration. For example, someone who is nervous often perspires more than someone who is happy. As perspiration is water based, it conducts electricity. Galvanic skin response devices can interpret the different levels of moisture on the skin by firing electrical currents through the skin and analysing the level of current it then receives [25].

C. Other

As well as trying to formulate new input methods, it is important not to ignore input that is already commonplace within computing. As one of these, text entry can be used to understand emotion specifically looking at both the speed and the context of the text itself. In relation to the context of the text, natural language processing is a technique which can be used to analyse the text to look for any emotional cues. Social media is an area in which this can be used to recognise emotion to a great effect as people often use these medium to say how they are feeling.

IV. APPLICATION AREAS

One of the main reasons why affective computing has seen such a rise in prominence as a research field since its conception is the significant potential that its integration can yield in a wide range of fields. The main theme running throughout these application areas is to improve interaction. Picard in her field-defining paper identified a number of these application areas such as entertainment, communication and environment [6]. Alongside these, other application areas include health, advertising and computer based areas such as usability and graphics.

A. Emotion within Media

Within entertainment mediums such as film, TV and music, it is the director's/conductor's aim usually to elicit a wide range of emotions based on requirements. Affective computing could not only help automate this feedback but has the potential to be used in dynamically changing media to make sure that the emotion that wants to be elicited is done so [6]. For example, a horror film that is getting a mild reaction could adapt to more extreme footage in order to ensure that the viewer is 'scared' [6].

B. Video Gaming

Video gaming has always been a field that has attempted to push boundaries. Traditionally, video games were played one way in a very linear fashion. However, to combat boredom, many games developers have consistently added extra dimensions to gaming from gesture-based controllers with the Microsoft Kinect and the Nintendo Wii to biological based environmental settings.

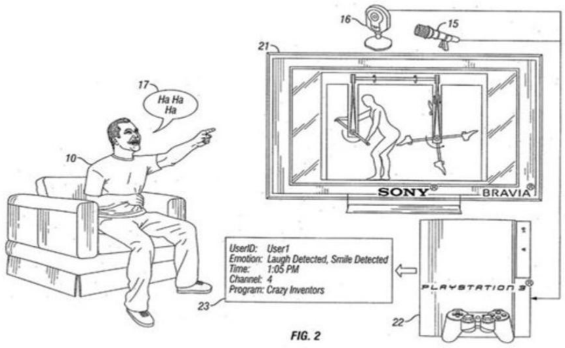

Figure 1 - Sony PS3 Emotion Control Patent[7]

Such as the demand for emotion-based media, both Nintendo (Wii Vitality)[8] and Sony (PS3 Unnamed) have valid patents that attempt to use a range of physiological data and biofeedback to let the respective games console understand your emotions. Research is already underway looking at how emotions can be used for indirect control within affective gaming [26].

C. Communicating Emotion

When communicating online, misinterpretation usually occurs. This is because this type of communication often involves just text and as a result, has little emotional context [6]. Widely used 'smileys' are a forced solution to address this but are limited in their use [6]. Therefore, an affective communication system would solve this issue as communication could include automatic emotional context. For example, an email client could automatically file emails either by emotional context or by importance.

---

[7] http://www.techradar.com/news/gaming/sony-patents-ps3-emotion-control-626668

[8] http://www.engadget.com/2009/06/02/nintendo-wii-vitality-sensor-detects-your-pulse/

D. *An Emotive Environment*

The environment that one is located in has a huge effect on that person's emotion. However, reactions to environment are entirely subjective [6]. Whereas one person might feel happy in a setting, another might feel anxious [6]. Many businesses understand that they can gain a competitive advantage if they can suit an environment to their customers. Therefore, by understanding physiological and biological feedback, they can adapt their environment dynamically in order to increase customer satisfaction.

E. *Usability/Interface Design*

One of the more obvious application areas is to assist people when using a device or a computer. It is common for people to become frustrated when using a computer if their intended actions are not replicated [6, 28, 29]. Using affective computing, frustration can be understood by the computer or device. It can then dynamically change to assist the users to help them. One of the changes could be in terms of interface design. For example, someone who is excited might prefer more options within the interface where as someone who is tired might want something simpler.

F. *Other*

As well as those listed above, there are other areas that an emotion recognition system can be integrated into. Examples include:

- Computer graphics (variable) [30]
- Teaching (gauging interest from pupils) [30]
- Driver Safety (spotting tiredness whilst driving)
- Robotics (artificial intelligence)
- Advertising (dynamically targeted to emotions)
- Health (tiredness/stress whilst using a computer)

V. RESEARCH DESIGN

The authors propose to undertake an extensive research project into the creation of an effective emotion recognition environment. By undertaking this research, the authors would like to achieve the following outcomes:

1. The development of an environment that combines data from a number of sensors to produce a data stream in order to reach a classification accuracy of over 80% (based on a 9 emotion framework)
2. The integration of the environment discussed in (1), into one of the application areas discussed in section 4 to prove that an emotion recognition environment will be successful in practice.

Within this research, there are also a number of other conditions that the authors aim to satisfy. These are:

A. Sensors are either readily available or affordable.
B. Unobtrusive sensors so that natural behaviour is not sacrificed.
C. The finalised data stream must work in real time based on the processing power of an average computer.

All three of these conditions are important to ensure that an emotion recognition environment is plausible in practice and in turn successful in the long run.

A. *Techniques and Technologies*

Based on the conditions presented in section 5, the authors have decided to use the technology and technique combinations presented in table 1. Some combinations that are commonly used within this domain such as vocal analysis, brain oxygenation and muscle contraction have been omitted for a variety of reasons such as being against natural behaviour, cost and obtrusiveness.

Code	Technology	Technique
C1.1	Microsoft Kinect	Facial Recognition
C1.2	Microsoft Kinect	Gesture Recognition
C2	Tobii Eye Tracker	Eye Tracking
C3	EPOC Emotiv	Brainwave Analysis
C4	HR/BF Monitor	Heart Rate/Blood Flow
C5	GSR Monitor	Perspiration

Table 1 – Technology and Technique Combinations used in this research

Even though there are possible condition conflicts with those listed in table 1, extra measures will be made within the setup stage in order to ensure that these conflicts will not be encountered. For example, C3 will avoid too many costly pre-processing techniques in order to ensure condition C was met.

B. *Initial Study Design*

In order to understand what combination of techniques and technologies would be best to use, the authors will undertake a study similar to those within the domain [19, 20]. The study will consist of 180 participants within a 'between participants design' setup. This will result in five groups of 36 participants each measured by one of the technologies outlined in table 1.

Across all five groups, the study setup will remain the same. Each participant will view 36 images independently (image order counterbalanced throughout the study), taken from the IAPS [11] carefully chosen to cover the 8 different emotions as outlined by Russell [10] as well as a neutral emotion for baseline purposes. As emotion is subjective, each participant will fill in a self-assessment manikin (SAM) for valence, arousal and dominance reactions (1-9) at the end of each image being viewed.

The conclusion of this study will leave the authors with two data sets, the sensory-based data and the emotions that the participant experienced. These data sets can then be thoroughly analysed to try and yield the greatest classification accuracy. To ensure that the data used in the analysis stage is as rich as possible, sensory data will only be used if the expected emotion is the same as that experienced.

There are two primary differences within the design of this study in comparison with those similar studies. The first of these is the amount of time the stimuli is presented to the participant. Whereas other studies limit the stimuli to short term reactions typically 2-8 seconds [11, 19, 20], the authors have extended the stimuli to 30 seconds. Timeframe will then be used as an extra independent variable within the data analysis stage to understand differences between short, mid and long-term reactions within each data stream.

The second difference is in respect to the independence of the data streams. Whereas other studies in this domain look at one classification accuracy across all the sensory data, this study uses the different sensor data as an additional variable. By separating the sensor data, the authors can understand how different combinations of sensors yield different accuracies.

C. *Accurate Data Stream*

The authors whilst dealing with issues have decided to adopt the *avoiding* approach as opposed to the *reduction* approach. This decision was made, as *reduction* is difficult to achieve without either technological advancements or introducing artificial behaviours into the environment, which goes against condition B. Avoidance therefore has been chosen, as this does not require the introduction of artificial behaviours.

The main avoidance strategy that the authors will use is to use the basis of the multi-modality (sensors) to eliminate the issues during the automated data analysis phase. For example, when an issue occurs such as blinking, it affects certain techniques (EEG/Facial Recognition/Eye Tracking) but doesn't affect others (Gesture Recognition). By treating the data from each sensor as an individual entity, the authors can eliminate the false data when fusing the data streams together.

Once the data analysis has been completed, the authors will be able to understand what combination of sensory data yields the best classification accuracy. This combination will be then used to develop a computer-based environment which best integrates the technology in order to be as unobtrusive as possible. This environment will then be used in an additional study to satisfy the secondary aim, domain to be decided once the initial study has been completed.

VI. Conclusion

Emotion has and always will be a difficult entity to understand. Technological advancements now mean that for the first time there is a prospect of an automated emotion recognition environment. The authors have reviewed the literature and outlined a method and a system that could potentially accurately recognise the emotion a person is experiencing, but also open up a whole host of potential application areas that the environment could be implemented into.

VII. References

[1] W.W. Fortenbaugh, "Aristotle on Emotion: A Contribution to Philosophical Psychology, Rhetoric," Poetics, Politics and Ethics.London, 2002.
[2] N. McNaughton, Biology and emotion, Cambridge Univ Pr, 1989, .
[3] R.R. Cornelius, "Theoretical approaches to emotion," in ISCA Tutorial and Research Workshop (ITRW) on Speech and Emotion, 2000.
[4] C. Darwin, "The expression of the emotions in man and animals," Am.J.Med.Sci., vol. 232, pp. 477, 1956.
[5] F. Strack, L.L. Martin and S. Stepper, "Inhibiting and facilitating conditions of the human smile: a nonobtrusive test of the facial feedback hypothesis." J.Pers.Soc.Psychol., vol. 54, pp. 768, 1988.
[6] R. Picard, "Affective computing. 1997," .
[7] P. Ekman, Universals and cultural differences in facial expressions of emotion, University of Nebraska Press Lincoln, 1971, .
[8] P. Ekman and W.V. Friesen, "Facial action coding system," 1977.
[9] P. Ekman, "All emotions are basic," The Nature of Emotion: Fundamental Questions, pp. 15-19, 1994.
[10] J.A. Russell, "A circumplex model of affect." J.Pers.Soc.Psychol., vol. 39, pp. 1161, 1980.
[11] P.J. Lang, M.M. Bradley and B.N. Cuthbert, "International affective picture system (IAPS): Affective ratings of pictures and instruction manual. Technical Report A-8," 2008.
[12] R. Plutchik, "The Nature of Emotions Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice," .
[13] M.H. Mahoor, S. Cadavid, D.S. Messinger and J.F. Cohn, "A framework for automated measurement of the intensity of non-posed facial action units," in Computer Vision and Pattern Recognition Workshops, 2009. CVPR Workshops 2009. IEEE Computer Society Conference on, pp. 74-80, 2009.
[14] M.F. Valstar, I. Patras and M. Pantic, "Facial action unit detection using probabilistic actively learned support vector machines on tracked facial point data," in Computer Vision and Pattern Recognition-Workshops, 2005. CVPR Workshops. IEEE Computer Society Conference on, pp. 76-76, 2005.
[15] E.T. Hall, The hidden dimension, Doubleday, 1966, .
[16] G. Caridakis, G. Castellano, L. Kessous, A. Raouzaiou, L. Malatesta, S. Asteriadis and K. Karpouzis, "Multimodal emotion recognition from expressive faces, body gestures and speech," .
[17] J. Claassen, S. Mayer, R. Kowalski, R. Emerson and L. Hirsch, "Detection of electrographic seizures with continuous EEG monitoring in critically ill patients," Neurology, vol. 62, pp. 1743-1748, 2004.
[18] J.R. Millán, F. Renkens, J. Mouriño and W. Gerstner, "Brain-actuated interaction," Artif.Intell., vol. 159, pp. 241-259, 2004.
[19] G. Chanel, J. Kronegg, D. Grandjean and T. Pun, "Emotion Assessment: Arousal Evaluation Using EEG's and Peripheral Physiological Signals," July 17th-August 11th. 2006.
[20] R. Horlings, D. Datcu and L.J.M. Rothkrantz, "Emotion recognition using brain activity," in Proceedings of the 9th International Conference on Computer Systems and Technologies and Workshop for PhD Students in Computing, pp. 6, 2008.
[21] O. Sourina, Y. Liu and M. Nguyen, "Emotion-enabled EEG-based interaction," in SIGGRAPH Asia 2011 Posters, pp. 10, 2011.
[22] S. O'Regan, S. Faul and W. Marnane, "Automatic detection of EEG artefacts arising from head movements," in Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE, pp. 6353-6356, 2010.
[23] S.C. Bunce, M. Izzetoglu, K. Izzetoglu, B. Onaral and K. Pourrezaei, "Functional near-infrared spectroscopy," Engineering in Medicine and Biology Magazine, IEEE, vol. 25, pp. 54-62, 2006.
[24] K.H. Kim, S. Bang and S. Kim, "Emotion recognition system using short-term monitoring of physiological signals," Medical and Biological Engineering and Computing, vol. 42, pp. 419-427, 2004.
[25] A. Haag, S. Goronzy, P. Schaich and J. Williams, "Emotion recognition using bio-sensors: First steps towards an automatic system," Affective Dialogue Systems, pp. 36-48, 2004.
[26] L. Nacke, M. Kalyn, C. Lough and R. Mandryk, "Biofeedback Game Design: Using Direct and Indirect Physiological Control to Enhance Game Interaction," in CHI 2011 - Olfacation, Breath and Biofeedback, pp. 103-104-112,.
[27] L. Marulanda-Carter and T.W. Jackson, "Effects of e-mail addiction and interruptions on employees," Journal of Systems and Information Technology, vol. 14, pp. 82-94, 2012.
[28] H. Thimbleby, Press On: Principles of interaction programming, The MIT Press, 2010, .
[29] B. Schneiderman, "Eight Golden Rules of Interface Design," Disponible En, 1986.
[30] R.W. Picard, "Affective computing: challenges," International Journal of Human-Computer Studies, vol. 59, pp. 55-64, 2003.