MODELING EMOTION FOR ANTHROMORPHIC AGENTS

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Abstract*: Emotions should play an important role in the design of interfaces since human beings interact with machines as if they were social actors. To investigate if and how machines can express emotions, it is necessary to investigate human-human interaction. Facial expressions are one of the most powerful, natural and immediate means by which human beings communicate their emotions and intentions. Face-to-face communication is inherently natural and social for human-human interactions. There is substantial evidence that suggests this may also be true for human-computer interactions. In other words, human beings regard computers as social agents with whom "face-to-interface" interaction may be most easy and efficacious. Based on Ekman's theory, SIX (6) universal emotion expressions that do not change too much from culture to culture were adopted in this study. The six emotion expressions are happiness, sadness, disgust, anger, surprise and fear. In addition, based on these six universal expressions, the AeMotion system was developed using Visual Basic 6.0. The Sony Digital Handycam video camcorder was used to capture the facial expressions. The system provides meaningful information for emotion detection through human facial expression. The final result of pixelization can be transferred into the set of processing array for emotion recognition purpose. The pixel formation provides indirect information for emotion (sad, anger, disgust, happy, fear and surprise) cues such as "brows lowered and drawn together" portrays action of disgust. The study demonstrates that the human facial expressions were successfully captured and pre-process to represent image-based emotions. The study also demonstrates that the image-based parameters could be used to interpret the facial affect space. In addition, the results also demonstrate that there is a need for both basic and applied research contributions to the rapid developing field of affective computing. Currently, experiments are still being conducted to see the impact of a variety of compressed image conditions has on affect space.*

Keywords: *Emotion, Image Processing, Facial Expression, Anthromorphic Agent*

INTRODUCTION

From the beginning of biologically inspired interaction, researchers have been fascinated by the possibilities of interaction between machine (computer) and its environment through social intention and perception. Inspired by how we are communicating makes social learning, emotion understanding, natural languages communication and interaction increasingly important. Thus human social emotional intelligence is useful and powerful means for understanding the behaviour, and for interacting with some of the most complex entities such as human when dealing with computers.

Emotions should play an important role in the design of interfaces since human beings interact with machines as if they were social actors. To investigate if and how machines can express emotions, it is necessary to investigate human-human interaction. Facial expressions are one of the most powerful, natural and immediate means by which human beings communicate their emotions and intentions. Face-to-face communication is inherently natural and social for human-human interactions. There is substantial evidence that suggests this may also be true for human-computer interactions. In other words, human beings regard computers as social agents with whom “face-to-interface” interaction may be most easy and efficacious.

Through the facial expressions, human emotions can be identified and, therefore allow the model to determine either the interaction is beneficial or detrimental without depending on some external evaluation. Hence, developing such a system and interaction would contribute to human computer interaction (HCI) and other applications such as multimedia queries, face recognition and other affective computing aspects.

The facial expressions considered in this study are limited to six universally defined emotions, namely: anger, disgust, fear, happiness, sadness and surprise

(Ekman and Rosenberg, 1997; Velasquez, 1997). The emotions representations were captured from the real images, rather being generated using simulation functions. The main focus of this study is on image capturing and processing that give rise to emotions representations, therefore provides some insight towards the understanding of the role and usefulness of the notions of emotions for anthromorphic agents.

An anthromorphic agent is defined as an interactive computational entity that imitates human forms (Laurel, 1990). It is used to produce emotional response through physical gestures and feedback. An anthropomorphic interface could use intonation, gaze patterns, and facial expressions, in addition to words for conveying information and affect. Anthropomorphic interfaces could make a computer more human-like, engaging, entertaining, approachable, and understandable to the user. As a result, thus a sense of trust is harboured and relationships can be established with users, and therefore make them feel more comfortable with computers (Catrambone *et al.*, 1999).

EMOTION AND FACIAL EXPRESSION

Emotion is one of the most controversial topics in psychology, a source of intense discussion and disagreement from the earliest philosophers and other thinkers to the present day. Philosophers have offered many proposals concerning emotion, throughout the ages, from the ancient Greeks to Sartre and modern scholars. Natural scientists, such as physiologists and animal behaviourists have speculated on the origins, evolution, and functions of emotion. Psychologists, anthropologists, and sociologists have proliferated theories about emotion and its significance to the individual and society. Other disciplines also have their views on emotion, including political science, economics, performing arts and others.

Emotions are essential part of our lives; they influence how we think and behave, and how we communicate with others. Velasquez (1996), Kitano (1995), Velasquez (1997) studies have demonstrated how emotions influences behaviour and learning. A distributed model for the generation of emotions and their influence in the behaviour of autonomous agents known as Cathexis has been developed by Velasquez (1997) and shown in Fig. 1.

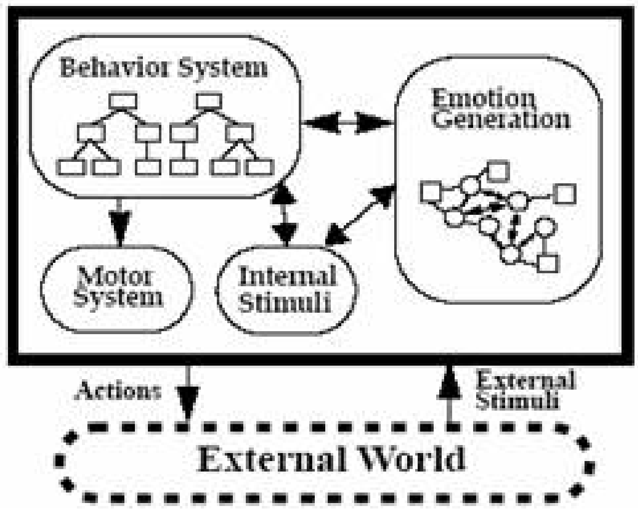

Figure 1: The Cathexis Architecture

Based on Cathexis Model, emotions, moods, and temperaments are regarded as a network composed of special emotional systems that represents a specific emotion family such as Fear or Disgust.

Facial expressions are one of the most powerful, natural and immediate means by which human beings communicate their emotions and intentions. The human face expresses emotions faster than people verbalize or even realize their feelings. Many psychologists have studied human emotions and there are many possible facial expressions, the same expression may have radically different meanings in different cultures. However, it is widely accepted that there are six universal expressions that do not change too much from culture to culture. These universal emotion expressions are happiness, sadness, disgust, anger, surprise and fear (Ekman and Rosenberg, 1997; Velasquez, 1997) as shown in Fig. 2.

Figure 2: Facial Expression

(Source: http://encarta.msn.com/media_461547581/Facial_Expression_and_Emotion.html)

RELATED RESEARCH ON COMPUTATIONAL EMOTION

Recent commercial applications are emerging where the ability to interact with people in an entertaining, engaging or anthropomorphic manner is an important part of the system's functionality. Although the ability of these systems to interact with people (and people's ability to interact with them) is limited, they are motivating the development of increasingly life-like and socially sophisticated systems. In order to achieve such attempt, several methods were developed. For example, *Decision Theoretic Preliminaries* (DTP) is being used to maximize the expected quality of its agent actions (Gymtrasiewicz and Lisetti, 1998). Using DTP, agent formulates its decision making situation in terms of finite set. The decision making process for social interaction is encoded using utility function that maps states of the world in real numbers. With this utility function, it fully describes the information of agent has about the present state of the world.

Affective Computing is a field of study that concentrates on how computers understand, express react appropriately with regard to emotions. Since its beginning, affective computing brings emotion and machines into different context. For example, works on Elliot's Affective Reasoner implements the simulated environment containing multiple agents with emotional states based on the cognitive theory model (Elliot, 1992). The study shows that machine, which is capable to understand human emotions will be able to develop sense of profiling.

Another example of affective computing is an adaptive algorithm for learning changes in user interests (Widyantoro *et al.*, 1999). This application employs personalized information filtering system that relies on users' feedback. Using the feedback information, the profile is modified such that it will be incorporated for future filtering task. Affective learning companion provides another success story using affective interaction in educational fields. Assisted with pedagogical approach, affective learning companion try to understand students' acceptance level via their emotional level towards certain subjects (Burlesan, 2004).

Ortony *et al.* (1988) developed the emotional states taxonomy. The taxonomy provides some insight into how emotional states and its transitions between them comprise the agent's personality. From the taxonomy, emotions space was divided into two parts, positive and negative affects. Each branch provides information about the valance, duration and event for emotional representation template. O'Neill (2000) extends this work using primitive representation which enables three dimensional emotion space can summarize using simple emotion maps. The emotion maps were developed using unsupervised learning algorithm. Another approach proposed by Sandholm and Crites (1995) focuses on computational emotion model using probabilistic approach. In this case, assumption about the world (environment) is important for personality development. The main advantage of using this approach is that a personality model can be learned, given limited amount of observations of the other agent's behaviour (Carmel and Markovitch, 1996).

Yacoob *et al.* (1995) utilized eigenface approach in recognizing faces showing expressions. The degree of correlation between an image and a set of images that constitute the face database was measured. Feature points were selected using Gabor wavelet for curvature changes evaluation. This approach was tested on a database of 303 images of 86 people with success rate of 86 percent. Bartneck (2000) conducted a study on affective expressions of machines through visual abstraction level. He proposed a model for the convincingness of affective expression based on Fogg and Hsiang Tseng (1999). His findings indicate that the type of emotion and multimedia presentation have an effect on convincingness. The distinctness of an expression depends on the abstraction and the media through which it is presented.

Anthropomorphism is another key issue when relating social interaction between human and computer. The humanlike features for social interaction with people can facilitate natural social understanding (Breazeal, 2002). Several experiments have highlighted the influence of appearance and voice/speech on people's judgements of another social interaction (Billiard, 1998; Billiard and Dautenhanhn, 1998; Blumberg, 2002). The studies of Premack and Premack (1995) show that people attribute mental states (for example: intents, beliefs, feelings, desires and others) to describe the behaviour of interaction shapes on a screen. As in biological counterpart, human anthropomorphize their pets, computers, toys, by assigning their intentional, mental and emotional states (Watt, 1995).

Based on this idea, Massaro *et al.* (2000) studied the development of talking agent using anthropomorphic head. Its main goal is to serve human-computer interfaces centred using virtual conversational agents. As the amount of interactivity increases, users prefer the agent characters to be more "believable" (Bates, 1994). Classical and computer animation are full of examples where people are willing to "suspend disbelief" in order to interpret the character's behaviour in human and social terms. By doing so, the entity seems more familiar and understandable to the human who in turn makes the interaction more comfortable, enjoyable and compelling.

Anthropomorphism allows natural interaction and sociability as well as providing capability for conveying message and interact in more natural manners. Works on sociable agents are considerably new, but gained many attentions from researchers alike. Breazeal and Scassellati (2002) pioneered the works of sociable robotics. The research works were based on the idea of human tendencies to respond socially to others. Other researchers have suggested that in order to interact socially with humans, a software agent / robot must be believable and life-like, must have behavioural consistency and must have ways of expressing its internal states (Bates, 1994; Blumberg, 1996).

In order to evoke such sociability, the computer must display human-like social cues and exploit human natural tendencies to respond socially to these cues (Brooks, 1990). The examples of human social cues are gaze direction, posture, gestures, vocal prosody and facial displays. Kismet, the sociable robot shows the capabilities to understand such cues and respond to it (Breazeal, 2002). Kismet was developed, inspired by natural interaction between infant and caregiver. The main focus on Kismet development is the ability to understand social and non-social stimuli using low level feature detectors from its attention and perception systems (Breazeal and Scassellati, 2000).

The related works in emotions and Cognitive Science indicate that the need for developing life-like and socially sophisticated system increases. Research has also shown that engaging anthromorphic agent for interacting with users has become an important part of the system functionality. In order to develop human like and socially sophisticated system, an understanding towards emotion modelling has become vital. In developing computational emotion modelling, several techniques have been discussed, however for an initial attempt, the emotion model developed by Ekman and Rosenberg (1997); and Velasquez (1997) were used as a basis for this study.

Figure 3 : The Six Universal Emotion Expression

(Source: Ekman and Roosenberg, 1997)

For this research, only these six emotion expressions will be used. The eyebrow and lip formations provide primitive structures, however they are important features in detecting such emotion expressions.

MODELING EMOTION FOR AeMotion SYSTEM

A number of motivations exist for relying research in social interaction between human and computer (robot/machine). The most general motivation arises from the fact that interaction is a primary skill for humans, and very early learned skill in order to allow better usage.

To describe a facial expression precisely, the following must be taken into account: intensity of the facial action, location on the face with respect to facial symmetry, and duration of the expression. In order to achieve this exact description, videotaped facial behaviour must be manually analyzed in slow-motion again and again. The time needed to code one minute of a recording of average facial activity has been estimated to take up to hundred minutes, depending on the complexity of the expressions. An automated procedure suggested by Kaiser and Wehrle (1992) can be used as a guidline.

Basically, the system comprises of TWO (2) main modules, namely: Image Processing module and Behaviour module. Fig. 4 depicts the basic design of AeMotion system. The process involved in these modules will be discussed in the following sections.

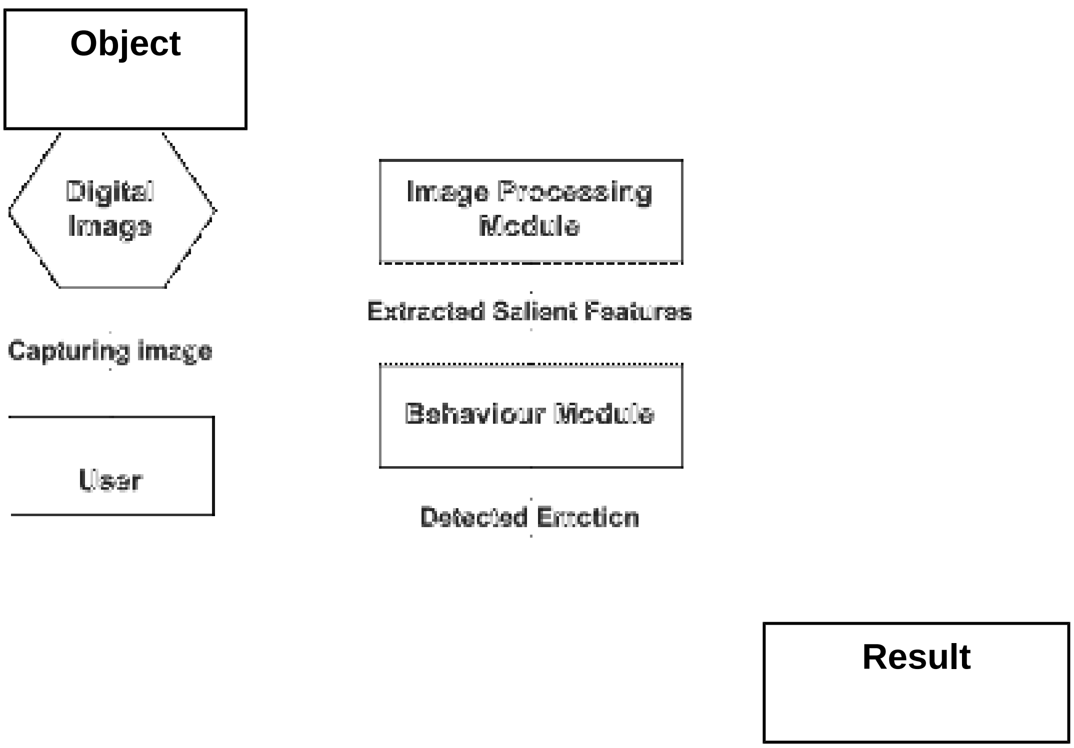

Figure 4: AeMotion System

Image Processing Module

The objective of this module is to identify and to extract salient features that contain important information about emotion condition. The object’s face is captured using imaging device and then its image undergoes several processes. Once the image has been captured and extracted, the mage processing techniques will be applied on this image. The overall stage of image processing is illustrated in Fig. 5.

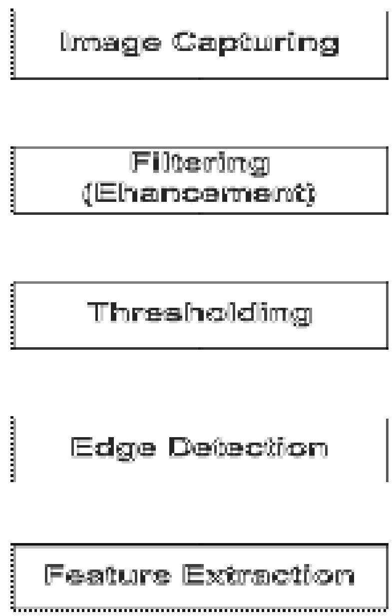

Figure 5: The Flow of Process of Image Processing

In this study, Sony Digital Handycam video camcorder is used to capture the human face (object) image and convert into digital representation. The sensor resolution for the Sony Digital Handycam is 640 x 480 VGA with programmable frame rate up to 30 frames per second (fps) in field view approximately around 54 fields. The captured image is stored in JPEG (Joint Picture Expert Group) format and later will be converted into TIFF (Tagged Image File Format). Fig. 6 depicts the example of the captured image from this device.

The images were captured under low illumination scene and contains noisy signal (such as redundant colour saliency). Most of the captured images are face mug shots since face to face interaction is a critical component in anthromorphic agent. Therefore there is an urgent need for the low-level vision system to process this part of image.
Image filtering (or image enhancement) is another important module to be developed in this research. The principal objective of image filtering is to process an image so that the result is more suitable than the original image for a specific application. To achieve this, gray scale transformation is performed using the

intensity component that is written as:

where R represents Red
G represents Green
B represents Blue

The effect of image filtering on the captured image is shown in Fig. 6.

Figure 6: The effect of image filtering

In order to extract the image without reducing the noise, smoothing technique is required. Smoothing mask is a low pass filter (averaging filter/ linear filter) that yields the blurring of an image. The mask used is

(1)

The process is straightforward by replacing the value of every pixel in an image by the average grey levels in the neighbour pixels (defined by the filter mask). As a result, the sharp transitions in grey levels will be reduced. The next step is image thresholding. Thresholding is an operation to remove intensity of the images to one of the two sets values the objects and background in order to reduce unnecessary information. It can be represented as:

$$f(x, y) \quad \{ \qquad (2)$$

where *f(x,y)* denotes the value of pixel after thresholding operation with threshold value *T*. Figure 7 shows the effect of smoothing and thresholding operation (image with smoothing contains noiseless binarized image)

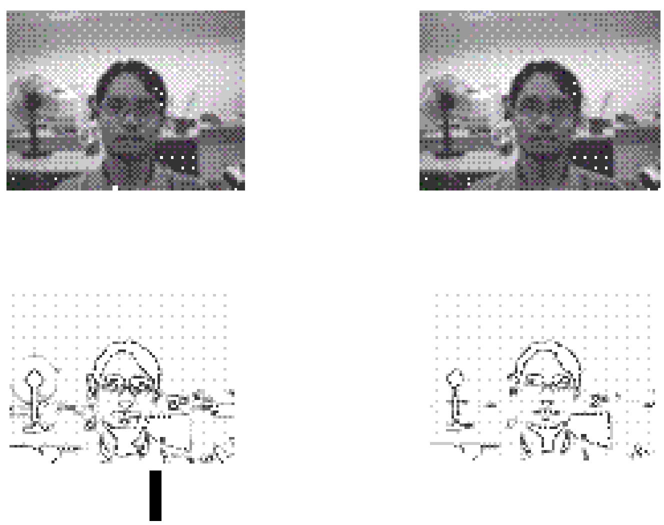

Figure 7: Effect of Smoothing and Thresholding

Once the smoothing and thresholding are performed, edge detection process will be carried out. Edge characterizes boundaries, therefore edge detection such as Sobel operator significantly reduces the amount of data and filters out useless information, while preserving the important structural properties of the image.

Sobel edge detection is one of the widely used techniques for computing digital gradients. It is an operator that performs a 2-D spatial gradient measurement of an image. This algorithm uses 3x3 convolution masks, one estimates the gradient of x–direction (columns) and the other estimates the gradient in the y-direction (rows). The Sobel masks are shown in Eqn. (3).

(3)

The magnitude of the gradient is then calculated using the formula:

(4)

As an illustration, the Sobel edge detection output is shown in Fig. 8.

Figure 8: The effect of Sobel edge detection Process.

Before salient features (information) about emotion can be extracted, the face region should be extracted first. Face shape generally resembles an oval or ellipse shape (known as exterior shape metric). The exterior shape metric attempts to recognize the boundary of the object is roughly oval or circle [2].

Thus, after edge detection process, the possible face feature can be estimated using equation of a circle is written as:

(5)

where (a,b) is the circular centre and r is the radius. The initial value of the radius is set smaller than the actual face radius. The radius will be increased when the value of r is smaller than a threshold. Using Eqn. (5), the possible face region detected is shown in Fig. 9.

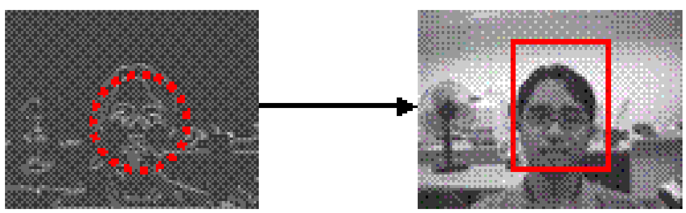

Figure 9: The Detection of Face Region

Behavioural Module

The organization and the operation of this module is heavily influenced by concepts of psychology, and cognitive science. There are two major stages involved, first is to identify the important location of facial features and, second is to detect the emotional stage. During the first phase, the extracted face region is then divided into four main regions. These are pre-determined regions that provide possible information about facial expression. The separated regions are expected to reduce searching space needed to locate the position of the eye brows and lip since the movement of eye brows and lip provides useful information to detect emotions (Fong *et al.*, 2002; Schmidt and Cohn, 2001). Table 1 depicts the example of possible features of emotion representation based on eye brows and lip's movement.

Table 1: Actions Unit for Emotions Stage

Eye brows	**Lip**	**Emotion**
Medial portion of the brows is raised and pulled together	The center of upper lip is pulled upward / Lips are parted and pulled back laterally	*Disgust*
Inner and outer portions of the brows are raised	Mouth is stretched open and the mandible pulled down	*Surprise*
Brows are slightly up	Lip corners are pulled obliquely	*Happy*
Brows lowered and drawn together	Lips are relaxed and parted with mandible is lowered	*Fear*
Brows lowered and drawn together	Lip corners are pulled down	*Anger*
Medial portion of the brows is pulled together	Lips are parted and pulled back	*Sad*

The pixels value orientations simplify the condition of these emotional states [5]. To detect possible emotion, the basic computational process is modelled as an emotion mapping model. Each facial expression indicator is modelled as a separate processing element process tailored for its role in the overall system architecture. The activation energy *x* of a processing element is computed by Eqn. (6).

$$\sum \qquad (6)$$

where are inputs, are learning weights, *b* is the bias and *n* is the number inputs. The weights can be positive or negative; a positive corresponds to an excitatory connections and a negative weight corresponds to an inhibitory connection. The process is *active* when its activation level exceeds an *activation threshold*. The activation level is calculated using binary sigmoid function given in Eqn. (7).

(7)

where *x* is a corresponding output signal from processing node. This activation value provides an active state for each emotion condition. The overview of the motivation system is shown in Fig. 10.

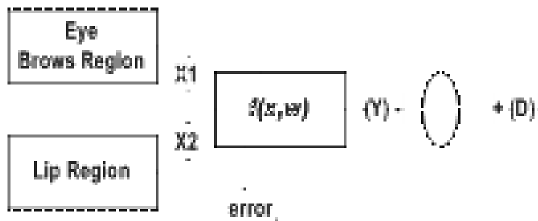

Figure 10: The General Structure of Behavioural Learning System

Learning error, *e* is calculated as a result of differences between actual and suggested emotion states. The learning weights, *w* are updated through error correction mechanism. The best learning weights (knowledge) is the weights which is yielding the lowest error rate. The learning process follows the *steepest descent* (gradient) method and written as:

(8)

CONCLUSION

The question of how to best characterize perception of facial expressions has clearly become an important concern for researchers in affective computing. In Ekman's theory, the basic emotions are considered to be the building blocks of more complex feeling states (Ekman *et al.*, 1972). Based on Elkman's emotion model, six universal expressions that do not change much from culture to culture was adopted in AeMotion system development.

To date, products like Sony's entertainment robot "Aibo" (Sony, 1999) is able to express six emotions and their blends. This achievement indicates that there is no question of whether machine can express emotions; contrarily it is more important to ask whether there is a difference in the perception of emotions expressed by either a machine or a human. Emotional expressions of machines are abstractions of human expressions. As the expression becomes more abstract, the more interpretation room towards the machines becomes available. Nevertheless, the machines do not have non-human emotions nor they have the ability to express them. Without additional learning, humans are unable to understand the machines. Since human-human interactions trained the user of an affective machine already, therefore, machines should use human expressions or their abstractions to communicate emotions. Emotional expression should be used by all media available to a machine. For example, in agent technology, an agent should express emotions when communicating with the user.

This paper has presented a basic framework (heavily inspired from work of social robots, cognitive science, image processing) for designing mechanism that allows basic social interaction between human and anthromorphic agent. The study demonstrates that the human facial expressions were successfully captured and pre-process to represent image-based emotions. The study also demonstrates that the image-based parameters could be used to interpret the facial affect space. Currently, experiments are still being conducted to see the impact of a variety of compressed image conditions has on affect space. The results from this study help to demonstrate the need for both basic and applied research contributions to the rapid developing field of affective computing.

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REFERENCES

Bartneck, C. (2000). *Affective Expressions of Machines*. Technical Report on Machine Expressions for IPO Centre of User Interaction.

Bates, J. (1994). *The Role of Emotion in Believable Characters. Communications of the ACM*.

Billiard, A.(1998). Experiments on Human-Robot Communication with Robota. *Proceedings of Socially Situated Learning Workshop*, CPM 98-38.

Billiard, A. and Dautenhanhn, K. (1998). Grounding Communication in Autonomous Robots. *Robotics and Autonomous Systems*, pp. 71-81.

Blumberg, B. (1996). *Old Tricks, New Dogs: Ethology and Interactive Creatures*. PhD Thesis, Media Laboratory MIT.

Blumberg, B. (2002). Integrated Learning for Synthetic Characters. *Proceedings of the 29th Annual Conference on Computer Graphics and Interactive Techniques (SIGGTAPH 2002)*, pp. 417-426. ACM Press.

Breazeal, C. (2002). Emotion and Sociable Humanoid Robots, *International Journal of Human Computer Interaction.*

Breazeal, C. and Scassellati, B. (2000). Infant-like Social Interactions Between a Robot and a Human Caretaker. *Adaptive Behaviour 2000.*

Breazeal, C. and Scassellati, B. (2002). Robots that Imitate Humans. Trends in *Cognitive Sciences Vol 6,* pp. 481-487.

Brooks, R. (1990). Challenges for Complete Creature Architectures. *Proceedings of Simulation of Adaptive Behaviour (SAB 1990)*.

Burlesan, W. (2004). Affective Learning Companion, *7th International Conference on Intelligent Tutoring Systems*, Brazil.

Carmel, D. and Markovitch, S. (1996). Learning Models for Intelligent Agents. *Proceedings of the National Conference on Artificial Intelligence*, pp. 62-67.

Catrambone, R., Byrne, M.D., and Stasko, J.T. (1999). Examining the effects of animation and predictions in student learning of computer algorithms. *Computers and Education*, 33, 253-278.

Ekman, P. (1972). Universals and cultural differences in facial expressions of emotion. In J. Cole (Ed.), *Nebraska Symposium on Motivation 1971*, 19, 207-283.

Ekman, P., and Rosenberg, E.L. (1997). *What The Face Reveals: Basic And Applied Studies Of Spontaneous Expression Using The Facial Action Coding System (Facs)*. New York: Oxford University Press. Second expanded edition 2004.

Elliott, C.D. (1992). *The Affective Reasoner : A Process Model of Emotions in a Multi-Agent System*, PhD Dissertation, Northwestern University, Illinois.

Fogg, B. J., and Hsiang Tseng (1999). The Elements of Computer Credibility. *CHI 1999*: 80-87

Fong T., Nourbakhsh I. and Dautenhanhn A. (2002) A Survey of Socially Interactive Robots, Technical Report (CMU-RI-TR-02-26), Carnegie Mellon.

Gmystrasiewicz, P.J. and Lisetti, C.L. (1998). Emotions and Personality in Agent Design and Modeling. *Proceedings of Artificial Intelligence Research Symposium*.

Kaiser, S. and Wehrle, T. (1992). Automated coding of facial behavior in human-computer interactions with FACS, *Journal of Nonverbal Behavior*, 16 (2), 67-83.

Kitano, H. (1995). A Model for Hormonal Modulation of Learning. *In:Proceedings of IJCAI-95 Montreal*.

Laurel, B. (Ed.) (1990). *The art of human-computer interface design*. MA: Addison-Wesley.

Massaro, D.W., Cohen, M., Beskow, J. and Cole, R.A. (2000). Developing and Evaluating Conversational Agents. Embodied Conversational Agents, *MIT Press*. pp. 292-296.

O'Neill, B. (2000). Approaches to Modelling Emotions in Game Theory. *Technical Report of dept. of Political Science*, Stanford University.

Ortony, A., Clore,G. and Collins,A. (1988).*Cognitive Structure of Emotions*. Cambridge University Press.
Premack, D. and Premack, A. (1995). *The Origins of Human Social Competence. The Cognitive Neurosciences*. Bradford, New York, pp. 205-218.

Sandholm, T. and Crites, R.H. (1995). Multiagent Reinforcement Learning and Iterated Prisoner's Dilemma: *Biosystems Journal, 37*: pp 147-166.

Schmidt K.L. and Cohn J.F. (2001). Human Facial Expressions as Adaptations: Evolutionary Questions in Facial Expression Research. Yearbook of Physical Anthropology 44:3-24. Wiley-Liss Inc.

Sony, 1999, Aibo. http://www.world.sony.com/aibo/frame13.html

Velásquez, J. (1996). *Cathexis: A Computational model for the Generation of Emotions and Their Influence in the Behavior of Autonomous Agents*. S.M. Thesis. Department of Electrical Engineering and Computer Science, Massachusetts Institute of Technology.

Velazquez, J. D. (1997). Modeling Emotions and Other Motivations in Synthetic Agents. *In Proceedings of the Fourteenth National Conference on Artificial Intelligence, 10-16. Menlo Park, Calif.*: American Association for Artificial Intelligence.

Watt, S. (1995). The Naïve Psychology Manifesto, *Technical Report KMI-TR-12,* The Open University Knowledge Media Institute.

Widyantoro, D.H., Ioerger, T.R. and Yen, J. (1999). An Adaptive Algorithm for Learning Changes in User Interests. *8th International Conference on Information and Knowledge Management (CIKM 99)*, Missouri.

Yacoob, Y., Lam, H.M. and Davis,L.S. (1995). *Recognizing Faces Showing Expressions. International Workshop on Automatic Face and Gesture Recognition.*