كلية التراث الجامعة
المؤتمر العلمي السنوي الحادي عشر

A Novel Facial Expression Recognition Method Based on Consecutive Video Images Sequences Using Frame Differences Technique.

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Abstract

This paper introduces a method for recognizing the basic prototypic facial expressions (happy, surprise, anger, sadness, fear, disgust and the natural case). The method analyzing a sequence of gray scales video images sequences using the unsupervised Self-Organizing Feature Map (SOFM), in order to compute and capture the topological relationship between the sequences of images on the map of SOFM for each basic prototypic expression. Two methods are implemented to classify the connected expression graphs resulting from SOFM connected ordered nodes, the two methods are, *Shape Direction Method* and *the Backpropagation neural network method.* The main aim is to present an exploratory method for finding signature of data describing behavior of complex facial expression recognition processes. The method presented is person-independent expression recognition for frontal video sequences of face images. The method is invariant to rotation, scale, translation, clutters, illumination, miscellaneous sources of facial variability (arising from age, illness, gender, or race) there is no need for face alignment and cropping is necessary. The method was tested using two publicly available databases, the (FACS-Coded expressions) of basic emotions database and the (FG-net facial Emotional and Expression) data base. The highest average recognition rates achieved regarding the *anger, surprise sadness and disgust* expressions for all the databases and the recognition methods were (95%, 92% , 93%, 96%) respectively. While the *happy* and *fear* expressions are achieving less recognition with (88% & 83%) rates respectively.

Author Keywords: Wavelet Transform, Self Organizing Feature Map, Back Propagation Neural Network, Facial Expression Recognition, Facial Action Coding **System.**

هذا البحث يهدف الى تقديم طريقة للتعرف على تعابير الوجه الاساسية (الفرح، الدهشة، الغضب، الحزن، الخوف، والاشمئزاز بالإضافة إلى الحالة الطبيعية). الطريقة تقوم بتحليل سلسلة من الصور الفيديوية الرمادية باستخدام الشبكة العصبية (خارطة التنظيم الذاتي للصفات) ، من أجل حساب وقياس العلاقة الطوبولوجية الحاصلة مابين الصور المتسلسلة على خارطة الصفات

ولكل تعبير أولي أساسي. تم استخدام طريقتين لتصنيف الرسوم الخاصة بالتعابير المتصلة والناتجة عن استخدام العقد المتصلة على الشبكة ، وهما طريقة الشبكة العصبية الاصطناعية وطريقة اكتشاف اتجاه شكل مخطط الحركة للتعبير . والهدف الرئيسي هو تقديم طريقة استكشافية للعثور على نمط موحد للعلاقات الطوبولوجية التي تصف سلوك تعابير الوجه المختلفة والمعقدة. الطريقة المعروضة هي التعرف على تعابير الوجه بشكل عام وليس لاشخاص محددين ضمن قواعد بيانات التعابير المستخدمة، وهذه الطريقة غير مشروطة بعوامل التدوير ، القياس، الازاحة، الازاحة، والإضاءة، والحالات المتنوعة لتغير صفات الوجه (الناشئة عن السن أو المرض أو الجنس أو العرق)، وليس هناك حاجة إلى محاذاة الوجه وتحديده ضمن مجال الرأس. وتم اختبار الطريقة باستخدام قاعدتي بيانات متخصصة بتعابير الوجه، واحده منها هي (فاكس-كوديد للتعابير الأساسية) وقاعدة البيانات الأخرى هي (اف-جي-نيت لتعابيرالوجه). وأعلى متوسط معدلات التعرف التي تحققت لجميع قواعد البيانات بأستخدام طرق التعرف، لتعابير الغضب والدهشة والحزن والاشمئزاز كانت (95% ، 94% ، 93% ، 96%) على التوالي. في حين أن تعبيري الفرح والخوف حققت معدلات تعرف بنسب أقل هي (81% و 83%) على التوالي.

1. Introduction

An increasing number of researchers in computer vision have developed various methods in providing capabilities for automatic facial expression recognition. Recently depth map estimation of Light Field has been implemented [8], 3D facial expression recognition algorithm using local threshold binary pattern and histogram of oriented gradient [9] with very promising recognitions rates in which achieved verification rates of more than 90% for the 3D facial expression recognition. HOG features implementation by [10], it is found in the experiment that HOG feature gives comparable good recognition rate in facial expression recognition. Fusion of Local Binary Pattern (LBP) with local gradient coding (LGC) and Fusion of HOG with other features like Local Directional Pattern (LDP) and wavelets also improved their respective recognition rates. Field-programmable gate array (FPGA) [14] implementation and efficiency of regression methods for automatic emotional state detection and analysis. It can be prove that the FPGA implementation is ready to be used on embedded devices for human emotion recognition from live cameras.

In this research a method is based on Facial Action Coding System (FACS) proposed by [1], for describing facial expressions by action units (AUs). other schemas were presented by Scherer et al. measured emotions using an assessment of defined components [11]; Davidson et al. published comprehensive studies on the relation between brain physiology and emotional expressions [12]; Stemmler's studies determined and revealed physiological outlines [13].
In this paper It is an attempt to automatically recognize the FACS action units for only the six basic prototypic expressions. The method was tested using two databases publicly available, one of them is FACS-Coded expressions of basic emotions: "Cohn-Kanade [AU-Coded] Facial Expression DataBase" [2]. The other database is "FEEDTUM the FG-net facial Emotional and Expression DataBase" [3]. Also special method has been developed, to recognize the patterns of the topological ordered relationships produced by SOFM for each basic expression.

Then Kohonen Self Organizing Feature Map for pattern clustering has been used to cluster the discriminated information vectors extracted from the wavelet transform. The technique suggested in this paper can serve as a pre-processing step in computer vision applications.

2. Measuring Facial Expression

Recent approaches to facial mensuration have different methodologies, from measurements of particular changes to a specific part of a face to effective descriptions of facial structure. Knowledge of the muscles of the face allows us to characterize exactly what is happening as an expression is emerging. Since everyone's face is different it is difficult to characterize an expression in any other way. For this reason a thorough understanding of the face is required prior to devising a scheme for the characterization and measurement of facial expression.

2.1 The Facial Action Coding System and "Expression Units"

For a description of detailed facial expressions, the Facial Action Coding System (FACS) was designed [4]. FACS consists of 44 basic Action Units (AU), with 14 additional AUs for head and eye positions (see figure 1).

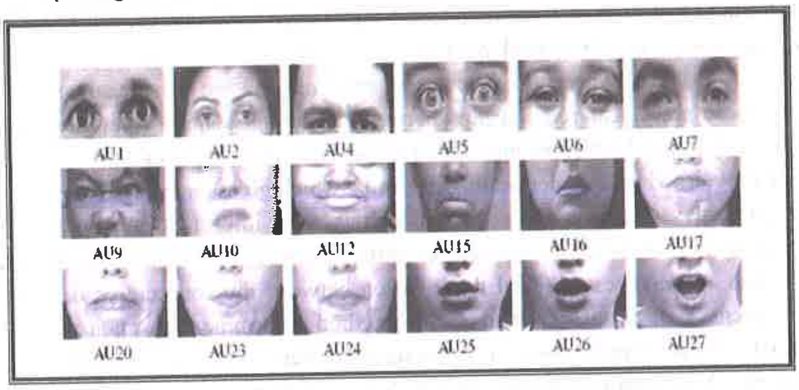


Figure (1) Face action units for the components of six basic facial expressions adapted from [7].

3. The Suggested Method

The facial expression recognition, with the variability of facial features, would be difficult to accomplish without having some adaptation in the recognition framework. Incorporate adaptation in this method, involving:

I) Consecutive facial expression images tracking.

The video 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. Also the uncontrolled lighting and illumination problem will be eliminated since all the images are relatively of the same environment at the moment being recorded. Facial characteristics , arising from age, illness, gender, race, facial hair and make-up, all these factors 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 without relying on any previous recorded characteristics.

II) Unsupervised Learning.

Unfortunately, supervised neural networks are difficult to train if used for the classification of not only basic emotions, but unconstrained facial expressions. 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. In this paper, the unsupervised Self-Organizing Map neural network has 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 had been used for capturing the topological relationships between cluster units for modeling 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, 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 suggested method focus on how to model the dynamic appearances of facial deformation between the consecutive occurrences in video image sequences of facial expression. The method determine the topological ordering (topological relationships) which gives the recognition patterns for each particular prototypic expression, and then use these patterns for each prototypic expression to recognize the sequence expression using an especially designed method for the recognition task.

III) Description of facial expressions and their deformations using frame differences technique of consecutive video frames.

The method suggested in this paper needs to be adaptable to the basic prototypic expressions in a systematic way, so that self organizing map neural network can map 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 in describing the facial expressions.

The assumption that has been made in this paper is that, any changes occurring 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 maps these two consecutive frames according to these changes (differences between two consecutive frames) 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 preserve the topological relationships between these changes. The facial deformations are non-linear and SOFM 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. Since SOFM shows the frame mapping according to expression evolvement (dynamic combinations of action units), 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, in which we believe that FACS is reliable to play these roles. The deformations that occur during facial expressions are as a consequence of facial features changes, changes that occur as a result of specific action units that are involved in that particular expression, and since these changes are coded according to FACS and considered similar expressions, therefore SOFM will map these changes in a systematic way which reflects the relationships between them. The deformation occurs in the same order of the frame sequence; from the first neutral frame to the last peak frame. Since these frames are consecutive in their deformation then this sequence is affecting the order of the mapping. To make the topological order relationships interprets the meaning of the expression, the clusters had been connected by lines to represents the consecutive frames in order 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 are sequential in time (occurring in that order). Figure (2) shows video image sequences of different expressions to show the spatial deformation in the expression for consecutive frames for many different subjects.

The subjects' performance is coded according to FACS coding system. In figure (2.a), the sequence shows the expression evolving from the neutral to peak expression. The second sequence in figure (2.b), shows the difference images (subtract the current frame from the neutral frame) from the neutral to the peak expression with a selection mask (current frame) to apply blending through the mask. The third sequence for different subject shows only the difference images (subtract the sequence of images from the neutral image).

From the figure sequences we can observe the evolving of absolute deformation between consecutive frames of the same expression but 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.

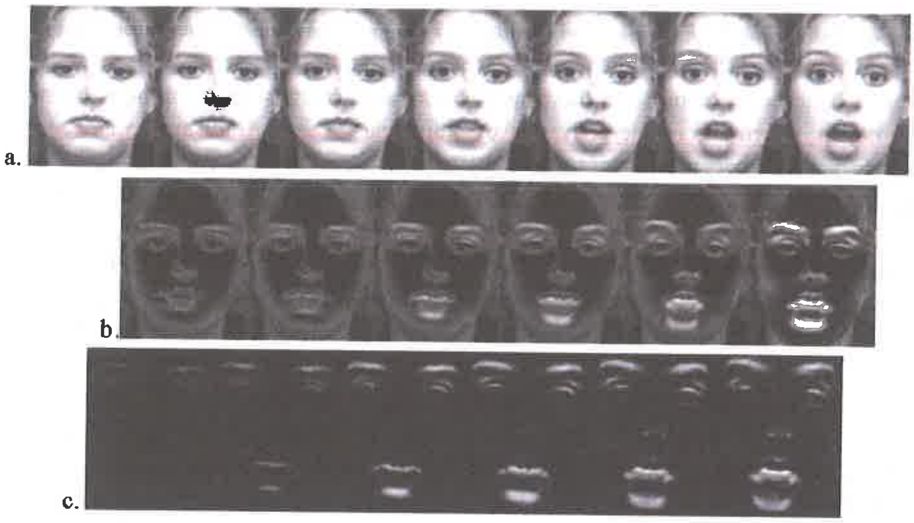


Figure 2 a. surprise expression. b. Difference images with selection mask c. The difference images without selection mask for different subject.

4. Facial Expression Databases

In this paper, two publicly available databases have been used for the experiments conducted on the suggested method:

1- "Cohen-Kanade [AU-Coded] Facial Expression DataBase" [2].
2- "FG-net Facial Emotional and Expression DataBase" [3].

5. Method Overview

The outline for the automatic recognition of facial expressions consists of four levels of processing (shown in Figure 3): Image Size Reduction, Topological Relationships Determination, Topological Relationships Representation, and Expression Representation Recognition. To implement the system, different programming platforms were used.

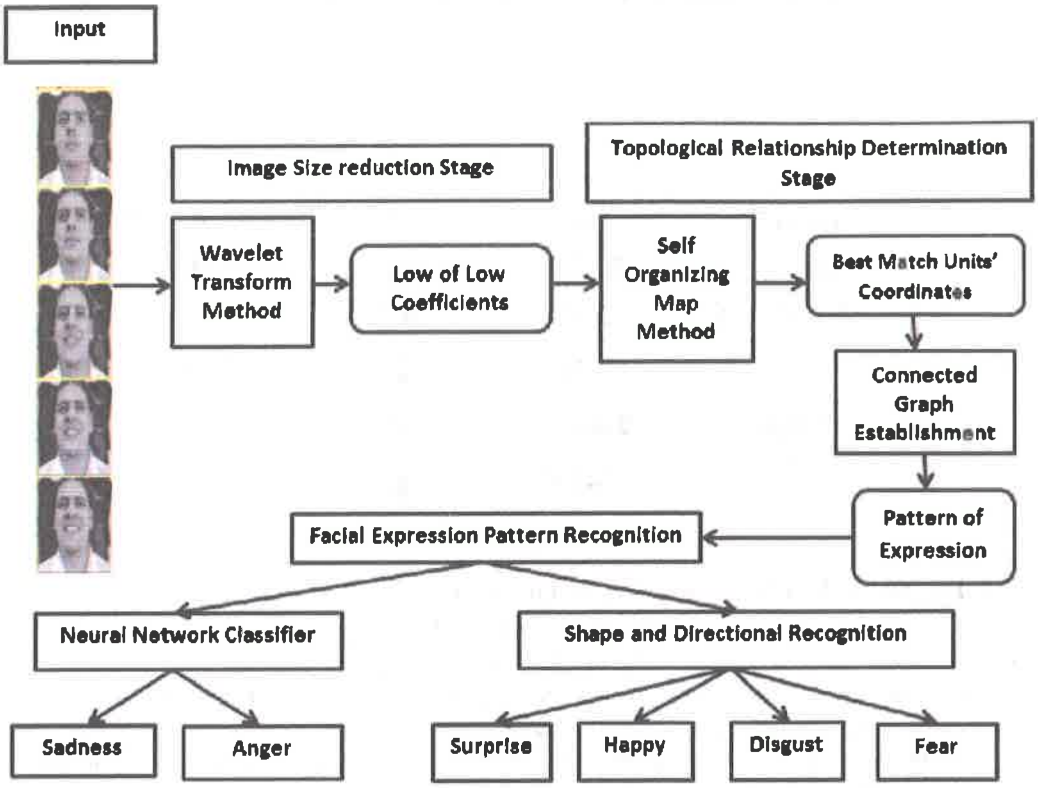


Figure 3 Outline of the Automatic Recognition System

5.1 Image Size Reduction

The reduction stage was implemented using the Wavelet transform to reduce the size of the input video images sequence of the expression before introducing them to the neural network. The reduction is applied for of decomposition were constructed two levels, the low resolution low of low (LL) image block is used as input for the next processing level.

5.2 Topological Relationships Determination

Using the above technique the sizes of the input images are reduced, and then these images are given as a sequence of expression formation to SOFM algorithm to determine the topological relationships between these images of the sequence expression.

Table 1 shows the numbers of images for each particular expression sequence from neutral to peak for the participants and for different databases.

Table 1 number of images in each expression sequence 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
Fear	6-8	X	N.A
Anger	10-13	X	N.A
Sadness	10-15	X	N.A

5.3 Topological Relationship Representation

The output of the SOFM map will be considered in this phase when the best match units or neurons are obtained, 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 was established. The order in which these lines were constructed depends on the order in which these images occurred in the expression sequence (see Figure 4). This connected graph is taken as a representative for that expression in an attempt to investigate the possibility of finding similar patterns of connected graphs for each particular prototypic expression and for different people.

If it found that there is similarity between the connected graphs in their appearance shapes for the participants who are performing a particular expression, then we can conclude that these patterns of connectivity may be considered to be universal signatures for these prototypic expressions.

Generally we found different and distinctive connected graphs (similar in their appearance shapes for each expression class) for each prototypic facial expression, in which we use to classify the expression sequence images. It is important to note that, the subjects who are performing happy expression for example should all be coded according to FACS, performing the AUs combination (AU6 + AU12 + AU25) or its major variants [4].

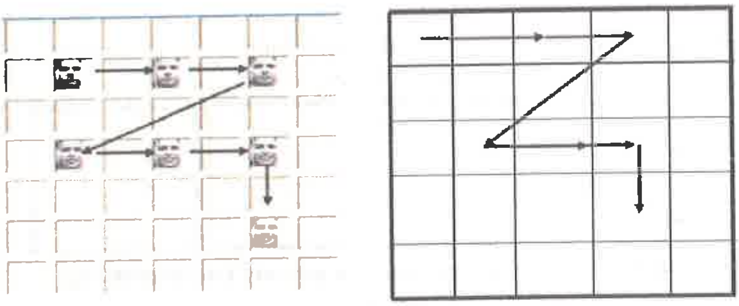


Figure 4

a. Consecutive images of happy expression. b. Connected graph between maps neurons coordinates corresponding to the consecutive images.

6. Facial Expression Graph Representation and Recognition

The topological ordered relationships produced by SOFM on the expression images sequences taken from the databases described above, show a 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 SOFM's map as a square shape graphs.

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

1- Happiness Graph: The connected graphs found in this category are Zigzags like graphs as shown some examples in (Figure 5). In which represent the deformation in the mouth, check and eye spatial locations of the face. These graphs represent expressions sequences corresponding to FACS code: (AU6+AU12) [4].

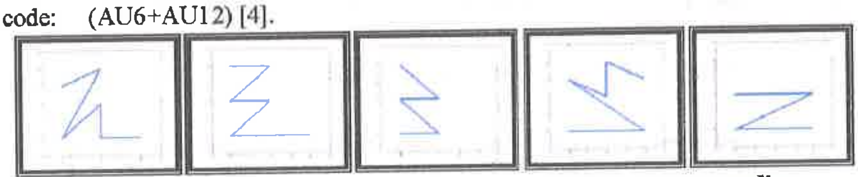


Figure 5 The graphs represent image sequences corresponding to happy expressions.

2- Surprise Graph: The connected graphs found in this category are square like graphs as shown in (Figure 6). These graphs represent the facial deformation in the mouth eye and brow. These graphs represent expressions sequences corresponding to FACS code: (AU1+AU2+AU5B+AU26) [4].

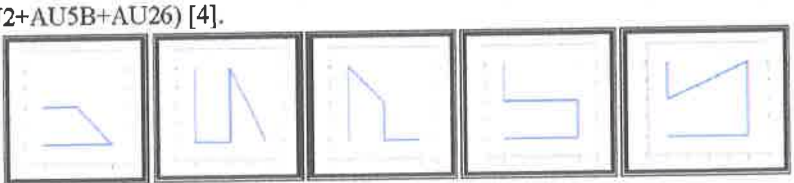


Figure 6 The graphs represent image sequences corresponding to surprise expressions.

3- Disgust Graph: The shapes of the graphs found in this category are combined form of Crossing-Inverse and fluctuated graphs, as shown in (Figure 7). These graphs represent expressions sequences corresponding to FACS code: (AU9+AU16+AU15)

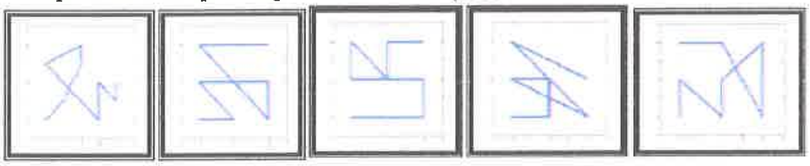


Figure 7 The graphs represent image sequences corresponding to disgust expressions.

4- Fear Graph: The connected graphs found in this category are triangular-box like graphs as shown in (Figure 8). These graphs represent the facial deformation in the mouth, eye, brow, chin and forehead. These graphs represent expressions sequences corresponding to FACS code: (AU1+AU2+AU4+AU5+AU20+AU25).

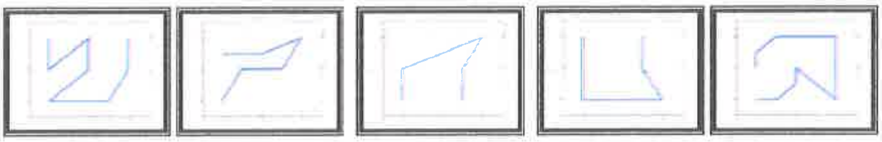


Figure 8 The graphs represent image sequences corresponding to fear expression.

5- Anger Graph: The connected graphs found in this category are double joint boxes like graphs as shown in (Figure 9). These graphs represent the facial deformation in the mouth, eye, brow, cheek and chin. These graphs represent expressions sequences corresponding to FACS code: (AU4+AU5+AU7+AU10+AU22+AU23+AU25).

Figure 9 The graphs represent image sequences corresponding to anger expression.

6- Sadness Graph: the connected graphs found in this category are an open entrance box-box like graphs (as shown in Figure 10). These graphs represent the facial deformation in the mouth, eye, brow, cheek and chin. These graphs represent expressions sequences corresponding to FACS code: (AU1+AU4+AU11+ AU15B).

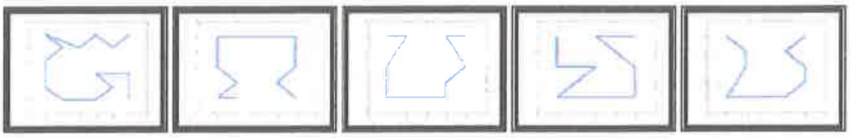


Figure 10 The graphs represent image sequences corresponding to sadness expression.

7- Method for Recognition and Classifying Expression Graphs

SOFM is accomplishing an important data visualization by reducing the high dimensional input space to a two dimensional regular lattice. In this final stage, the pattern of expression has been found for each expression sequence which is represented by the connected graph of the ordered topological relationships between the consecutive images of expression sequence. A method must be found to recognize these connected graphs in order to classify them according to the six basic prototypic expressions which they are belong to. The connected graphs which have been found in each category are not identical, they are only similar in their appearance as it has been displayed in (Figures 5-10), they all differ in their detailed descriptions (length and local directions) even for the same category and this is expected since they represent different subjects in different environments, also it can't be expected that all the subjects' FACS coding is performed in a perfect way.

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

A) Neural Network Method:

The Multi-layer perceptron neural network trained with Back propagation 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 (2) and (Figures 5-10) so they will not interfere with the other expression graphs during the recognition phase. The neural networks are able to learn the training data (connected graphs) very well and to validate the testing examples with a very good level of recognition.

B) Direction and Shape Recognition Method

SOFM has 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. From the discussion of (Section 6) there are distinctive shapes for each graph requiring also distinctive method for their recognition. The direction of the line segments of the graph between two points on the positive quadrants on the Cartesian coordinate (positive quadrants only) can be determined as follows:

Line segment direction = X2 – X1…………….(1)

The line segment is heading from point X1 to point X2; whereX1 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 11).

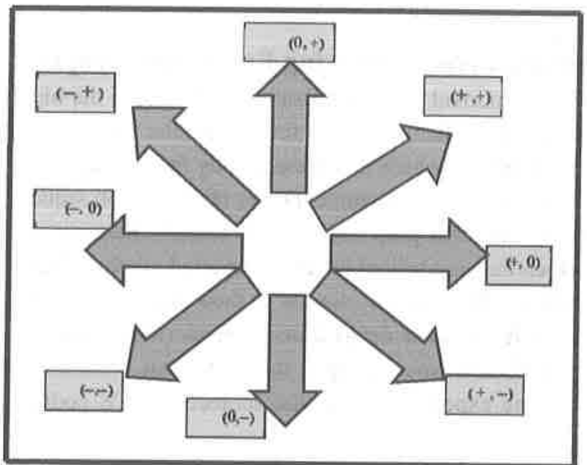


Figure 11 The magnitude of the motion direction in positive quadrants.

The following are the procedures that have been implemented to recognize the shape of these graphs using C++ programming language and (table 11) shows the Magnitude Motion Direction Schema used in coding the line segment of the Expression Graphs.

Happy graph recognition procedure.

In general the shapes of the graphs which have been found in this category are zigzags like shapes (See Sec. 5.3). To determine this shape the direction of the graph must be considered. In Figure (12) 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 (3) summarizes all the possible directions stated in Figure (12).

Table (2) Magnitude Motion Direction Schema for Coding Line segments

First Element	Second Element	Code	Direction
= 0	>0	7	NORTH
>0	>0	1	NORTH EAST
>0	= 0	8	EAST
>0	<0	2	SOUTH EAST
=0	<0	6	SOUTH
<0	<0	4	SOUTH WEST
<0	= 0	5	WEST
<0	>0	3	NORTH WEST

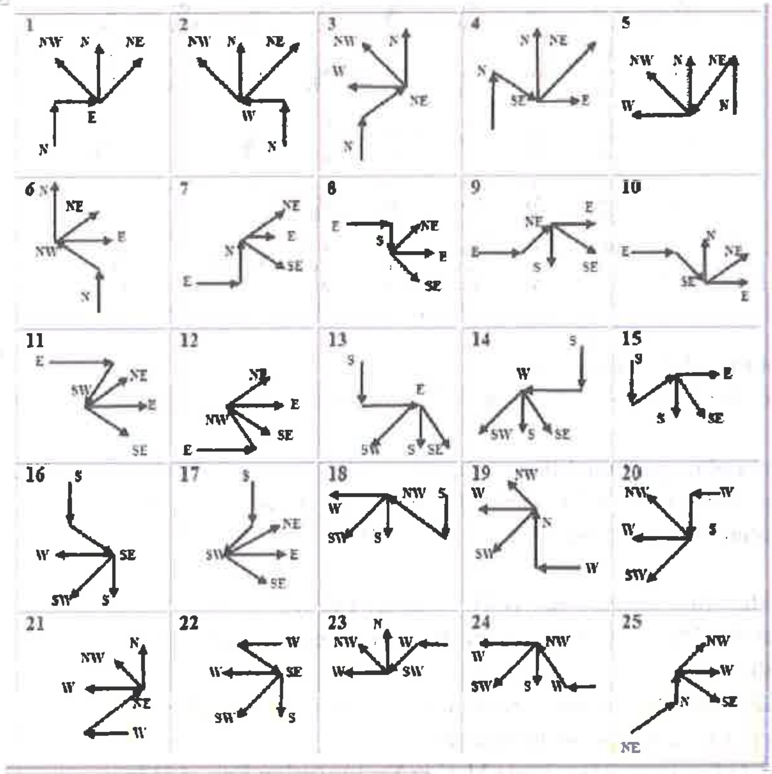


Figure 12 All the possible directions form zigzags like shapes (happy graphs).

Table 3 The summary of all possible directions stated in Figure (12) of happy graphs.

	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

The abbreviations of directions are:
N: North, S: South, W: West, E: East, NW: Northwest, NE: Northeast, SW: Southwest, SE: Southeast.

The Happy procedure perform different steps to check if the graph draws a square or Zigzag like shape graph as it was described in Table (3) and Figure (12). The Steps are proceeding as follow and the procedure flowchart displayed in Figure (13):

Step 1: Initialize Best Match Unit (BMU) counter I to 1;

Step 2: Input the BMU's coordinates for the current presented Expression Graph.

Step 3: While Happy Expression Graph not Recognized and not End Of Data perform the following Sub-Steps:

Step 3.1: Compute Magnitude Motion Vector (using Equ. 4.1) for two line segments between BMUs (i, i+1) and (i+2, i+3).

Step 3.2: Determine the directions of the line segments of step (3.1) Using the Sign of the Magnitude Motion Vector and the Schema described in Table (2).

Step 3.3: Check the Happy Directions Existence formed by line segments specified in Step (3.2) according to directions specified in Table (3). Assign Happy Graph Status if Happy Graph Exist.

Step 3.4: Increment BMU counter by one.

Step 4: If Happy Graph Exist Then Output Result Else Perform Surprise Graph Procedure.

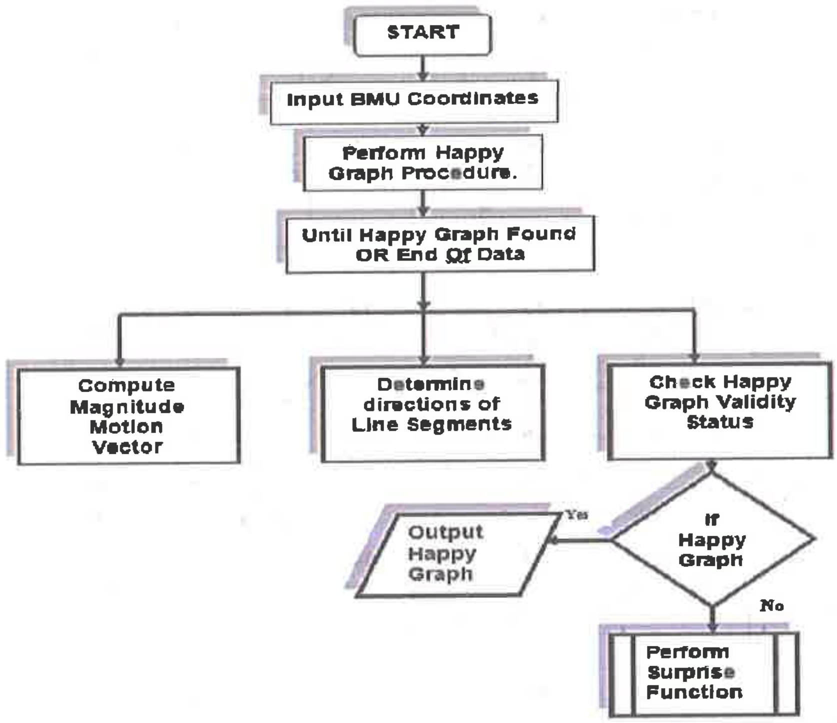
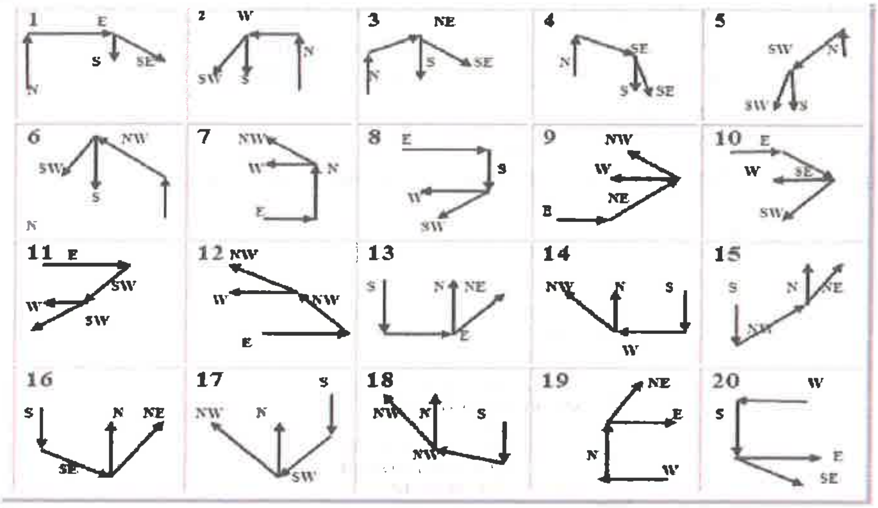


Figure (13) Flowchart of Happy Graph recognition procedure.

2) Surprise Graph Recognition Procedure.

In general the shapes of the graphs found in this category are box like shapes (See Sec. 5.3). To determine this shape, the direction of the graph must be considered. In Figure (14) 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 (4) summarizes all the possible directions stated in Figure (14).


1 E S SE N
2 W SW S N
3 NE S SE N
4 SE N S SE
5 SW N SW S
6 NW SW S N
7 NW W N E
8 E S W SW
9 NW W NE E
10 E W SE SW
11 E SW W SW
12 NW W NW E
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14 NW N S W
15 S N NE NW
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19 NE E N W
20 W S E SE

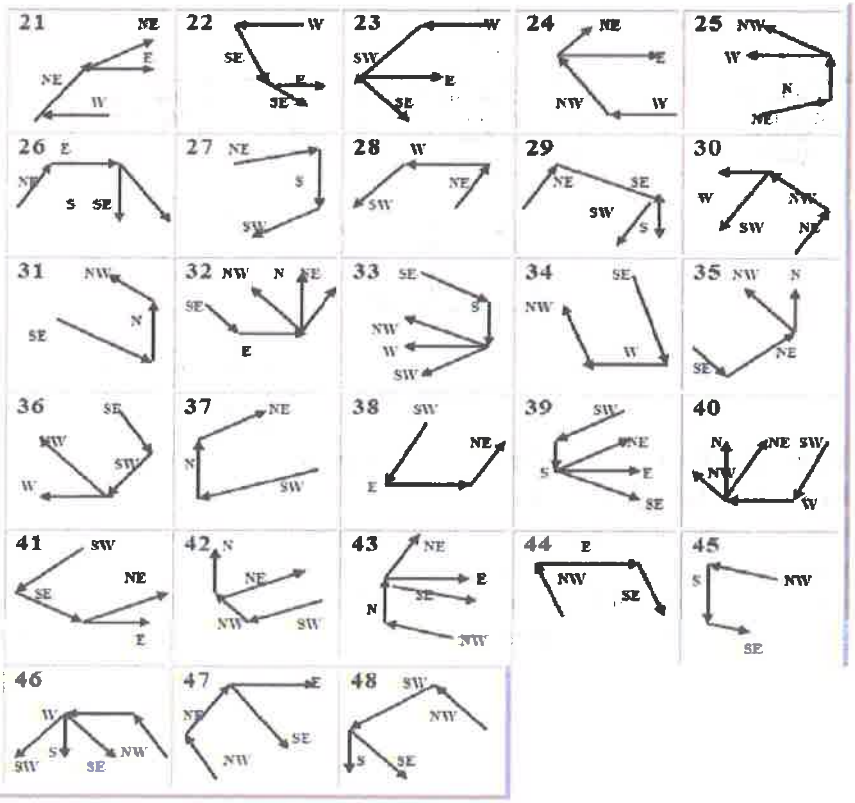

21 NE E NE W
22 W SE E SE
23 W SW E SE
24 NE E NW W
25 NW W N NE
26 E NE S SE
27 NE S SW
28 W NE SW
29 NE SE SW S
30 W NW SW NE
31 NW N SE
32 NW N NE SE E
33 SE S NW W SW
34 SE NW W
35 NW N SE NE
36 SE NW SW W
37 NE N SW
38 SW NE E
39 SW NE S E SE
40 N NE SW NW W
41 SW NE SE E
42 N NE NW SW
43 NE E SE N NW
44 E NW SE
45 S NW SE
46 W S NW SW SE
47 E NE SE NW
48 SW NW S SE

Figure 14 All possible directions from the current line segment direction to the next line segment direction on the graph form box like shapes (Surprise Expression).

The Surprise procedure perform different steps to check if the graph draws a Square or Simi-Square like shape graphs as it was described in Table (4) and Figure (14). The Steps are proceeding as follow and the procedure flowchart displayed in Figure (15):

Step 1: Initialize BMU counter I to 1;

Step 2: Input the BMU's coordinates for the current presented Expression Graph.

Step 3: While Surprise Expression Graph not Recognized and not End Of Data Perform the following Sub-Steps:

Step 3.1: Compute Magnitude Motion Vector (using Equ.1) for two line segments between BMUs (I, i+1), (i+1, i+2) and (i+2, i+3).

Step 3.2: Determine the directions of the line segments of step (3.1) Using the Sign of the Magnitude Motion Vector and the Schema described in Table (2).

Step 3.3: Check the Surprise Directions Existence formed by line segments specified in Step (3.2) according to directions specified in Table (4). Assign Surprise Graph Status if Surprise Graph Exist.

Step 3.4: Increment BMU counter by one.

Step 4: If Surprise Graph Exist Then Output Result Else Perform Disgust Graph Procedure.

Table 4 The summary of all possible directions stated in Figure (14) of surprise graphs.

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

3) 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 (See Sec. 5.3). The reversed directions of the line segments can be found in the similar way as described in the previous section (See Figure 16), Table (5) summarizes all the possible directions stated in Figure (16).

The crossing line segments can be found by calculating the intersection point between any two crossing line segments:

Suppose the line segments equations are defined as follows:

$y1 = m1\ x + b1$ .... (2)

$y2 = m2\ x + b2$ .... (3)

Now if there is some point (xi,yi) shared by both lines, then

$yi = m1\ xi + b1$ and $yi = m2\ xi + b2$ .... (4)

will both be true. Equating over yi gives:

$m1\ xi + b1 = m2\ xi + b2$ .... (5)

Solving for xi yields

$xi = (b2 - b1)/(m1 - m2)$ .... (6)

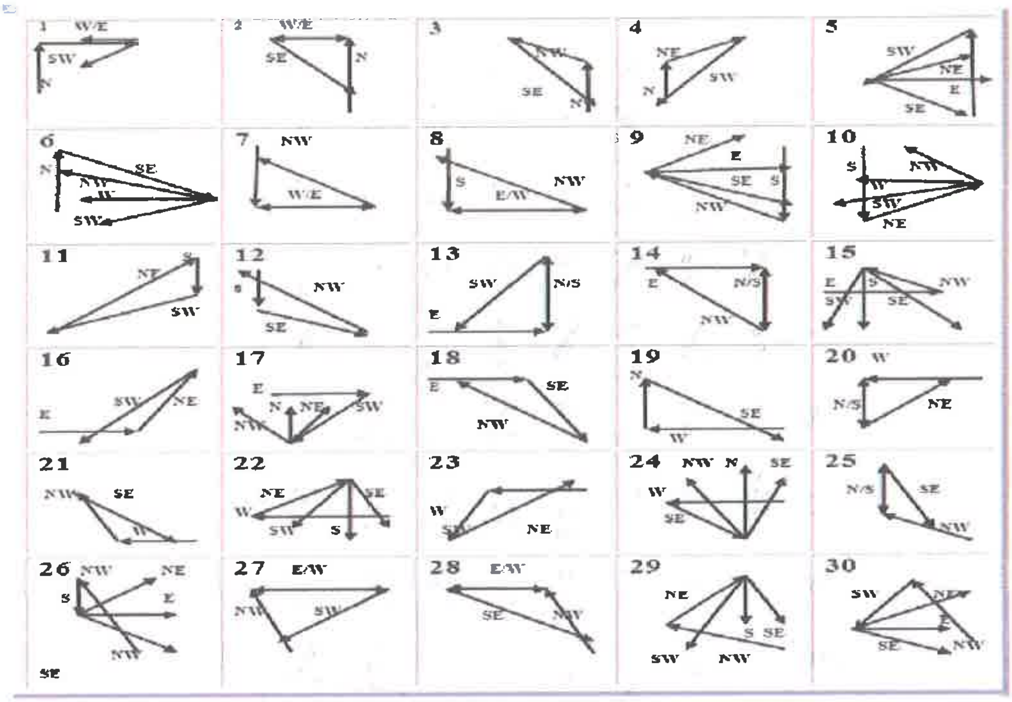
Substituting this into the equation for either line 1 or line 2 gives:

$yi = ((m1b2 - m2b1)/ (m1 - m2))$ .... (7)

Therefore the point:

$$(((b2-b1)/(m1-m2)), ((m1b2-m1b1)/(m1-m2))) \quad \ldots\ldots\ldots\ldots (8)$$

is the intersection point.



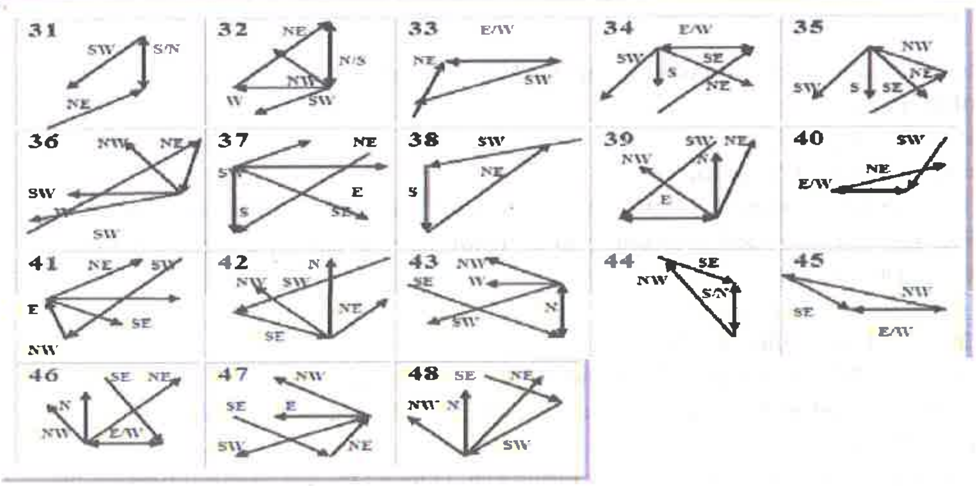


Figure 16 the summary of all possible directions in determining the disgust expression.

Table 5 All possible directions stated in Figure (14) of disgust expression.

	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

The Disgust procedure performs different steps to check if the graph has two main characteristics as described above:

1- Crossing like shapes.

2- Reverse Direction Line Segments.

For the crossing line segments the equations (2-8) are used and for the reverse directions Table (5) is used. The step is proceeding according to the following steps and the procedure flowchart displayed in Figure (17):

Step 1: Initialize BMU counter I to 1;

Step 2: Input the BMU's coordinates for the current presented Expression Graph.

Step 3: While Disgust Expression Graph not Recognized and not End Of Data Perform the following Sub-Steps:

Step 3.1: Compute Magnitude Motion Vector (using Equ. 1) for all the line segments between the consecutive BMU's Coordinates.

Step 3.2: Determine the directions of the line segments of step (3.1) using the Sign of the Magnitude Motion Vector and the
Schema described in Table (2).
Step 3.3: For every two consecutive line segments check if they are in opposite direction to each other. If opposite direction Exist Then Disgust Graph Exists.
Step 3.4: If Disgust Graph does not Exist Yet, Then Compute Line Equations Parameters according to (Equ. 2-8).
If Lines are not Parallel to each other, Then Check if Segments are Intersecting at any point along the Ray Of the segment.
Step 3.5: Check if Crossing point lie on the current line segment determined by the BMU's Coordinates and not on the Ray along its direction outside the segment boundary.
If crossing point Exist Then the Disgust Graph Status
Set to True.
Step 3.6: Increment BMU counter by one.
Step 4: If Disgust Graph Exist Then Output Result Else Perform Fear Graph Procedure.

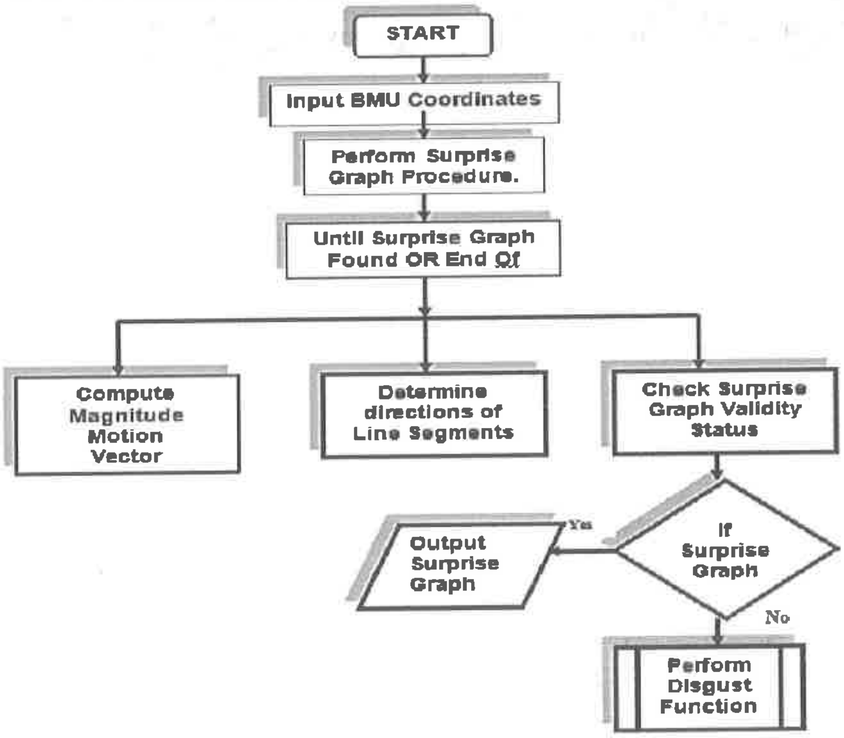
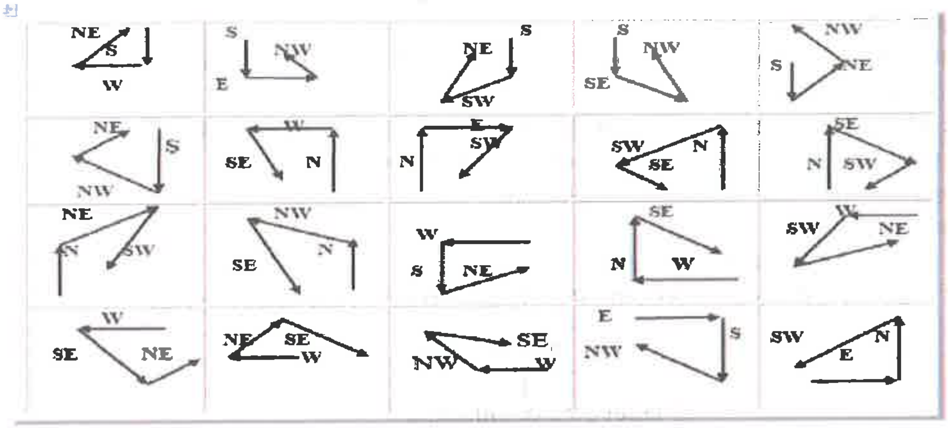


Figure (17) Flowchart of Disgust Graph recognition procedure

4) Fear Graph Recognition Procedure.

In general the shapes of the graphs which have been found in this category are cone like shapes as shown in (Figure 18). Table (6) summarizes all the possible directions. To recognize a cone like shape figure, three consecutive line segments must satisfy the directions stated in the Table (6).



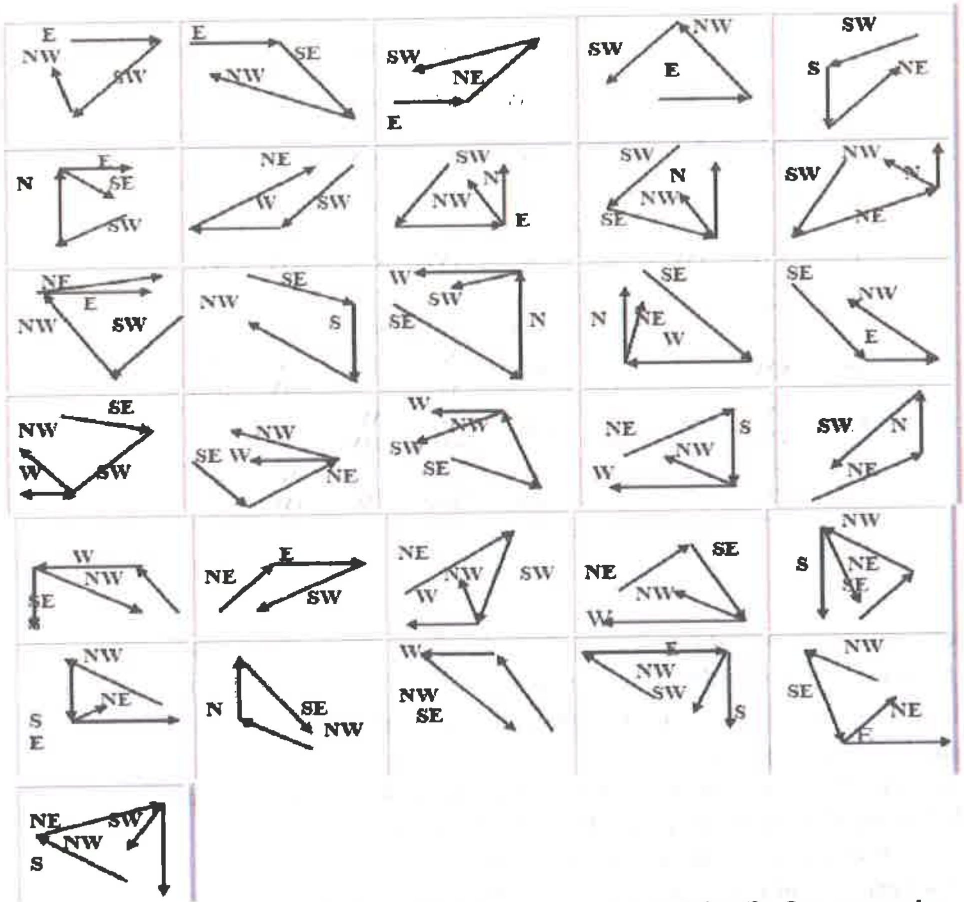


Figure 18 The summary of all possible directions in determining the fear expression

Table 6 The summary of all possible directions stated in Figure (18) of fear expression.

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

The Fear procedure perform different steps to check if the graph draws a Cone like shape graphs as it was described in Table (6) and Figure (18). The Steps are proceeding as follow and the procedure flowchart displayed in Figure (19):

Step 1: Initialize BMU counter i to 1;

Step 2: Input the BMU's coordinates for the current presented Expression Graph.

Step 3: While Fear Expression Graph not Recognized and not End Of Data Perform the following Sub-Steps:

Step 3.1: Compute Magnitude Motion Vector (using Equ. 1) for two line segments between BMUs (i, i+1), (i+1, i+2) and (i+2, i+3).

Step 3.2: Determine the directions of the line segments of step (3.1) Using the Sign of the Magnitude Motion Vector and the Schema described in Table (2).

Step 3.3: Check the Fear Directions Existence formed by line segments specified in Step (3.2) according to directions specified in Table (6). Assign Fear Graph Status if Fear Graph Exist.

Step 3.4: Increment BMU counter by one.

Step 4: If Fear Graph Exist Then Output Result Else UNKNWON GRAPH.

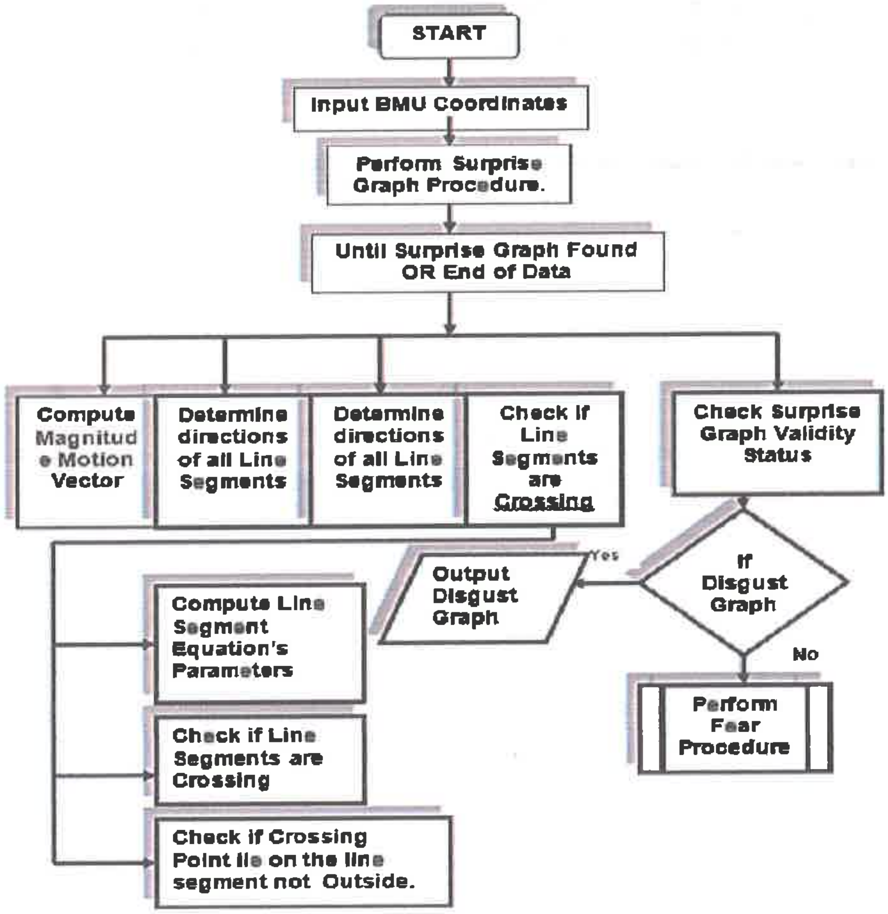


Figure (19) Flowchart of Disgust Graph recognition procedure

8. Evaluation of the Experiments' Results

A central characteristic of the Facial recognition technique is that the technique has to cope with unlimited number of different persons (person-independent). Each person is with different face topology and other number of characteristics, such as environment clutter and illumination, miscellaneous source of facial variability and view or pose of the head.

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

$$Efficiency = \frac{\textbf{Number of Correctly Recognized Expression Shapes}}{\textbf{Total Number of Shapes for each particular Expression}}$$

X100 ……….. (9)

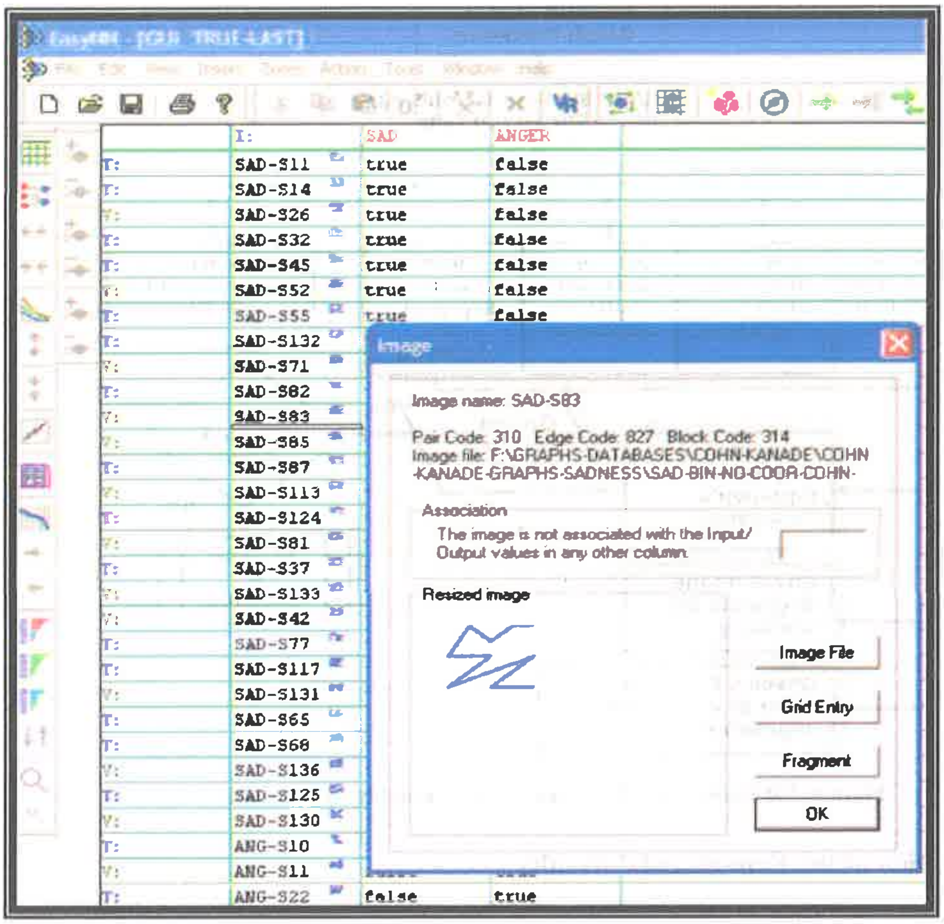


Figure (20) The training and validating graphs of the sadness and anger expressions.

8.1 Method Implementation

For implementing the suggested method an Automatic Recognition System for Facial Expression Recognition has been built and applied using the sequence images for different databases as described with a Graphical User Interface (as shown in Figure 21) .The system is written using two main languages (C++ and Visual Basic) and also by incorporating an external shareware package (EasyNN-Plus [6]) for implementing multi-layer neural network trained with BackProbagation to facilitate the expression graphs classification. In Figure (21), the Graphical User Interface consists of the command buttons, the Wavelet Transform button (image reduction process), the SOFM button (topological relationships determination process) and the recognition buttons (graph shape determination process).

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 (22) illustrates the flowchart of the Facial Expression Recognition's user interface with processing steps of proposed Facial Expression Recognition System and the language that is used for the implementation of the steps.

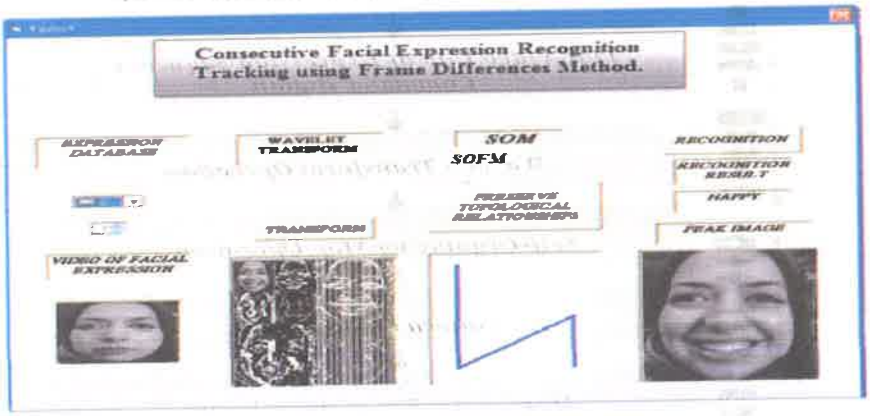


Figure 21 Graphical User Interface for the Automatic Recognition System.

8.2 Results of Testing Basic Facial Expression Sequences

In the following sections the results of the experiments conducted on the expression sequences from different databases to recognize the basic six facial expressions are presented. The expressions are recognized by using two different methods. For the Sadness and Anger expressions, neural network method is used based on the number of images located from neutral to peak as stated in (sec.6), while the remaining expressions, the shape and direction method is used.

Table 7 The number of video image sequences tested for each prototype expression and the recognition results for each database.

	Happy		Surprise		Disgust		Sadness		Fear		Anger		Total	
Cohn-Kanade	33		23		24		28		12		19		139	
	27T	6F	19T	4F	22T	2F	26T	2F	10T	2F	18T	1F	122T	17F
FG-net	16		15		12		N.A		N.A		N.A		43	

	15T	1F	15T	0F	12T	0F							42T	1F
Total	49		38		36		28		12		19		182	
	42T	7F	34T	4F	34T	2F	26T	2F	10T	2F	18T	1F	164T	18F

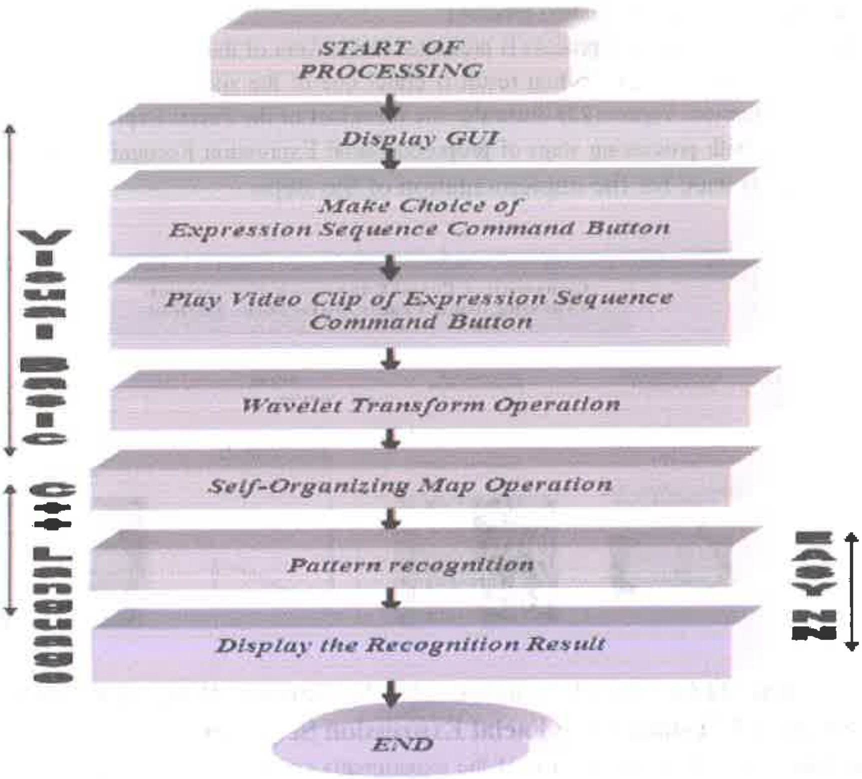


Figure 22 Block Diagram of the implementing the Automatic Recognition System with the types of programming languages used.

The subjects' identification numbers in the database are also coded as sequence numbers and presented in cross reference table. The sample test result for each expression will be presented in a different table and the header of each table will consist of the following fields:

Test Number- indicates the sequence number of the subject in the reference Table (8) for each database.

Type of data- the kind of the database used.

Face Label- the labels for each face expression according to FACS System for D1 database and (N.V) for D2 and databases to indicate Not Available.

Map Shape- the directed and connected graph that appears on the SOFM map, for each expression sequence.
Used method- the name of recognition method used for the expression.
Decision result- the state of the face expression as classified by the databases, either TRUE to be replaced with T or False to be replaced with F.
Test Image- a peak image of a particular expression sequence.

Table(8) The sample test result for surprise expression

TEST NO.	TYPE OF DATA	FACS LABEL	MAP SHAPE	SHAPE & DIRECTION METHOD	DECISION RESULT	SEQUENCE'S PEAK IMAGE
1	D2	N.A		SURPRISE	T	
2	D2	N.A		SURPRISE	T	
4	D2	N.A		SURPRISE	T	
5	D2	N.A		SURPRISE	T	
7	D2	N.A		SURPRISE	T	
8	D2	N.A		SURPRISE	T	

A) The Numerical Results of the Happy Expression

The Happy expression graph is recognized using the shape and direction method. The average recognition rate of the happy expression for all the databases used in the experiments is (87.66 %) using (Equ.9).

B) The Numerical Results of the Surprise Expression

The surprise expression graph is recognized using the shape and direction method. The average recognition rate of the surprise expression for all the databases used in the experiments is (94.44 %) using (Equ. 9).

C) The Numerical Results of the Disgust Expression

The Disgust expression graph is recognized using the shape and direction method. The average recognition rate of the disgust expression for all the databases used in the experiments is (96.2%) using (Equ. 9).

D) The Numerical Results of the Fear Expression

The fear expression graph is recognized using the shape and direction method. The average recognition rate of the fear expression for all the databases used in the experiments is (83%) using (Equ. 9).

E) The Numerical Results of the Sadness & Anger Expressions.

For these expressions, neural network technique (Multi-Layer perceptron network trained with Back Propagation) is used to classify the graphs presented. The classification results are obtained after two sets of graphs are presented to the net, the first set is the train data which consists 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 graphs.

Two hidden layers network is used which yields validation results with 95% positive of the validation examples as shown in Figure (23).

For the network used, the learning rate is (0.6) and the target error is (0.03) as shown in Figure (24). The accuracy of the validation of sadness expressions graphs according to the formula (Equ.9) is 92.8% after excluding the disgust graph of subject (S14-02). The accuracy of the validation of anger expressions graphs according to the (Equ.9) is 94.7% after excluding the unknown graph of subject (S34-03).

Figure 26 shows the detail description of the neurons states such as the Net input, Activation level, Bias level and relative errors. The information displayed inside the neurons represents the run of the last exemplar presented to the network. The information in the output layer neurons in shows that the pattern presented is Sad expression graph since the error is below the target error (0.03) on the sad node on the output layer. While the anger node shows a negative response with an error above target error.

In Figure 24, the relative errors associated with each exemplar row indicated the differences between the target pattern and its associated code vector representation for the corresponding active neuron.

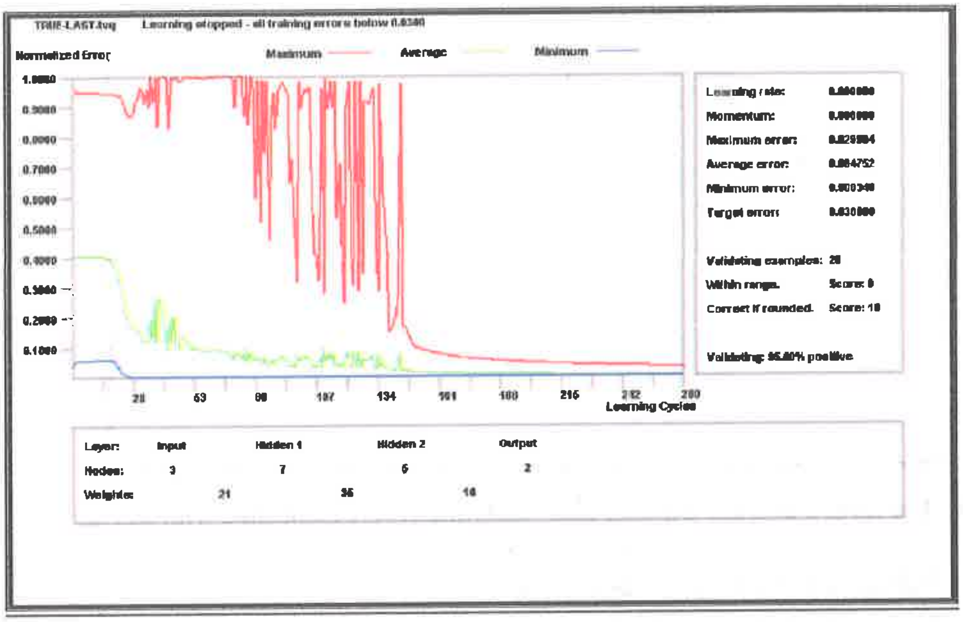


Figure 23 Validation result of the sadness expression with two hidden layer network.

Figure 24 The target, average training and validating errors associated with neural network for sad & anger.

8.3 Cross Validation of all Expressions Tests

A cross validation is made between all the expression recognition tests to explore the overlapping recognition between any expressions in favor of the others.

Table (9) and Figure (25) shows the overlapping between all the expressions if any exists.

Table 9 Overlapping recognition results between expressions.

	HAPPY	SURPRISE	DISGUST	FEAR	SAD	ANGER
HAPPY	0.82	0.0	0.02	0.0	0.0	0.0
SURPRISE	0.16	0.94	0.087	0.077	0.0	0.0
DISGUST	0.02	0.02	0.90	0.077	0.052	0.0
FEAR	0.01	0.04	0.0	0.846	0.0	0.0
SAD	0.0	0.0	0.0	0.0	0.896	0.0
ANGER	0.0	0.0	0.0	0.0	0.052	1.0

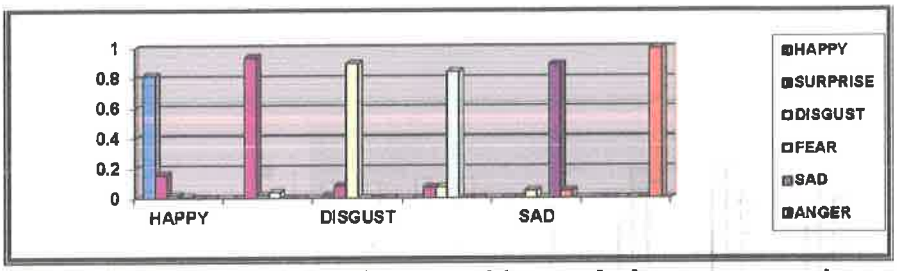


Figure 25 Charts of overlapping recognition results between expressions.

8.4 Recognition Rates

From the analysis of the (Table 10) and the charts of (Figure 26), there are numbers of observations can be stated as follows:

If the database size is considered and the number of the expressions exists in each database then Cohn-Kanade can be considered the database with highest rate of recognition in comparison with other two databases.

Regarding the methods used, the neural network technique is achieving better recognition rates (an average of 94%) than the direction and shape method (an average rate of 91.7%) when applied to Anger and Sadness expressions graphs. No attempt had been made to recognize the other expressions graphs using neural network for comparison purposes.

The highest average recognition rates achieved for all the databases and for the recognition methods, are for the Disgust, Anger and Sadness with (96%, 95% & 93%) respectively. While the Happy and Fear expressions are achieving less recognition rates (88% & 83%) respectively.

These observations can be considered to be consistent for the following reasons:

Cohn-Kanade database are coded with FACS system enabling better classification of the video image sequences in the experiments.

FG-Net database achieved fewer rates of recognitions because it is not FACS based expressions and the subjects were instructed not to play any role in their performance.

Table 10 Average recognition rates for all Databases used in the experiments using the Shape-Direction method and Neural Network Method.

	Happy	Surprise	Disgust	Fear	Anger	Sadness
	Shape& Direction	Shape& Direction	Shape& Direction	Shape& Direction	N.N	N.N
Cohn-Kanade	82%	83%	92%	83%	95%	93%
FG-Net	94%	100%	100%	N.A	N.A	N.A
Average	88%	92%	96%	83%	95%	93%

Recognition						

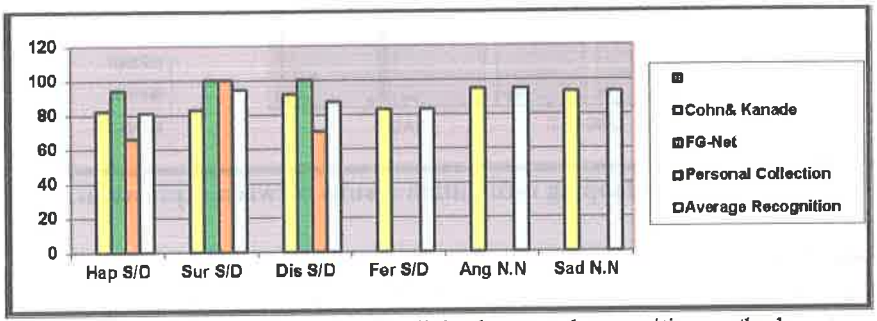


Figure 26 Recognition rates for all databases and recognition methods.

Conclusions

The result shows that the system has the following properties:

1.Six basic graphs were found, one for each particular basic expression, in which considered universal patterns or features for these expressions regardless of the miscellaneous sources of facial variability.

2. The method has the capability of modulating the facial deformation into meaningful graphical representation, hence providing a powerful tool for interpreting the facial deformation process.

3. Since the method had been implemented on video image sequences therefore there is no need to perform the alignment and normalization using affine translation process which is considered a crucial step as well as a manual tedious work before the facial feature extraction step takes place.

4. Regarding of the methods used, the neural network technique is achieving better recognition rates (an average of 94%) than the direction and shape method (an average rate of 90%) when applied to Anger and Sadness expressions graphs.

5. The highest average recognition rates achieved for all the databases and for the recognition methods, are for the Disgust, Anger and Sadness with (96%, 95% & 93%) respectively. While the Happy and Fear expressions are achieving less recognition rates (88% & 83%) respectively.

6. A very good accuracy in facial expression recognition. An average recognition rate of 90% has been achieved for six basic expressions.

7.The topological relationships method has proved to capture the subtle changes of facial features. In the test set, which includes 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.

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