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Facial Expression Recognition from Video Sequence Using Self Organizing Feature Map

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Abstract Automatic analysis of facial expressions is rapidly becoming an area of intense interest in computer vision and artificial intelligence research communities. In this paper an approach is presented for facial expression recognition of the six basic prototype expressions (i.e., joy, surprise, anger, sadness, fear, and disgust) based on Facial Action Coding System (FACS). The approach utilizes the topological ordering patterns produced by Kohonen Self Organizing Map, in which implemented on expression image sequence for each prototype facial expression. The map will compute the topological relationship between the particular expression sequences, starting from the neutral expression to peak. This method tried to find a topological ordering pattern (shape) for each expression; it will not require any pre-processing tedious work such as normalization. The only requirement is that, image background must be kept constant, also with non-rigid head motion. The feature extraction phase had been performed by this method, while the classification phase done by especially designed procedures for shape and direction finding to recognize the pattern of the shape, thereafter the type of the expression also backpropagation neural network is implemented for the classification task. An average recognition rate of 88.7% was achieved for six basic expressions, where different databases had been used for the test of the method.

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Keywords: *Facial expression recognition; Video-frame; Self-Organizing Maps (SOM); Image sequences.*

1. INTRODUCTION

Human beings are capable of communicating with each other in many different ways. The most common methods exploited for this include the use of words, gestures and facial expressions, either individually or in some combination. Using facial expressions has to be one of the most complicated forms, if not the most complicated form. Much can be communicated by even a single facial expression, and hence these expressions have become a very important aspect of our communication. Consequently, it is only natural that the demand for a computer system that can recognize human facial expressions has arisen.

It is argued that to truly achieve effective human-computer intelligent interaction (HCII), there is a need for the computer to be able to interact naturally with the user, similar to the way human-human interaction takes place. Humans interact with each other mainly through speech, but also through body gestures, to emphasize a certain part of the speech and display of emotions. One of the important ways humans display emotions is through facial expressions. Automatic facial expression analysis is a complex task as the topology of faces varies from one individual to another quite considerably due to different age, ethnicity, gender, facial hair, cosmetic and occluding objects such as glasses and hair. Further, faces appear disparate because of pose and lighting changes. Variation such as these have to be addressed at different stages of an automatic facial expression analysis system, such as normalization task including (pose and illumination), and face segmentation task including (background and facial feature separation).

Automatic analysis of facial expressions is rapidly becoming an area of intense interest in computer vision and artificial intelligence research communities. Automated systems that sense, process, and interpret human facial expressions have important commercial potential; they seem to have a natural place in commercial products such as computer systems for video conferencing, video telephony, video surveillance, video indexing, robotics as well as virtual reality, image understanding, psychological studies, facial nerve grading in medicine, face image compression and synthetic face animation.[6-1]

Furthermore, monitoring and interpreting facial expressions are important to lawyers, the police, and security agents, who are often interested in issues concerning deception and attitude. Facial expression intensities may measured by determining either geometric deformations of facial features or the density of wrinkles appearing in certain face regions. For example the degree of smiling is communicated by the

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magnitude of cheek and lip corner rising as well as wrinkle displays. Since there are inter-personal variations with regard to the amplitudes of facial actions, it is difficult to determine absolute facial expression intensities, without referring to the neutral face of a given subject. Note that measuring the intensity of spontaneous facial expressions is more difficult than measuring posed facial expression, which are usually displayed with an exaggerated intensity and can thus be identified more reliably.[8-7]

Not only the nature of the deformation of facial features conveys meaning, but also the relative timing of facial actions as well as their temporal evaluation. Static images do not clearly reveal subtle changes in faces and it is therefore essential to measure also the dynamics of facial expressions. Facial expressions can be described with the aid of three temporal parameters: onset (attack), apex (sustain), offset (relaxation). There is one main methodological approach of how to measure the afore mentioned three characteristics of facial expressions, this is the FACS (Facial Action Coding System), which was developed by (Ekman and Friesen [9-10]) and has been considered as a foundation for describing facial expressions.

Neural networks were often used for facial expression classification [15-21] and were either applied directly on face images [22, 23] or combined with facial features extraction and representation methods such as PCA (Principal Component Analysis), ICA (Independent Component Analysis) or Gabor wavelet filters [18] .The former are unsupervised statistical analysis methods that allow for a considerable dimensionality reduction, which both simplifies and enhances subsequent classification. These methods have been employed both in a holistic manner [16, 26, 27, 28, 29, 30] as well as locally using mosaic-like patches extracted from small facial regions.[32 ,25 ,28 ,12 ,15]

Mu-Chun Su and Liu [25] proposed a new facial image algorithm based on the Kohonen Self-Organizing Feature Map (SOFM) algorithm to generate a smooth 2D transformation that reflects anchor point correspondences. Using only a 2D face image and a small number of anchor points, the proposed morphing algorithm provides a powerful mechanism for processing facial expressions. In this paper an approach is presented for facial expression recognition of the six basic prototype expressions (i.e., joy, surprise, anger, sadness, fear, and disgust) based on Facial Action Coding System (FACS). The approach utilizes the topological ordering patterns produced by Kohonen Self Organizing Map, in which implemented on sequence expression images for each prototype facial expression.

2. SELF-ORGANIZING MAPS (SOM)

The Self-Organizing Feature Map (SOFM) was introduced by Teuvo Kohonen [7, 8]. The basic idea is the following: a SOM defines a mapping from a high dimensional input data space onto a regular two-dimensional array of neurons. Every neuron i of the map is associated with a n-dimensional reference vector mi = [mi1, . . ., min] T, where n denotes the dimension of the input vectors. The set of reference vectors is called a codebook .

The neurons of the map are connected to adjacent neurons by a neighborhood relation, which dictates the topology, or the structure, of the map. The most common topologies in use are rectangular and hexagonal. The network topology is defined by the set Ni of the nearest-neighbors of neuron i: in the basic SOM algorithm, the topology and the total number of neurons remain fixed .

The total number of neurons determines the granularity of the mapping, which has an effect on the resolution and generalization ability of the SOM. The algorithm controls the net as it tries to approximate the density of the data, and the reference vectors in the codebook drift to the areas where the density of the input data is high. Eventually, only few codebook vectors lie in areas where the input data is sparse.

The learning process of the SOM goes as follows:

1) One sample vector x is randomly drawn from the input data set and its similarity (distance) to the codebook vectors is computed by using e.g. the common Euclidean distance measure:

$$\|x - mc\| = \{\|x - mi\|\}$$

2) After the Best Matching Unit (BMU) has been found, i.e., the codebook vector closest to the random input vector, the codebook vectors them-selves are updated. The BMU itself as well as its topological neighbors are moved closer to the input vector in the input space i.e. the input vector attracts them. The magnitude of the attraction is governed by the learning rate.
   As the learning proceeds and new input vectors are given to the map, the learning rate gradually decreases to zero according to the specified learning rate function type. Along with the learning rate, the neighborhood radius decreases as well. If the neighborhood of the code- book vector closest to the input data vector x(t) at step t is Nc(t), then the reference vector update rule:
3) Steps 1 and 2 together constitute a single training step and they are repeated until the training ends. The number of training steps must be fixed prior to training the SOM because the rate of convergence in the neighborhood function and the learning rate is calculated accordingly.
   After the training is over, the map should be topologically ordered: this means that input data vectors that are close to each other in input space map onto neurons that are close to each other in the SOM.

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3. SUGGESTED ADAPTATIONS

In our opinion that robustness of expression recognition, against the variability of facial characteristics, would be difficult to achieve without incorporating adaptation in the recognition framework. Incorporate adaptation in this approach, involving:

i. Consideration of all sequence images of the expression being analyzed.

The sequence images are taken from the neutral expression face image to the peak expression face image. In this case there is no need for normalization regarding the shift, scale and translation, since all the sequence images are considered as whole without a return to any database for comparison or match process (it is often taken for granted that there are only small rigid head motions between two consecutive frames). Also the uncontrolled lighting and illumination problem will be reduced greatly since all the images are relatively of the same environment at the moment being shot. Facial characteristics, arising from age, illness, gender, race, facial hair and make-up, all these factor will be neutralized, since the computation of the relationships between the deformed features are based on the same sequence images, in which they carry the same person characteristics regarding his age , gender, race, facial hair and make-up, without relying on any previous recorded characteristics.

ii. Unsupervised Learning.

Unfortunately, neural networks are difficult to train if used for the classification of not only basic emotions, but unconstrained facial expressions. A problem is the great number of possible facial action combinations, about 7000 AU combinations have been identified within the FACS framework [25].

Since we have a great number of possible facial action combinations also a great number of facial characteristics, therefore the supervised neural network is not a suitable technique to resolve facial action classification; especially if the whole face my considered for the analysis process and any subtle change in the face deformations will affect modeling the structure of recognition process. An alternative and for the system to be adaptive to great number of possible facial action combinations, unsupervised pattern recognition methods can be used to explore large records of process data.

Self-Organizing neural networks group similar input vectors together without the use of training data to specify what atypical member of each group looks like or to which group each vector belongs. A sequence of input vectors is provided, but no target vectors are specified. The net modifies the weights so that most similar input vectors are assigned to the same output (or cluster) unit. The neural network will produce an exemplar (representative) vector for each cluster formed (L. Fausett 1994 [24]). In other words, if the class labels of the data vectors are not available (as it is in our case), the unsupervised methods can be used to model the structure of the data. Using the model all the data vectors can be given an interpretation, (i.e., labeled), and used as a basis of a classifier. Unsupervised learning neural network which carries out a topology preserving mapping from high-dimensional input data space onto a low-dimensional output grid.

In this paper, the unsupervised Self-Organizing Map neural network had been used to cluster input patterns representing the whole images of expression sequence (from neutral expression image to peak expression image-the highest magnitude of the target expression).

Self-organizing map's topological relationships between cluster units is used to model the dynamic aspects of a facial expression. The facial deformations are non-linear and SOFM is implicitly maps these non-linear relationships between these consecutive changes in the facial expressions. The topological relationships between cluster units in Kohonen's self-organizing map are indicated by drawing lines connecting the units, in which gives an interpretation to explore and visualize properties of multivariate data, which is very important.

A topology of two-dimensional rectangles is assumed for the cluster units. The focus here is on how to model the dynamic appearances of facial deformation between the consecutive occurrences in image sequences of facial expression. The topological ordering (topological relationships) is used as a recognition patterns for each particular prototypic expression, and then use these patterns for each prototypic expression to recognize the expression sequence images using an especially designed method for the recognition task.

iii. Description of facial expressions.

The approach suggested in this paper need to be adaptable to the basic prototypic expressions in a systematic way, so that self-organizing map neural network can maps similar features in close proximity according to the changes of a particular spatial deformation for a particular expression. In other words, we are looking for elements that uniquely describe the actions of one particular spatial location systematically; therefore, any deformation in spatial location will be the same for every person for that particular expression and can be described by these elements. To facilitate our method, we found that the Facial Action Coding System (FACS) is better suited for this task, and the term AU can be used as an alternative for the term element in describing the facial expressions.

The assumption had been made in this paper is that, any changes occurred between two consecutive frames are results of the activation of individuals AUs and not due to any other factors (such as head and hear movements or iconic eyes...etc.). Therefore, SOFM will

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maps these two consecutive frames according to these changes because of the activation of these units and since the people are using the same AUs to produce the same expression according to the FACS coding, so it is possible in principles that SOFM will map the consecutive frames for a particular expression in the same way for each person and preserving the topological relationships between these changes. The facial deformations are non-linear and SOFM is implicitly maps these non-linear relationships between these consecutive changes in the facial expressions. In this way it is possible to neutralize all other factors that come from the age, gender, race facial hair and make-up. Therefore pre-defined conditions must be satisfied during the experiments to insure that the mapping is done according to the facial deformation and not any other changes, hence the mapping is representing a particular facial expression. Since SOFM shows the frame mapping according to expression evolvement (dynamic combinations of action units), therefore the evolution of the expressions to be tested and classified must be coded according to well defined and established roles or standards that govern the whole facial expression process, which we believe that FACS is reliable to play these roles. Therefore, there are predefined conditions must be satisfied to investigate the validity of this approach:

1) There must be no rigid motion in the head (only small rigid head motions between two consecutive frames).
2) The image background must be constant in the consecutive frames, such as moving objects (like moving people, opening and closing door) or clutters.
3) No iconic objects (like eye blinking).
4) Facial expressions are coded according to a systematic method (in our case FACS action units is adopted).

According to the above stated conditions, the only deformations that occurs during facial expressions are as a consequences of facial features changes, changes that occurred as a result of specific action units that involved in that particular expression, and since these changes are coded according to FACS and considered similar expressions, therefore we expected that SOFM will map these changes in a systematic way in which reflects the relationships between them regardless of the miscellaneous sources of facial variability (differences across people arising from age, illness , gender and race) .These conditions are influencing the SOFM's mapping directly since any spatial deformations representing feature deformation. The deformation is sequential in time (we mean by that if images or frames selected not in a periodical manner, say images 5 1 3...), this factor effecting the ordering of the mapping, since these frames are consecutive in its deformation . To make the topological order relationships interpreting the meaning of the expression, therefore the clusters representing the consecutive frames are connected by lines to obtain a directed graph and this directed graph can be used as a pattern for that expression. The justification of connecting these frames and not any other frames in the sequence is- that they were sequential in time (occurring in that order). Figures (8-13) shows image sequences of different expression to show the spatial deformation in the expression for consecutive frames for many different subjects.The subject's performance is coded according to FACS coding system. The first sequence shows the expression evolving from the neutral to peak expression. The second sequence shows only the difference images (subtract the sequence of images from the neutral image). Observe the evolving of absolute deformation between consecutive frames of the same expression and for different subjects. Each subject is performing according to the same FACS coding; the deformation is occupying the same spatial location and evolving relatively at the same aspect ratio.

***Figure 1.**a Subject S052 (Cohen-Kanade Database [31,32]) performing happy expression coded according to Facial Action Coding System, the code combination is (AU6 + AU12 + AU25).*

***Figure 1.**b difference images of (figure 1.a)*

***Figure 2.**a Subject S055 (Cohen-Kanade Database [31,32]) performing surprise expression coded according to Facial Action Coding System, the code combination is (AU1 + AU2 + AU5 + AU25 +AU27).*

***Figure 2.**b difference images of (figure 2.a)*

***Figure 3.**a Subject S074 (Cohen-Kanade Database [31,32]) performing disgust expression coded according to Facial Action Coding System, the code combination is (AU4 + AU6 + AU7 + AU9d +AU17d + AU25).*

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Figure 3.*b difference images of (figure 3.a)*

Figure 4.*a Subject S132 (Cohen-Kanade Database [31,32]) performing fear expression coded according to Facial Action Coding System, the code combination is (AU1 + AU4 + AU15c + AU1).*

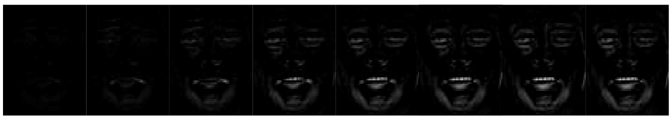

Figure 4.*b difference images of (figure 4. a).*

Figure 5.*a Subject S132 (Cohen-Kanade Database [31 ,32]) performing sadness expression coded according to Facial Action Coding System, the code combination is (AU1 + AU4 + AU15c + AU17c).*

Figure 5.*b difference images of (figure 5.a)*

Figure 6.*a Subject S106 (Cohen-Kanade Database [31,32]) performing anger expression coded according to Facial Action Coding System, the code combination is (AU4 + AU11 + AU17 + AU39 + AU54a).*

Figure 6.*b difference images of (figure 6.a).*

4. REPRESENTATIONS OF TOPOLOGICAL RELATIONSHIPS AND MEASURING FACIAL EXPRESSION

The output of the SOFM map will be considered in this phase, when the best match units (BMUs images) or neurons are obtained, in which they represent the input patterns (sequence of images of expressions). In order to make these ordered topological relationships on the map interpreting the meaning of the expression under consideration, a line connecting every two consecutive neurons' coordinates were established. The order in which these lines were constructed is depending on the order in which these images occurred in the sequence expression (see Figure 7).

This connected graph is taken as a representative for that expression in an attempt to investigate the possibility of find similar patterns of connected graphs for each particular prototypic expression and for different people. The similarity does not mean to be identical graphs for the same expression (the graph also preserves the participant facial characteristics and other elements such as the back ground and the whole environments effects).

Figure 7*. (a) consecutive images of expression on SOFM.*

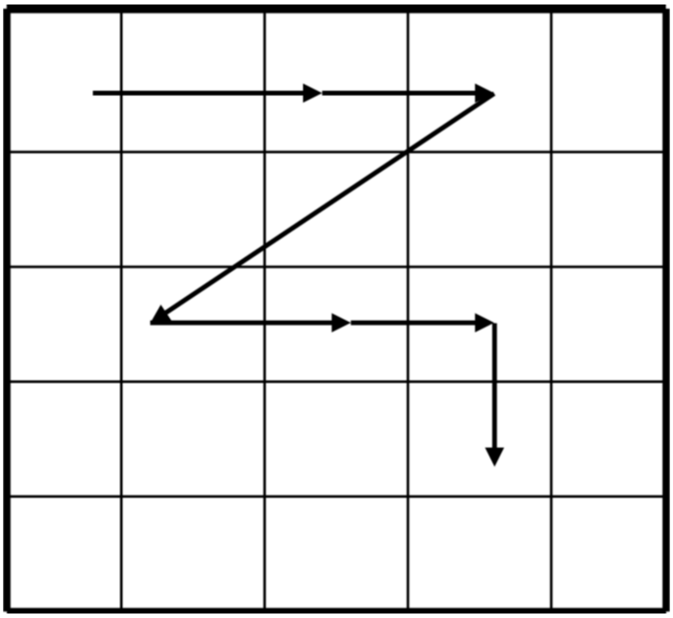

Figure 7(b) *Connected directed graph happy between map's coordinates correspond to sequence of images coordinates in*

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Therefore, if we found that there is similarity between the connected graphs in their appearance shapes for the participants who performing a particular expression, then we can conclude that these patterns of connectivity may consider being universal signatures for these prototypic expressions .

Generally, we found different and distinctive connected graphs (similar in their appearance shapes for each expression) for each prototypic facial expression, in which we used to classify the sequence expression images. It is important to note that, this approach is implemented on expressions of similar types according to FACS coding, in other words the subjects who are performing happy expression for example should all be coded according to FACS performing the AUs Prototype combination (AU6 + AU12 + AU25) or its major variants.

Figure 7(a). Also, there is another important condition, the deformation between two consecutive images should be occurring according to the facial feature deformation and not because any other external effects such as changes in lighting, head and body motion or any other moving objects in the background.

5. RECOGNITION OF EXPRESSION'S REPRESENTATIONS

The topological ordered relationships produced by SOFM on the expression images sequences taken from the databases, shown variety of connected graphs. These connected graphs appear to be sharing similar characteristics regarding their shape appearances. For example, the surprise expression sequences appear on the map as a square shape graph.

The following are types of connected graph shapes that associated with each prototypic expression:

- Happiness Graph: the connected graphs found in this category were Zigzags like graphs as shown in(Figure 8). In which they represent the deformation in the mouth, check and eye spatial locations of the face. These graphs represent expressions sequences corresponding to FACS code: (U6+U12+U25).

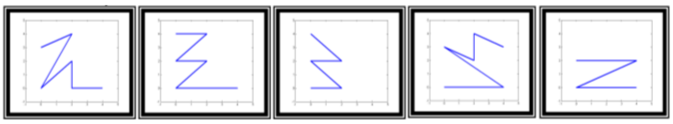
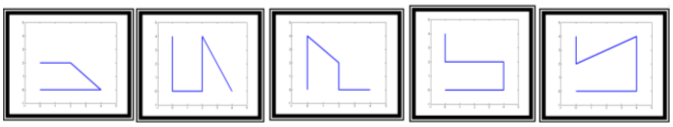


Figure 8. *graphs represent imge sequences corresponding to happy expressions.*

- Surprise Graph: the connected graphs found in this category were square like graphs as show in (Figure 9). These graphs represent the facial deformation in the mouth eye and eye brow. These graphs represent expressions sequences corresponding to FACS code: (U1+U2+U5B+U27).



- Disgust Graph: The shapes of the graphs found in this category were combined form of Crossing-Inverse and fluctuated graphs, as show in (Figure 10). These graphs represent expressions sequences corresponding to FACS code: (U9+U16+U15).

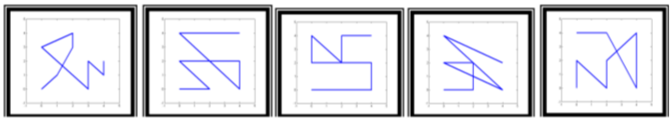


Figure 10. *graphs represent image sequences corresponding to disgust expressions.*

- Fear Graph: the connected graphs found in this category were triangular-box like graphs as show in (Figure 11). These graphs represent the facial deformation in the mouth, eye, eye brow, chin and forehead. These graphs represent expressions sequences corresponding to FACS code: (AU1+AU2+AU5+AU7+AU26).

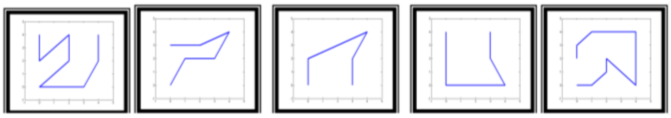


Figure 11. *graphs represent image sequences corresponding to fear expression.*

- Anger Graph: the connected graphs found in this category were an double joint boxes like graphs as show in (Figure 12). These graphs represent the facial deformation in the mouth, eye, eye brow, cheek and chin. These graphs represent expressions sequences corresponding to FACS code: (U4+U5+U10+U23+U26 or 25).

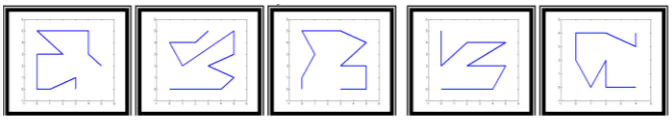


Figure 12. *graphs represent image sequences corresponding to anger expression.*

- Sadness Graph: the connected graphs found in this category were an open entrance box-box like graphs as show in (Figure 13). These graphs represent the facial deformation in the mouth, eye, eye brow, cheek and chin. These graphs represent expressions sequences corresponding to FACS code: (AU1+AU4+AU7 (or AU6) +AU15).

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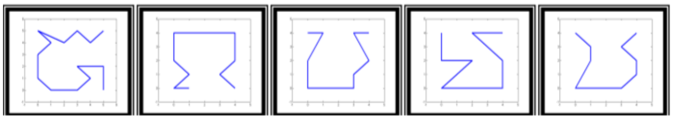

Figure 13. *graphs represent image sequences corresponding to anger expression.*

6. METHOD FOR RECOGNITION AND CLASSIFYING EXPRESSION GRAPHS THE CONNECTED GRAPHS HAD BEEN FOUND IN EACH CATEGORY ARE NOT IDENTICAL, THEY.

are only similar in their appearance as it had been displayed in (Figures 8-13), they all differ in their detail descriptions (length and local directions) even for the same category and this was expected since they represent different subjects in different environments, also it can't be expected that all the subjects' FACS coding were performed in a perfect way, for example the mean kappa for interobserver agreement was 0.86 as described in Cohn-Kanade [AU-Coded] Facial Expression DataBase " [26].

Two methods are implemented in this paper to classify the connected expression graphs:

- Neural Networks method

The Multi-layer perceptron neural network trained with Backpropagation and implemented is used to classify the connected graphs. This technique is implemented on two types of expression graphs-the Sadness and Anger graphs.

These two graphs vary dramatically from any other expression graphs in their shapes and number of images in each expression sequence, as shown in (Table 1) and Figures (8-13) so they will not interfere with the other expression's graphs during the recognition phase. The neural networks were able to learn the training data (connected graphs) very well and to validate the testing examples with a very good level of recognition.

Table1. *number of images in each sequence expression, for each particular Database.*

Prototypic Expression	Cohen Kanade DB	FG-Net DB	Personal Collection
Surprise	5-8	6-7	5-6
Disgust	8-10	8-10	7-9
Happiness	5-8	5-8	5-8
Anger	10-13	x	N.A
Fear	6-8	x	N.A
Sadness	10-15	x	N.A

Direction and shape recognition method

SOFM had accomplished important data visualization by projecting the high dimensionality input space to two dimensional spaces. To utilize this accomplishment the suggested method works on the 2 dimensional coordinate system instead of N-dimensional system and not as it was attempted in neural network method above. It had been observed that the connected graphs are directed graphs since the order of the images in the sequence had been considered in the establishment of these graphs .

Accordingly, the direction of the graph can be utilized in order to determine the shape of these graphs. The direction of the line segments of the graph from the current line segment to the next line segment on the Cartesian coordinate (positive quadrants only) can be determined as follow:

Line segment direction = X1 – X2, where X1 and X2, are two points on the positive quadrants. The magnitude of the motion direction is used to determine the direction of each line segment between X1 and X2, as shown in (Figure 14).

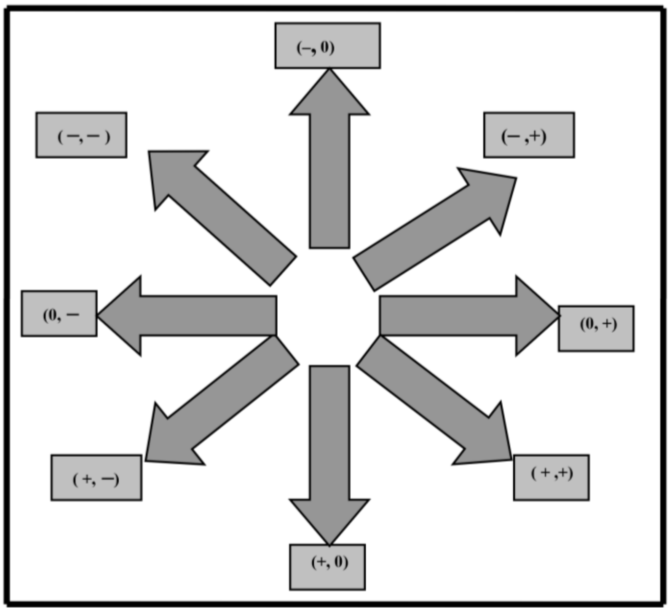

Figure 14*. the magnitude of the motion direction in positive quadrants.*

The following are the methods that had been implemented to recognize the shape of these graphs using C++ programming language.

A. Happy graph recognition procedure.

In general, the shape of the graphs had been found in this category are zigzags like shapes. To determine this shape direction of the graph must be considered. In Figure (15) all the possible directions from the current line segment direction to the next line segment direction on the graph are stated to form the zigzags like shapes. Table (2) summarizes all the possible directions stated in Figure (15).

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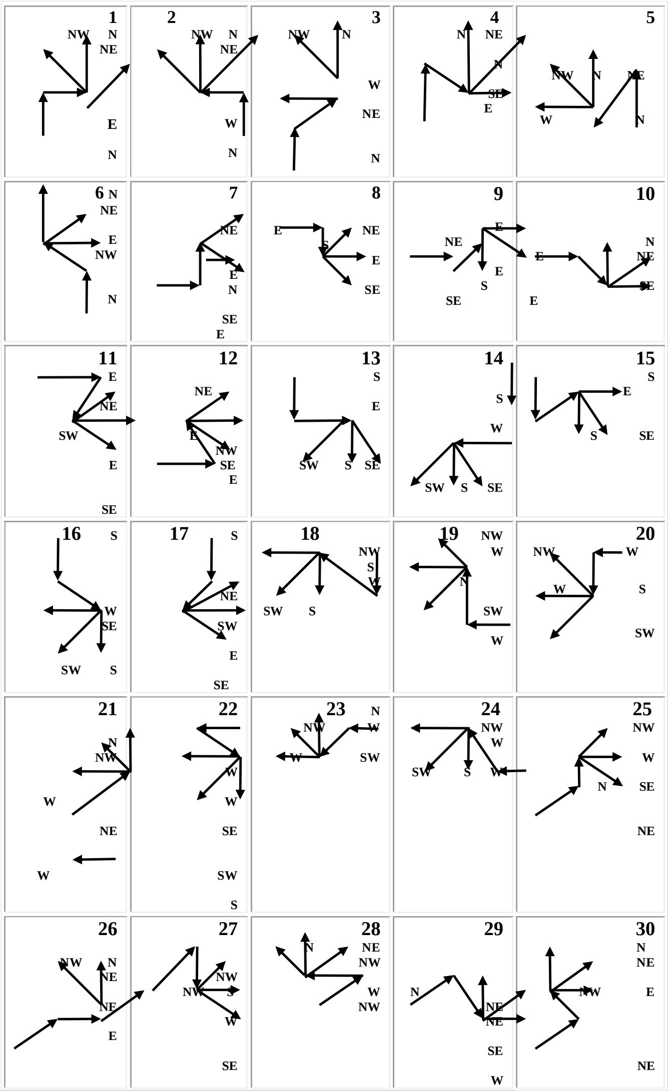

Figure 15. all the possible directions from the current line segment direction to the next line segment direction on the graph form zigzags like shapes. The abbreviation of directions on the graphs are N: North, S: South, W: West, E: East, NW: Northwest, NE: Northeast, SW: Southwest, SE: Southeast

***Table 2**. the summary of all possible directions stated in Figure (15).*

	N	E	S	W	NE	SE	SW	NW
N	X	N NE NW	X	N NE NW	N W NW	N NE E	N NW W	N NE E
E	E NE SE	X	E NE SE	X	E SE S	E N NE	E S SE	N E NE
S	X	S SW SE	X	S SW SE	S E SE	W SW S	S E SE	S W SW
W	W NW SW	X	W NW SW	X	N NW W	W S SW	N W NW	W S SW
NE	E NE SE	N NW NE	E SE NE	N NE NW	X	E NE N	X	N E NE
SE	E NE SE	S SW SE	E NE SE	S SE SW	E S SE	X	E S SE	X
SW	W SW NW	S SW SE	W NW SW	S SW SE	X	W S SW	X	S W SW
NW	W NW SW	N NE NW	W SW NW	N NE NW	N NW W	X	N W NW	X

B. Surprise Graph Recognition Procedure.

In general, the shape of the graphs had been found in this category are box like shapes.

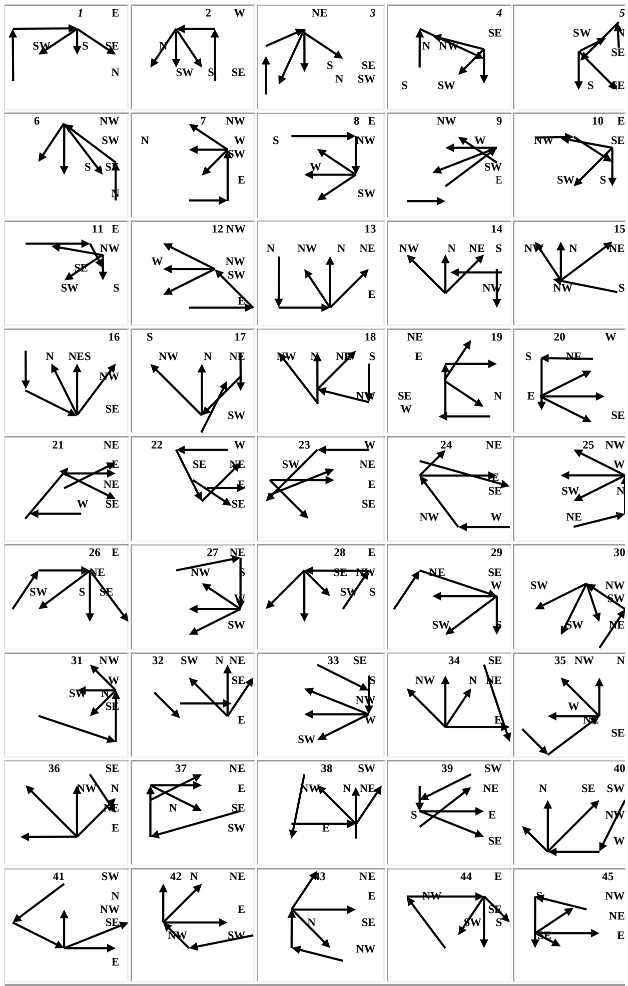

Figure 16. all possible directions from the current line segment direction to the next line segment direction on the graph form box like shapes.

To determine this shape direction of the graph must be considered. In Figure (16) all the possible directions from the current line segment direction to the next line segment direction on the graph are stated to form the box like shapes. Table (3) summarizes all the possible directions stated in Figure (16)

***Table 3**. the summary of all possible directions stated in Figure (16)*

	N	E	S	W	NE	SE	SW	NW
N	X	S SW SE	X	S SW SE	S SE SW	S SW NW	S SE NE	S SW SE
E	W NW SW	X	W NW SW	X	W NW SW	S SW NW	W NW SW	W NW SW

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S	X	N NW NE	X	N NW NE	N NW NE	N NE NW	N NE NW	N NW NE
W	NE E SE	X	NE E SE	X	E NE SE	E SE NE	E SE NE	E NE SE
NE	W SE NE	S SW SE	W NW SW	S SW SE	X	S SW W	X	S SW W
SE	NW W SW	N NW NE	W SW NW	N NW NE	N NW W	X	N NW W	X
SW	E NE SE	N NE NW	E NE SE	N NE NW	X	N NE E	X	N NE E
NW	NE SE E	S SE SW	E SE NE	S SE SW	E S SE	X	E SE S	X

C. Disgust Graph Recognition Procedure.

The shapes of the connected graphs found in this category in general are crossing like shapes and reversed direction line segments; Table (4) summarizes all the possible directions stated in Figure (17).

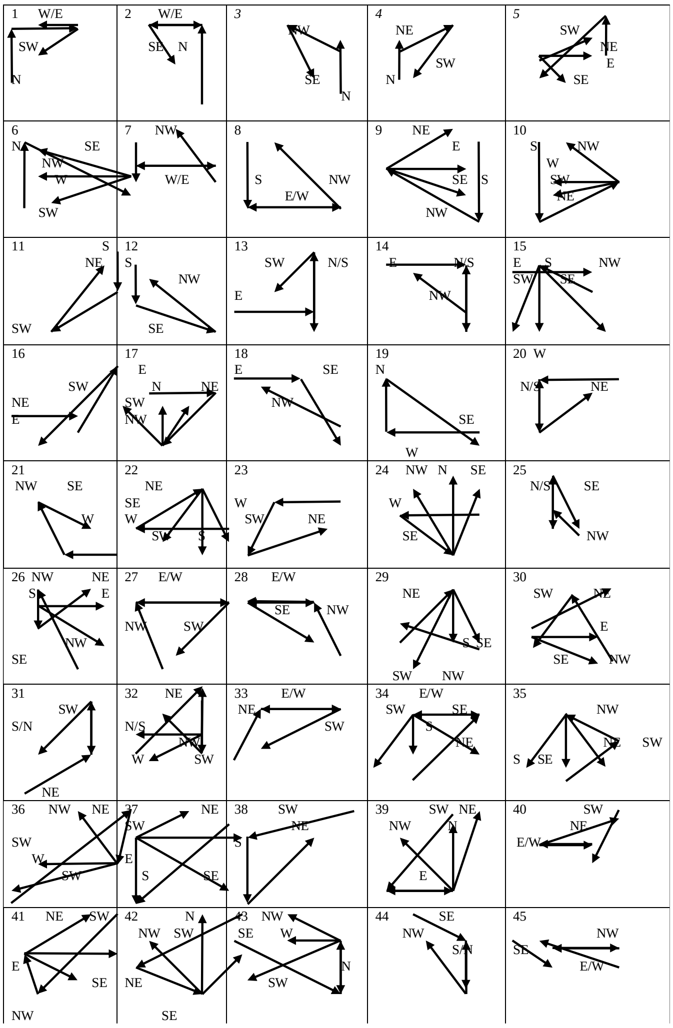

***Figure 17**. the summary of all possible directions in determining the disgust expression.*

***Table 4**, the summary of all possible directions stated in Figure (17).*

	N	E	S	W	NE	SE	SW	NW
N	X	SW W	X	SE E	SW	W NW SW	E NE SE	SE
E	S SW	X	N NW	X	SW	NW	N NW NE	S SW
S	X	NW W	X	NW E	W NW SW	NW	NE	E NE SE
W	S SE	X	NE N	X	S SE SW	N NE NW	NE	SE
NE	S SW	W SW	N W NW	E SE S SW	X	W NW SW	X	S SE SW
SE	W SW NW S	NW W	NW N	E N NE NW	W SW NW	X	N NE NW	X
SW	NE E SE	N NW W	NE N	NE E	X	N NW SW	X	NE E SE
NW	S SW	SW W	E NE SE N	SE E	S SW	X	E NE SE	X

D. Fear Graph Recognition Procedure.

In general, the shapes of the graphs had been found in this category are triangular-box like shapes. Table (5) summarizes all the possible directions. To recognize a triangle-box like shape figure, four consecutive line segments must satisfy the directions stated in the Table (5); these directions can be investigated as follow:

Starting from the column "From" choosing the current line segment direction, then from the "To" row in which indicated the next direction from the current one, each crossing cell in the table does contain two levels of inputs to the current direction from top to bottom. For example the direction from (NW to S) must have three possible directions (N, NW, NE) followed by one direction W to form the triangle-box like shape in total:

a. N→W→NW→S
b. NW→W→NW→S
c. NE→W→NW→S

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Table 5. the summary of all possible directions for fear graphs.

<table>
<tr><th></th><th colspan="6">S</th><th colspan="6">N</th><th colspan="6">E</th><th colspan="6">W</th><th>NW</th><th>SW</th><th>SE</th><th>NE</th></tr>
<tr><td rowspan="2">S</td><td colspan="6" rowspan="2">X</td><td colspan="6" rowspan="2">X</td><td colspan="3">W</td><td colspan="3">NW</td><td colspan="3">E</td><td colspan="3">NE</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td></tr>
<tr><td colspan="3">NW</td><td colspan="3">X</td><td colspan="3">NE</td><td colspan="3">X</td></tr>
<tr><td rowspan="2">N</td><td colspan="6" rowspan="2">X</td><td colspan="6" rowspan="2">X</td><td colspan="3">W</td><td colspan="3">SW</td><td colspan="3">E</td><td colspan="3">SE</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td></tr>
<tr><td colspan="3">SW</td><td colspan="3">X</td><td colspan="3">SE</td><td colspan="3">X</td></tr>
<tr><td rowspan="2">E</td><td colspan="3">N</td><td colspan="3">NW</td><td colspan="3">S</td><td colspan="3">SW</td><td colspan="6" rowspan="2">X</td><td colspan="6" rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td></tr>
<tr><td colspan="3">W</td><td colspan="3">X</td><td colspan="3">SW</td><td colspan="3">X</td></tr>
<tr><td rowspan="2">W</td><td colspan="3">N</td><td colspan="3">NE</td><td colspan="3">S</td><td colspan="3">SE</td><td colspan="6" rowspan="2">X</td><td colspan="6" rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td></tr>
<tr><td colspan="3">NE</td><td colspan="3">X</td><td colspan="3">SE</td><td colspan="3">X</td></tr>
<tr><td rowspan="2">NW</td><td colspan="2">N</td><td colspan="2">NW</td><td colspan="2">NE</td><td colspan="2">S</td><td colspan="2">SE</td><td colspan="2">SW</td><td colspan="2">NW</td><td colspan="2">W</td><td colspan="2">SW</td><td colspan="2">E</td><td colspan="2">NE</td><td colspan="2">SE</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td></tr>
<tr><td colspan="2">NW</td><td colspan="2">W</td><td colspan="2">X</td><td colspan="2">E</td><td colspan="2">SE</td><td colspan="2">X</td><td colspan="2">NW</td><td colspan="2">N</td><td colspan="2">X</td><td colspan="2">SE</td><td colspan="2">S</td><td colspan="2">X</td></tr>
<tr><td rowspan="2">SW</td><td colspan="2">NE</td><td colspan="2">NW</td><td colspan="2">N</td><td colspan="2">S</td><td colspan="2">SE</td><td colspan="2">SW</td><td colspan="2">W</td><td colspan="2">NW</td><td colspan="2">SW</td><td colspan="2">S</td><td colspan="2">SE</td><td colspan="2">SW</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td></tr>
<tr><td colspan="2">NE</td><td colspan="2">E</td><td colspan="2">X</td><td colspan="2">SW</td><td colspan="2">W</td><td colspan="2">X</td><td colspan="2">SW</td><td colspan="2">S</td><td colspan="2">X</td><td colspan="2">E</td><td colspan="2">NE</td><td colspan="2">SE</td></tr>
<tr><td rowspan="2">SE</td><td colspan="2">N</td><td colspan="2">NW</td><td colspan="2">NE</td><td colspan="2">S</td><td colspan="2">SW</td><td colspan="2">NE</td><td colspan="2">W</td><td colspan="2">NW</td><td colspan="2">SW</td><td colspan="2">E</td><td colspan="2">SE</td><td colspan="2">NE</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td></tr>
<tr><td colspan="2">W</td><td colspan="2">NW</td><td colspan="2">X</td><td colspan="2">X</td><td colspan="2">E</td><td colspan="2">SE</td><td colspan="2">NW</td><td colspan="2">N</td><td colspan="2">X</td><td colspan="2">SE</td><td colspan="2">S</td><td colspan="2">X</td></tr>
<tr><td rowspan="2">NE</td><td colspan="2">N</td><td colspan="2">NW</td><td colspan="2">NE</td><td colspan="2">S</td><td colspan="2">SE</td><td colspan="2">SW</td><td colspan="2">W</td><td colspan="2">SW</td><td colspan="2">NW</td><td colspan="2">E</td><td colspan="2">NE</td><td colspan="2">SE</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td><td rowspan="2">X</td></tr>
<tr><td colspan="2">NE</td><td colspan="2">E</td><td colspan="2">X</td><td colspan="2">SW</td><td colspan="2">W</td><td colspan="2">X</td><td colspan="2">SW</td><td colspan="2">S</td><td colspan="2">X</td><td colspan="2">NE</td><td colspan="2">N</td><td colspan="2">X</td></tr>
</table>

E. Anger & Sadness Graph Recognition Procedure.

The neural network technique is used for recognizing the anger and the sadness graphs. The Multi-layer perceptron neural network trained with Backpropagation is implemented to classify the connected graphs of. This technique is implemented on two types of expression graphs-the Sadness and Anger graphs.

- The network structures

The neural network had been constructed as follows:

- Input layer: three nodes had been used. Each image in the Grid will have three numeric values. These numeric values are the Pixel Pair Code (PC), the Edge Code (EC) and the Block Code (BC). PC is derived by comparing a thousand pairs of pixels. The positions of the top, bottom, left and right outer edges are used to produce EC. The position of the largest block of pixels that do not vary in color is used to produce BC.
  - Hidden Layers: 2 Layers with (7-5) nodes in each layer.
- Output Layer: two nodes are used one for each expression.

7. EXPERIMENTS AND RESULTS

The method presented is person-independent expression recognition for frontal face image sequences. The method tested using two databases publicly available. One of them is FACS-Coded expressions of basic emotions: “Cohn-Kanade [AU-Coded] Facial Expression DataBase” [26]. The other database is “FEEDTUM the FG-net facial Emotional and Expression DataBase” [27]. As well as limited dataset is collected in computer science Department College of Education/Al-mustansyria University for only three basic facial expressions (Joy, sadness and disgust). Also especial method had been developed, to recognize the patterns of the topological ordered relationships produced by SOFM for each basic expression. The framework for the automatic recognition of facial expressions is consisting of four levels of processing as shown in (Figure 18):

1) Image Size Reduction 2.
2) Topological Relationships Determination
3) Topological Relationships Representation
4) Expression Representation Recognition.

To evaluate the performance of the technique, the accuracy of the tests can be calculated as:

$$Accuracy = \frac{Number\ of\ correctly\ recognized\ expression\ shapes}{Total\ number\ of\ shapes\ for\ each\ particular\ expression} \quad \ldots\ldots\ldots (1)$$

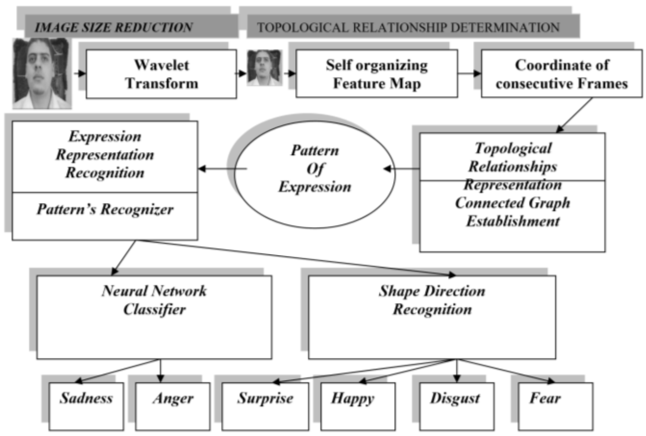

***Figure 18** Architecture of the Automatic Recognition System*

The reduction stage was implemented using the wavelet transform to reduce the size of the input images of the expression sequence before introduce them to the neural network to speed up the computational process. Hence only the low resolution (LL) image block is used as input for the next processing level. The GUI for this module is displayed in (Figure 19).

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Figure 19. *Two level Decomposition showing sub-bands.*

A computer vision Facial Expression Recognition System had been implemented with a user interface as shown in Figure (20). The result of the recognition process is presented in the form of the final image of the expression sequence given and the recognition result is either one of the six prototypes expressions or as unknown expression.

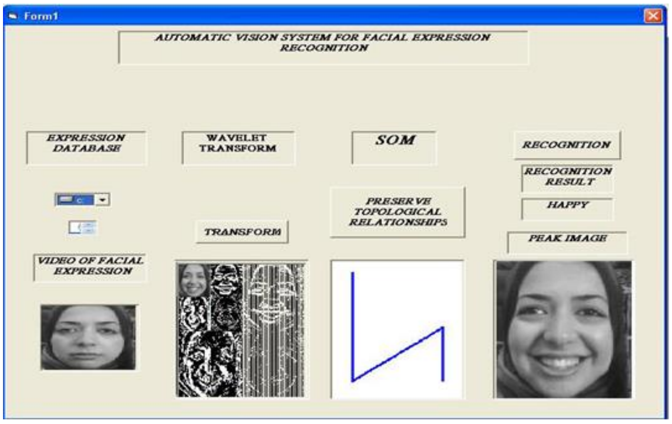


Figure (20) *the facial expression recognition user interface.*

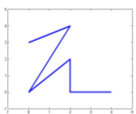
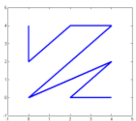
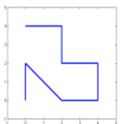
Table (6) *shows the number of image sequences tested and the recognition results by the approach for each expression and database*

	Happy		Surprise		Disgust		Sadness		Fear		Anger		Total	
Cohn-Kanade	34		24		24		28		13		19		142	
	26T	8F	21T	3F	22T	2F	26T	2F	11T	2F	18T	1F	124T	18F
FG-NET	17		15		12		N.A		N.A		N.A		44	
	16T	1F	15T	0F	12T	0F							43T	1F
Personal Collection	13		10		10		N.A		N.A		N.A		33	
	8T	5F	10T	0F	7T	3F							25T	8F
Total	64		49		46		28		13		19		219	
	50T	14F	46T	3F	41T	5F	26T	2F	11T	2F	18T	1F	192T	27F

1) The Happy Surprise, Disgust and Fear Expressions Recognition

The happy surprise, disgust and fear expressions graphs are recognized using shape and direction method. The accuracy of the recognition is calculated according to formula (1). The accuracy of the happy expression recognition is 80%, the accuracy of the surprise expression recognition is 93%, the accuracy of the disgust expression recognition is 87% and the accuracy of the fear expression recognition is 84.5%. Table (7) shows samples taken from the original tables of the expression graphs recognition.

Table 7. *Results of Graphs' Expression Recognition*

TEST NO.	TYPE OF DATA	FACS LABEL	MAP SHAPE	SHAPE & DIRECTION METHOD	DECISION RESULT	TEST IMAGE
1	"COHN-KANADE"	6+12+ 16C+25		HAPPY	T	
2	"COHN-KANADE"	6+12+25		HAPPY	T	
1	"COHN-KANADE"	1+2+5+25+27		SURPRISE	T	

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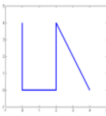
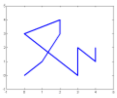
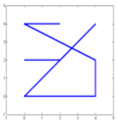
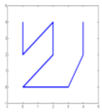
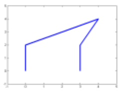
2	“COHN-KANADE”	1+2+25+27		SURPRISE	T	
2	“COHN-KANADE”	4+7+9+25		DISGUST	T	
3	“COHN-KANADE”	4+7+9+17		DISGUST	T	
1	“COHN-KANADE”	1+2+20+21 +25		FEAR	T	
2	“COHN-KANADE”	1+4+7+20 +25		FEAR	T	

2) The Sadness & Anger Expression Recognition

For these expressions, neural network technique (multi-Layer perceptron network trained with backpropagation) is used to classify the graphs presented. The classification results is obtained after a two sets of graphs are presented to the net, the first set is the train data in which consist of sixteen sadness graphs and eleven anger graphs while the second set is considered as validation data and contains twelve sadness graphs and eight anger.

Two hidden layers network is used in which yields validation results with 95% positive of the validation examples as shown in Figure (21). For the network used, the learning rate is (0.6) and the target error is (0.03). The accuracy of the validation of sadness expressions graphs according to the formula (1) is 92.8%. The accuracy of the validation of anger expressions graphs according to the formula (1) is 94.7% . Table (8) shows samples taken from the original tables of the expression graphs recognition.

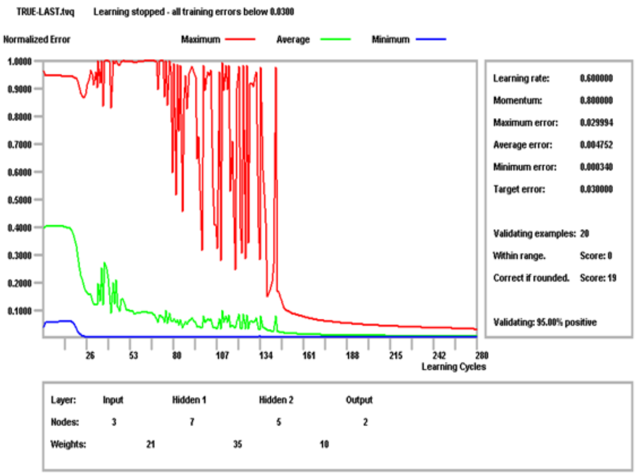


Figure 21. *Validation result of the sadness expression with two hidden layer network.*

Table 8 *Sample of Results of Sadness and Anger Expression*

TEST NO.	DATA TYPE	DATA BASE	FACS CODE	SHAPE OF GRAPH	RECOG RESULT	MATCH RESULT	PEAK IMAGE
5	VALIDATING	“COHN-KANADE”	1+Ra4+ 15d+17b		SAD	T	

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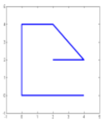
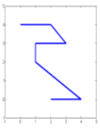
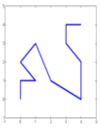
6	TRAINIG	"COHN-KANADE"	1+4+10 +15d+17d		SAD	T	
1	TRAINING	"COHN-KANADE"	4+7e+17d +23d+24d		ANGER	T	
2	VALIDATING	"COHN-KANADE"	4+7b+17c +23+24d+ 39		ANGER	T	

3) A summary of all the recognition results are presented in Table (9).

Table. 9 *Summary of all the recognition results obtained from the experiments using the Shape and Direction method and the Neural Network technique.*

	RECOGNITION METOD	RECOGNITION RATE
HAPPY	Shape & Direction	80%
SURPRISE	Shape & Direction	93%
DISGUST	Shape & Direction	87%
FEAR	Shape & Direction	84.4%
SADNESS	Neural Network	92.8%
ANGER	Neural Network	94.7%

4) Cross Validation of all Expressions Tests

A cross validation made between all the expression recognition tests to explore the overlapping recognition between any expressions in favors of the others. Table (10) shows these overlapping between all the expressions if any exist.

Table 10 *Overlapping recognitions results between expressions.*

	HAPPY	SURPRISE	DISGUST	FEAR	SAD	ANGER
HAPPY	1.0	0.16	0.02	0.01	0.0	0.0
SURPRISE	0.0	1.0	0.02	0.04	0.0	0.0
DISGUST	0.02	0.087	1.0	0.0	0.0	0.0
FEAR	0.0	0.077	0.077	1.0	0.0	0.0
SAD	0.0	0.0	0.052	0.0	1.0	0.052
ANGER	0.0	0.0	0.0	0.0	0.0	1.0

The results presented in the (Table 10), shows that the overlapping recognition rates between any two different expression's graphs are insignificant. These results suggested that the methods used for the recognition task are effective and does not confuse between most graphs of the expressions despite their complexity structures and variations. The most significant overlapping was between the happy and surprise graphs (i.e., 0.16).

5) Conclusions

This paper addressed the problem of automatic facial expression recognition based on FACS AUs. A computer vision system is developed that automatically recognizes the six basic prototypes facial expressions. An approach is presented where Unsupervised SOFM neural network is used to analyzing gray scales image sequences of varying length in order to compute and capture the topological relationships between the image sequences on the map for each expression .

The topological ordering (topological relationships) between the consecutive occurrences of expression image sequences for each basic prototype expression were represented on the SOFM map by a connected and directed graphs. These graphs are considered as a patterns or features for that particular expression. Six basic graphs were found, one for each particular basic expression .

To recognize the basic expressions, two methods are used to distinguish these six different connected graphs. The first method is a multi-layer perceptron neural network trained with backprobagation method, in which applied on sadness and anger graphs, while the second method is a collection of especially designed procedures based on shape and direction

Mahmoud, W. A., Stephan, J. J., & Razzak, A. A. W. (2020 Facial Expression Recognition from Video Sequence Using Self Organizing Feature Map. *Journal Port Science Research*, *4*(2), 53–68. https://doi.org/10.36371/port.2021.2.2

features of the graphs to recognize the remaining four basic expressions.

Facial expressions of different types, intensities and durations from different databases have been tested. The result shows that the system has a very good accuracy in facial expression recognition. An average recognition rate of 88.7% was achieved for six basic expressions. Also it has the capability of modulates the facial deformation into a graphical representation. This system can be implemented on image sequences without the need to perform the aligned and normalization using affine translation process in which considered a crucial step also a manual tedious work before the facial feature extraction step took place. This can be done on a condition that, the corresponding face images in an image sequence with only non-rigid head motion to ensure the assessment of correct motion information.

This research is of interest in computer vision, since a new model for human facial action in video stream can be found. Unlike previous methods which build a separate model for each AU and AU combinations, a single model is build using this approach for each expression that recognizes AUs whether they occur in their primary combinations or with major variants. This is an important capability since the number of possible AU combinations is too large for each combination to be modeled separately. A rate of, 88.7% AUs combinations are correctly classified regardless of whether these action units occur in the primary combination or with major variants.

The topological relationships model based approach was proved to capture the subtle changes of facial features. In the test set, which include subjects of mixed ethnicity, age and gender, average recognition rate for six basic prototypic expressions is comparable to the level of inter-observer agreement achieved in manual FACS coding.

Potential applications of our automatic facial expression recognition system include: assessment of nonverbal behavior in clinical and research settings such as psychological research of facial behavior coding, lip-reading to compliment speech recognition (audio-vision analysis), and the human-computer interface/interaction. Based on the work in this paper, the following problems are suggested for further research:

1 .Recognition of more facial expressions by adding more "expression units" of individual AUs and AU combinations into the automatic recognition system.

2 .Separation of non-rigid facial motion from rigid head motion.

3 .Automatic segmentation of facial expression subsequences from a video sequence based on, for example, expression graph representation.

4. multi-state face or nearly front-view facial expressions recognition.

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