

Expressive Image Generator for an Emotion Extraction Engine

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We report an expressive image generator suitable for an emotion extraction engine which we have developed for a real-time internet text communication system. Real time expressive communication provides aspects of the visual clues that are present in face-to-face interaction. We have demonstrated an engine that can analyse the emotional content of text input and can deliver the emotional parameters necessary to invoke an appropriate expressive image in a real-time chat environment. The engine requires a set of emotionally expressive images from each participant for the display of emotions. The aim of this paper is to present a fast and user-friendly method to automatically generate the set of expressive images from a single default image. Using a combination of warping and morphing, images belonging to six expressive categories are generated from one original neutral image provided by each user. In each expressive category, three different intensities can be depicted. [The method only requires a single default image per user, six control points and two control shapes.](#) In [a series of experiments](#) we have [tested the effectiveness of the generated images.](#) [The preliminary findings are also presented in this paper.](#)

Keywords: Emotion, Expression, Warping, Morphing

1 Introduction

Real-time expressive communication is beneficial as it provides some aspects of the visual clues that are present in face-to-face interaction but are not available in ordinary text only-based communications.

This paper is concerned with the generation of expressive images that are displayed in a specially developed text input communications system which automatically detects the emotions expressed by the users. The associated emotion extraction engine identifies the emotions expressed by individuals in their text communications, and the output displays the appropriate expressive images.

The specific problem addressed in this paper is how to generate the unique set of expressive images for individual users without the need for them to pose for photographs portraying all categories of emotion. We present a quick and user-friendly method to generate the expressive images from a single neutral image. Images can be generated for six emotion categories, and for each category, typically we achieve three different emotion intensities. Users need to define only six control points and three control shapes in order to generate all the images. This paper also presents the findings from a series of experiments that have been carried out to test the effectiveness of the generated images. Users correctly identify the emotion expressed by the majority of images. The level of recognition improves by increasing the emotion intensity and by adding a suggestive text label.

This paper is organised as follows: In section 2 the emotion extraction engine is reviewed. In section 3 the background knowledge of image generation is discussed. In section 4 the motion image generator is described in detail. In section 5 the test strategy for the expressive image generator is given. Section 6 illustrates possible applications using the engine. Finally in section 7 conclusions are presented.

2 The real-time emotion extraction engine:

We have developed an emotion extraction engine Zhe et al. (2002) that can analyse user text input in real time, and has been applied to an internet chat environment. The engine uses a client/server architecture. The client side engine analyses the user input sentences and searches for emotional content. Subsequently, the emotional parameters detected are sent to the server. The server will forward these parameters to the related clients. When the client receives the parameters, the engine analyses the parameters, selects and displays corresponding expressive images. The server-side engine will send the parameters needed for selecting the images. In this way, image transmissions are avoided since the only data transmitted over the network are the parameters. As a result the network bandwidth requirement is extremely low.

Two sub-systems constitute the emotion extraction engine: the emotion analysis system and the expressive image generator. The emotion analysis system includes three parts: *input text analysis*, *tagging system* and *parser* (figure 1).

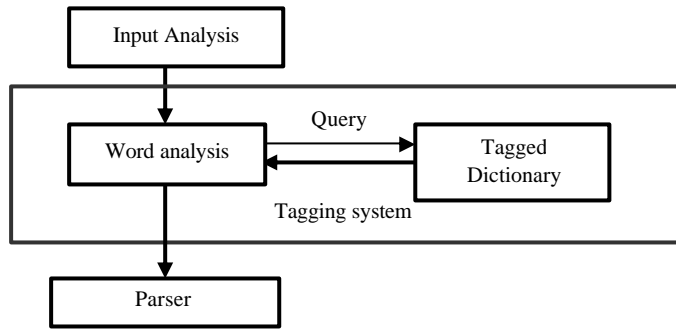


Figure 1: The working flow of the emotion analysis system.

2.1 Input analysis function

The engine provides a user interface similar to ordinary chat rooms. However the user interface first splits user input into sentences and each sentence will be sent to *the input analysis function*. The *input analysis function* will replace all the punctuation with pre-defined characters and remove the blank and space characters. The analysed sentences will be sent to the *tagging system*.

2.2 The Tagging system

The tagging system includes two components: the *word analysis function* and the *tagged dictionary*. The *word analysis function* splits the sentences into words and searches the *tagged dictionary* to find the corresponding tag category.

From (Kuehn, 1993) daily communications involve about two thousand words. A dictionary that includes around 16400 words was set up. In order to identify the words, the dictionary was tagged. The dictionary tagged each word entirely in order to keep the response time to a minimum, which is different from the tagging methods in some existing systems, e.g., BNC (Leech, 1997) and Brown Corpus (Francis & Kucera, 1979).

The created dictionary database includes three fields: *word field*, *word category field* and *emotional tag field*. The *category* field contains the corresponding word category (noun, verb, adjective etc) and the *emotional tag* field describes whether that word belongs to one of the six emotion types.

Those sentences containing emotional words will be sent to the *parser* for further analysis.

2.3 Parser

The parser's analysis is accomplished through the use of rewrite rules and tree representations (Russell & Norvig, 1995). According to pre-defined rules, the parser will search for the current emotional words, the person to whom the emotional words refer to and the intensity of the emotional words.

The output from the parser will be sent out through the network to related users. When receiving the output, the corresponding expressive images are

selected from a database and displayed. Two possible approaches have been implemented to generate expressive images. The first is a static approach, in which users upload their default facial images together with all other expressive images generated photographically. The second approach using the expressive image generator is a dynamic approach that is discussed here.

2.4 The effectiveness of the expressive interface

Zhe et al. (2002) demonstrated an effectiveness experiment. In that experiment, testers were asked to watch the three interfaces (an interface with expressive image, voice and text, an interface with expressive image, text and an interface with text only). The results show that most testers prefer the interface with expressive image, voice and text. A significant number of subjects like the interface with expressive image, voice and text much more than the text only interface. This means that with the expressive images, the effectiveness of the human interface can be considerably improved. The problem remained in that experiment is how to generate the expressive images for each user in a fast and user-friendly way.

3 Expressive image generation

2D and 3D images are both commonly used in facial image generations. For 3D facial expression generations, current methods are based on different 3D face models. e.g., in (N. Magnenat-Thalmann 1988) and (Parke & Waters, 1996), . The common problems are the long computation time and poor user interface interactions.

2D approaches are attractive from computational complexity and are supported by psychophysical theories (Bulthoff & Edelman, 1992 and Riesenhuber, et al.). For real time communication, a fast and efficient approach is most desired. We have adopted, 2D approaches for the expressive image generation engine.

Six universal categories of facial expressions have been suggested in facial expression research, (Parke & Waters, 1996). The categories are *happiness, sadness, anger, fear, disgust* and *surprise* and are recognised across cultures. A wide range of expression intensity and variation of detailed expression exists within each of the categories. The emotion extraction engine requires a set of expressive images for each of these categories to represent the emotions found in the sentences.

There are number of techniques used to solve the problems of reducing the computation time and providing a user-friendly interface. For example, some programs hold large databases of facial expressions and when presented with a new image the program will search for matches. Alternatives build complex models of the face, and users are required to identify between twenty to thirty control points to define the location of facial features. The main problems with this type of program are that it is difficult for users to select all of the required points

accurately, and it is not always possible to generate images fast enough to be used in real time communication systems.

In contrast to the systems that use complex facial models that require a high degree of computation to generate the finished image, we developed a simple algorithm based on image warping and image morphing. The facial model requires users to identify only six control points and draw two control areas on the original neutral image. The engine then automatically generates 18 images corresponding to the six expression categories, each with three different emotion intensities. These images are distributed among the users of the system and stored for future use.

In image warping a source image is distorted into a destination image according to a transformation between source space (u,v) and destination space (x,y) (Wolberg, 1990). The transformation function $f()$ describes the destination (x,y) for every location (u,v) in the source.

To apply warping to an image, we may apply the transformation function $f()$ to each pixel. Some well known techniques include radial functions and spline lines. The pseudocode is shown in figure 2.

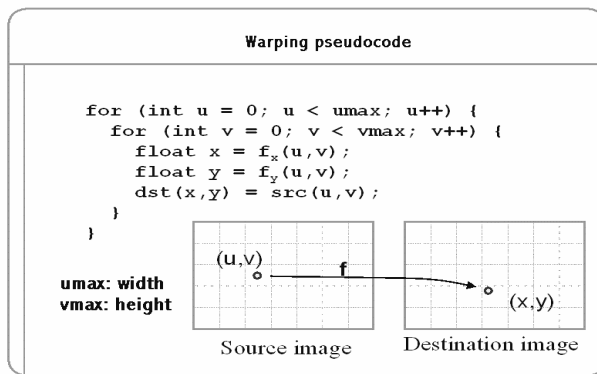


Figure 2: The warping pseudocode.

According to *Ekman's Facial action Coding System* (Ekman et al. 2001) and *PARKE's Computer facial animation* (Parke & Waters, 1996), specific muscles on the faces are responsible for the expression generations. For example only four muscles contribute to expressing happiness. Limited parts of muscles on the face are involved in generating different facial expressions. It is much more efficient to carry out manipulation only in those areas.

According to the above analysis, we suppose that in some segmented areas exist the noticeable facial distortions, while in the other part of the image the distortion should be so small that it can be neglected.

The segmented area is a square that covers the facial distortion area. To choose the segmented area, two anchor points (R_1 , R_2) are needed. R_1 represents the edge before transforming and R_2 represents the edge after transformation. The width of the segment area is $2 * ||R_1 - R_2||$ and the central point is the point R_2 . For example to create a happy expression, the anchor point R_1 is the right edge of the

mouth. The R_2 is the finish point. An example of segmented area is shown in figure 3.

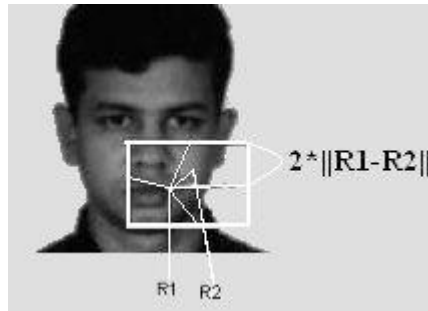


Figure 3: Segment warping area.

We use image morphing, an image processing technique applied for the metamorphosis from one image to another. The usual morphing technique is to generate a sequence of intermediate images which when put together with the original images would represent the change from first image to the last (Zhang, 2001).

4 Expressive image generator

To generate expressive images, users need to upload a neutral face image to the expressive image generator. The generator is based on combining local area warping and morphing technologies. The expressive image generator is implemented in Java applet and can be used in an Internet explorer or Netscape environment. The structure of the expressive image generator is shown in figure 4.

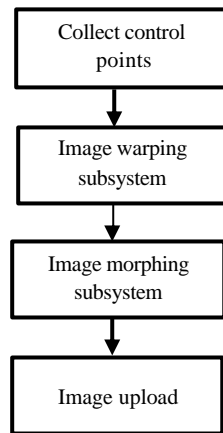


Figure 4: Expressive image generator structure

4.1 Expressive categories

To generate expressive images for the six emotion categories, the characteristics of each category are evaluated. Ekman et al. (2001) and Parke & Waters (1996) demonstrated that 64 action units on the face generate the facial expressions. However determining the actual positions for the 64 action units require tedious human operator interaction and it is not practical in real time communication. In our expressive image generator, for each emotion type the action units were summarised and simplified from Parke & Waters (1996) to be applied in a real time communication environment. Specifically we adopt the following rules:

Happiness: The eyebrows are relaxed, the mouth is wide with the corners pulled up toward the ears.

Sadness: The inner portions of the eyebrows are piled up above the upper eyelid and the mouth is relaxed.

Anger: The eyebrows are pulled downward and together. The mouth is closed with the upper lip slightly compressed or squared off.

Disgust: The middle eyebrows are pulled upward and the mouth is slightly opened with the upper lip squared off.

Fear: Eyebrows are raised, pulled together and bent upward. The mouth may be dropped slightly open.

Surprise: The eyebrows are raised up, the upper eyelids are opened and the mouth is dropped open.

For each expression category, three different emotion intensities are automatically produced. Based on the above rules, the movement of mouth, eyebrows and lips are quantified. From low intensity to high intensity, the movement is enlarged.

4.2 Control Points

To generate different expressions, two sets of parameters: start points and finish points are required. Users only need to select the start points. The finish points are calculated automatically based on the user's selection.

After uploading the neutral image to the system, users will be guided to select six start points and three control areas. The six start points include: left corner of the mouth (LM), right corner of the mouth (RM), outer edge of the left eye (LOE), inner edge of the left eye (LIE), outer edge of the right eye (ROE) and inner edge of the right eye (RIE).

The three control areas include the outer edge of the lips, and the inner edge of the eyelids for the left eye and right eye. These areas will be used in image morphing subsystem.

An example of control points and control areas is shown in figure 5.

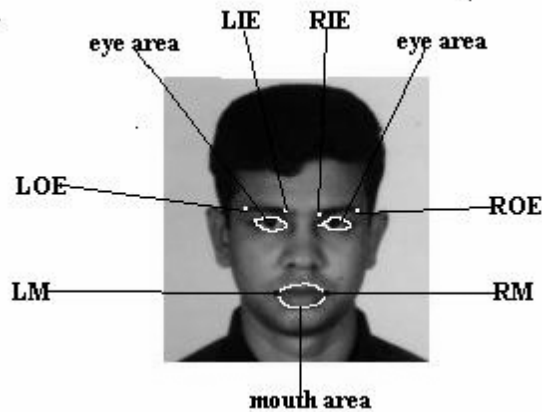


Figure 5: example of control points

These parameters will be sent to the image warping subsystem to generate the expressive images.

4.3 Image Warping subsystem

The image warping subsystem implements the model based warping. Instead of interactive manipulation, the destination positions will be calculated according to pre-defined rules. Users only need to define the start positions. The model based warping subsystem has the advantages of accuracy and speed.

To generate the model, the facial action coding system and several different expressive images from different persons were analysed. We have named the kernel that generates the images as the "expression model mask". The mask is constituted by two sets of points. The first set is the start points selected by users. The second set is the control points of the start points, which we call the finish points. The values of the finish points are calculated relative to the start points. By

applying the masks to images of individual faces, corresponding expressions can be generated.

The first step of the image warping subsystem is to choose the segment area. On choosing the segment area, the finish points will be calculated. The six finish points are FLM, FRM, FLOE, FLIE, FROE and FRIE (FLM = finish point of LM, FRM = finish point of RM, FLOE = finish point of LOE, FLIE = finish point of LIE, FROE = finish point of ROE and FRIE = finish point of RIE).

The functions to calculate the finish points are the same. The finish points are calculated as the start points plus an integer value that depends on the emotion being generated.

$$\text{Finish. } x = \text{Start. } x + a$$

$$\text{Finish. } y = \text{Start. } y + b$$

The actual values for all the finish points are shown in table 1-3. (Int1, Int2 and Int3 correspond to the intensity level of each emotion category).

	Happiness Int1	Happiness Int2	Happiness Int3	Sad Int1	Sad Int2	Sad Int3
FLM. x FLM. y	LM. x-2 LM. y-2	LM. x-3 LM. y-4	LM. x-4 LM. y-6	LM. x-1 LM. y+2	LM. x-3 LM. y+3	LM. x-4 LM. y+4
FRM. x FRM. y	RM. x+2 RM. y-2	RM. X+3 RM. y-4	RM. x+4 RM. y-6	RM. x+2 RM. y+2	RM. x+3 RM. y+4	RM. x+4 RM. y+6
FLOE. x FLOE. y	LOE. x-0 LOE. y-0	LOE. X-0 LOE. Y-0	LOE. x-0 LOE. y-0	LOE. x-0 LOE. y-0	LOE. x-0 LOE. y-0	LOE. x-0 LOE. y-0
FLIE. x FLIE. y	LIE. x LIE. y	LIE. x LIE. Y	LIE. x LIE. y	LIE. x+2 LIE. y-2	LIE. x+4 LIE. y-4	LIE. x+6 LIE. y-6
FROE. x FROE. y	ROE. x-0 ROE. y-0	ROE. X-0 ROE. Y-0	ROE. x-0 ROE. y-0	ROE. x-0 ROE. y-0	ROE. x-0 ROE. y-0	ROE. x-0 ROE. y-0
FRIE. x FRIE. y	RIE. x RIE. y	RIE. x RIE. Y	RIE. x RIE. y	RIE. x RIE. y	RIE. x-4 RIE. y-4	RIE. x-6 RIE. y-6

Table 1 control points value for emotion "happiness"and "sad"

	Surprise Int1	Surprise Int2	Surprise Int3	Anger Int1	Anger Int2	Anger Int3
FLM. x FLM. y	LM. x LM. y	LM. x LM. y	LM. x LM. y	LM. x+2 LM. y	LM. x+3 LM. y	LM. x+4 LM. y
FRM. x FRM. y	RM. x RM. y	RM. x RM. y	RM. x RM. y	RM. x-2 RM. y	RM. x-3 RM. y	RM. x-4 RM. y
FLOE. x FLOE. y	LOE. x+8 LOE. y-3	LOE. x+8 LOE. y-6	LOE. x+8 LOE. y-8	LOE. x-0 LOE. y-0	LOE. x-0 LOE. y-0	LOE. x-0 LOE. y-0
FLIE. x FLIE. y	LIE. x LIE. y	LIE. x LIE. y	LIE. x LIE. y	LIE. x+2 LIE. y+2	LIE. x+4 LIE. y+4	LIE. x+6 LIE. y+6
FROE. x FROE. y	ROE. x-8 ROE. y-3	ROE. x-8 ROE. y-6	ROE. x-8 ROE. y-8	ROE. x-0 ROE. y-0	ROE. x-0 ROE. y-0	ROE. x-0 ROE. y-0
FRIE. x FRIE. y	RIE. x RIE. y	RIE. x RIE. y	RIE. x RIE. y	RIE. x-2 RIE. y+2	RIE. x-4 RIE. y+4	RIE. x-6 RIE. y+6

Table 2: control points value for emotion "surprise"and "Anger"

	Disgust Int1	Disgust Int2	Disgust Int3	Fear Int1	fear Int2	fear Int3
FLM. x	LM. x-2	LM. x-4	LM. x-6	LM. x	LM. x	LM. x
FLM. y	LM. y+2	LM. y+4	LM. y+6	LM. y	LM. y	LM. y
FRM. x	RM. x+2	RM. x+4	RM. x+6	RM. x	RM. x	RM. x
FRM. y	RM. y+2	RM. Y+4	RM. y+6	RM. y	RM. y	RM. y
FLOE. x	LOE. x-0	LOE. x-0	LOE. x-0	LOE. x+8	LOE. x+8	LOE. x+8
FLOE. y	LOE. y-0	LOE. y-0	LOE. y-0	LOE. y-4	LOE. y-7	LOE. y-10
FLIE. x	LIE. x-8	LIE. x-8	LIE. x-8	LIE. x	LIE. x	LIE. x
FLIE. y	LIE. y-3	LIE. y-5	LIE. y-8	LIE. y	LIE. y	LIE. y
FROE. x	ROE. x-0	ROE. x-0	ROE. x-0	ROE. x-8	ROE. x-8	ROE. x-8
FROE. y	ROE. y-0	ROE. y-0	ROE. y-0	ROE. y-4	ROE. y-7	ROE. y-10
FRIE. x	RIE. x+8	RIE. x+8	RIE. x+8	RIE. x	RIE. x	RIE. x
FRIE. y	RIE. y-3	RIE. y-5	RIE. y-8	RIE. y	RIE. y	RIE. y

Table 3: Control points value for emotion "Disgust" and "Fear"

When the segment area is selected, some parts of segment area are stretched while other parts are suppressed, thus making facial expressions achievable. In figure 6, it can be seen that the segment areas 3 and 4 are compressed and areas 1 and 2 are stretched. By stretching areas 1 and 2, the lip was moved to upper right, which simulates the smile effect.

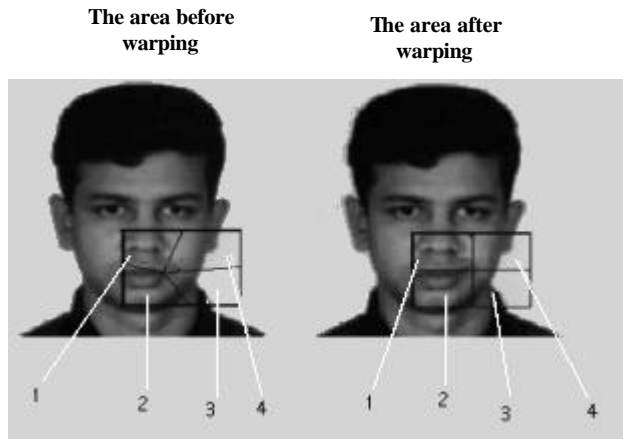


Figure 6: local area warping example

For the expression categories of *happiness*, *sadness*, *anger* and *disgust*, the image warping subsystem can create the corresponding facial characteristics. The weakness of the image warping subsystem is that it can not generate new pixels. For the expressions of *fear* and *surprise*, opened mouth and widened eyes are important characteristics that can not be achieved by the warping subsystem.

To generate *fear* and *surprise* images, The generated images are sent to the image morphing subsystem.

4.4 Image morphing subsystem

To achieve characteristics for expression *surprise* and *fear*, an image morphing subsystem is implemented.

First several different image clips of mouths and eyes are selected from different surprised and feared facial expression images. When the morphing subsystem receives the intermediate images, it will first find all the images belong to the emotion categories *fear* and *surprise* and then replace the mouth and eyes with the pre-selected mouths and eyes. The user selected mouth and eye areas are the keys for the morphing subsystem. The morphing subsystem first zooms the pre-selected mouth and eyes according to the size of the corresponding selected area and then replace all the pixels in the selected area with the pre-selected images. One common defect of morphing technology is the gap between the replaced part and the pre-prepared images. To fill in the gaps that are generated when the mouth is opened or the eyes are widened, a gaussian blur operation is applied. The structure of the image morphing subsystem is shown in figure 7.

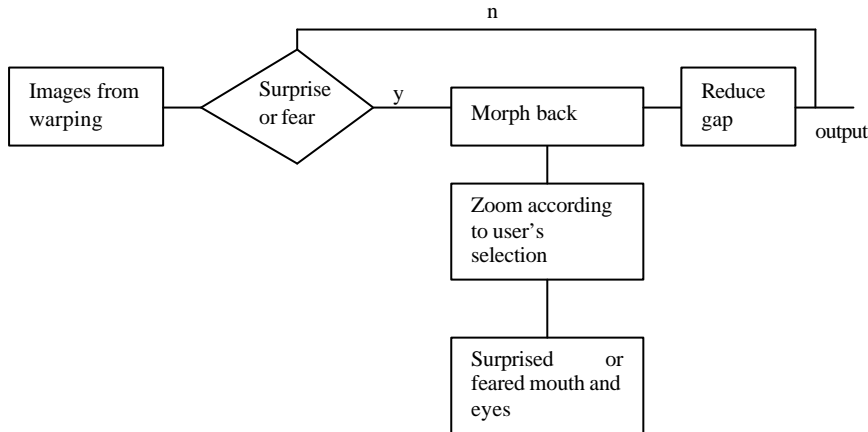


Figure 7: Structure of the morphing subsystem

Examples of expressive images generated by our expressive image generator are shown in figure 8.

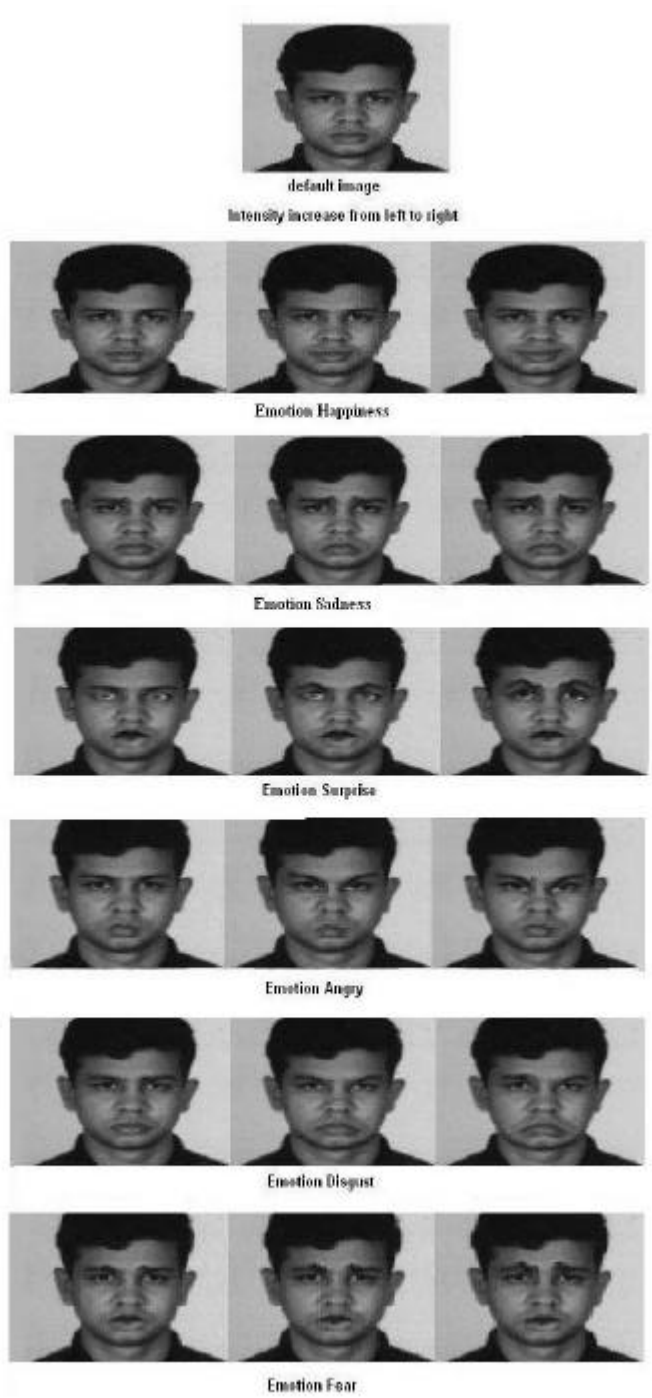


Figure 8 Generated expression images

5 Experiments

5.1 experiment strategy

The generated expressive images can be used in isolation or in text-accompanied environments, i.e. chatting rooms or online games. Two types of experiments were carried out in order to test the quality of the generated images by the expressive image generator.

The first experiment presented the expressive images only, in which the test participants viewed the generated expressive images in isolation and had to recognise the emotion. The second test presents the image plus suggestive text, to the users to agree or not on the intended emotion.

5.2 Test participants and methods

Thirty-five individuals participated in the experiments. Participants were from Bournemouth University. There were nine women and twenty-six men.

In first experiment, participants viewed the synthesised images and were asked to choose the one best describing the emotions expressed in the images from six expression types.

In second experiment, participants viewed the default images, synthesised images with suggestive text. For example, the accompanying text for the generated sad image is "I am sad". Then participants will answer the question: Compared to the default image, are the corresponding pictures appropriate to the text ?

5.3 Image only test result analysis

The results are shown in table 4 (1, 2, 3 in the x axis represent the intensity in the corresponding emotion category. 1 is the lowest and 3 is the highest; the y axis shows the percentage of participants, who identified the emotion correctly).

The chi-square test result shows that for the six emotion categories *happiness*, *sad*, *surprise*, *anger*, *fear* and *disgust*, the corresponding obtained values are 245.3, 456.1, 563.2, 123.4, 245.7 and 156. The values mean that they are extremely significant $p < .01$. In this case users did not classify the images randomly.

5.4 Image plus text result analysis

The results are shown in table 5 (In these figures, 1, 2, 3 in the x axis represents the intensity in the corresponding emotion category. 1 is the lowest and 3 is the highest; the y axis shows the percentage of the participants who agree that the image is appropriate with the text).

The chi-square test result shows that for the emotion categories *happiness*, *sad*, *surprise* and *anger*, the corresponding obtained values 8.257, 24.03, 9.91 and 9.94. The values mean that they are extremely significant $p < 01$. For categories *fear* and *disgust*, the obtained values are 3.671 and 4.82, which are marginally

significant ($0.05 < p < 0.1$). For each case there is evidence that users did not classify the images randomly.

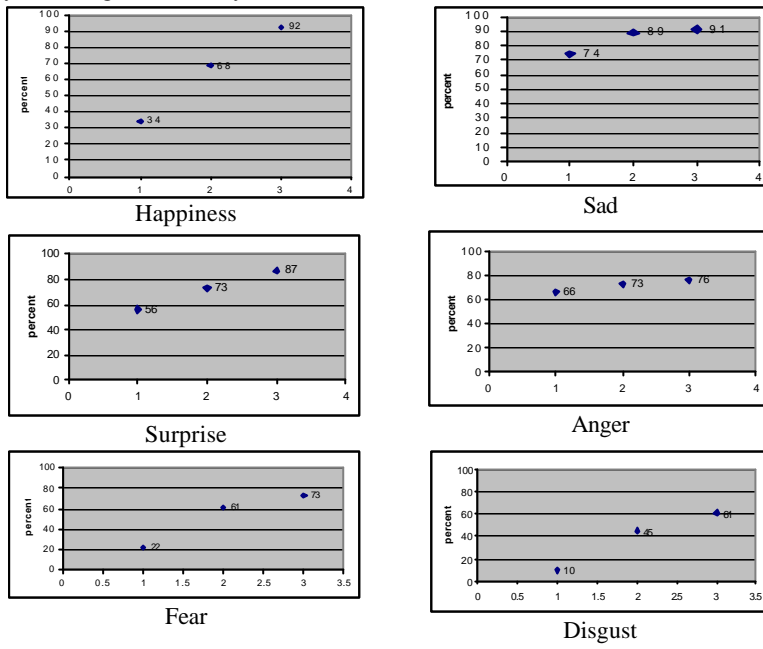


Table 4 results for image only test

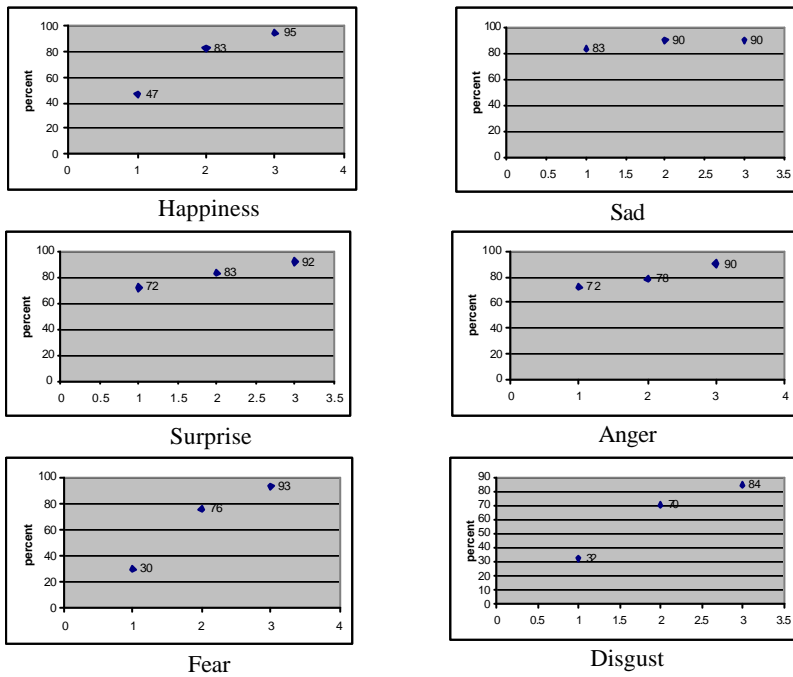


Table 5: results for image plus text test

It is shown that accompanying text context information to the expressive images, the participants correctly recognised more expressive images than in the first test. By increasing intensity, even more participants also correctly recognised the expressive images. For emotion categories *happiness*, *sad*, *surprise*, *fear*, more than 70% images were correctly recognised. For emotion categories *fear* and *disgust*, on average more than 60% images were correctly recognised. For all images with medium and high intensity, more than 78% are recognised correctly.

This experiment shows that by increasing the emotion intensity, acceptable expressive images can be obtained. In this case, the expressive image generator can be used together with the emotion extraction engine in a chatting environment.

6 Conclusions

Generating facial expression images will always be a challenge. The expressive image generator generates a discrete set of expressive images of varying expressive intensity using warping and morphing technologies. The process is fast and user-friendly. Once the control points are selected the algorithm is very fast and could be used in real time applications.

The expressive image generator is an inherent part of the emotion extraction engine. With a neutral facial image uploaded by each user, the generator in its current form creates eighteen different expressive facial images. The generated facial images belong to six universal categories: *happiness*, *sadness*, *disgust*, *anger*, *surprise* and *fear*. For each category, three images with different emotion intensities are archived.

The generator can be used within the emotion extraction engine in a number of environments that require text input information e.g. chatting room, story reader and online games. It is possible that the generator's effectiveness may be enhanced with improvements to the expression model mask. Possible refinements include adding more control points and more control areas, although this should not be at the expense of reducing the ease of use of the system.

The experiments demonstrated that more acceptable expressive images could be obtained by increasing the emotion intensity.

The test results also proved that the generator could create satisfactory expressive images for a chat environment which are easily recognisable, and even more so when accompanied by suggestive text, which is normal in chat environments.

References

- Bulthoff, H. H and Edelman, S. Psychophysical support for 2D view interpolation theory of object recognition. *Proceedings of the National Academy of Sciences*, 89 (1) 60-64, 1992
- Buck, R., *Emotional Expression, Communication, and Competence: Applications of a Developmental-Interactionist Theory of Biological, Social, Cognitive and Moral Emotions*. University of Connecticut. <http://wattlab.coms.uconn.edu/ftp/users/rbuck/Germany01/>, 2001. Accessed 27 Jan 2003.
- Dautenhahn, K. and Werry, I., *The AURORA Project: Using Mobile Robots in Autism Therapy*. *Learning Technology*, IEEE Computer Society Learning Technology Task Force, 3(1), January 2001, ISSN 1438-0625
- Ekman, P., Friesen, W.V. and Hager, J.C., *Facial action coding system, (CDRom), A Human Face*, Salt Lake City, Utah, 2003
- Fellous, J-M. and Hudlicka, E. *A Historical Perspective On Emotion*, <http://emotion.salk.edu/Emotion/History/Hgeneral.html>, accessed 27 Jan 2003.
- Francis, W.N. and Kucera, H., *Brown Corpus Manual*, Department of Linguistics, Brown University. <http://www.hit.uib.no/icame/brown/bcm.html>. Accessed 27 Jan 2003.
- Kuehn, S.A., *Communication innovation on BBS, Interpersonal Computing & Technology*, 1(2), 1993. ISSN: 1064-4326
- Leech, G. 1997. *A Brief Users' Guide to the Grammatical Tagging of the British National Corpus*. <http://info.ox.ac.uk/bnc/what/gramtag.html>, Accessed 27 Jan 2003.
- N. Magnenat-Thalmann, E. Primeau, D. Thalmann, *Abstract Muscle Action Procedures for Human Face Animation, The Visual Computer*, Springer, Vol.3, No5, 1988, pp.290-297.
- Parke, F.I. and Waters, K., *Computer Facial Animation*, A.K. Peters, Wellesley, Massachusetts, 1996.
- Pighin, F., Hecker, J., Lischinski, D., Szeliski, R. and Salesin, D., *Synthesizing Realistic Facial Expressions From Photographs*", *SIGGRAPH 98 Conference Proceedings*, 1998, 75-84.
- Riesenhuber, M. and T. Poggio. *Computational Models of Object Recognition in Cortex: A Review*, CBCL Paper #190/AI Memo #1695, Massachusetts Institute of Technology, Cambridge, MA, August 2000.
- Russell, S. and Norvig, P., *Artificial Intelligence - a modern approach*, Prentice Hall, New Jersey, 1995.
- Velasquez J.D. and Maes, P., *Cathexis: A Computational Model of Emotions*, *Proceedings of the First International Conference on Autonomous Agents*, 1997, 518-519.
- Wolberg, G., *Digital Image Warping*, IEEE Computer Society Press, Los Alamitos, 1990, ISBN: 0-8186-8944-7
- Zhang, Y., *Image Morphing*, www.fmrib.ox.ac.uk/~yongyue/morphing.html, 2001. Accessed 27 Jan 2003.
- Zhe, X. and Boucouvalas, A.C., *Text-to-Emotion Engine for Real Time Internet Communication*. *International Symposium on Communication Systems, Networks and DSPs*, 15-17 July 2002, Staffordshire University, UK, 164-168.
- Zhe, X., John, D. and Boucouvalas, A.C., 2002. *Text-to-Emotion Engine: tests of user preferences*. *ISCE 2002*, 22-25 September 2002, Erfurt, Germany, B25-B30.