DIFFERENCE THEORETIC TEXTURE FEATURES ALONG THREE ORTHOGONAL PLANES FOR FACE RECOGNITION FROM VIDEOS

Major Project Report submitted in partial fulfillment of the requirements for the award of degree of

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CERTIFICATE

This is to certify that **Ms Roni Chakre (2K13/ISY/21)** has carried out the major project titled **"Difference Theoretic Texture Features Along Three Orthogonal Planes for Face Recognition From Videos"** as a partial requirement for the award of the Degree of Master of Technology in Information Systems by Delhi Technological University, New Delhi.

The major project is a bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2013-2015. The contents of this thesis have not been submitted elsewhere for the award of any other degree.

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ABSTRACT

The efficiency of a human face recognition system depends on the capability of the system to recognize faces accurately in the presence of different changes in the appearance of face. The appearance of a person may change with varying lighting conditions, facial expressions, occlusions or facial features, such as beard, mustache and glasses. Several face recognition techniques have been introduced by researchers which are being used for many practical applications such as identity verification at highly secured locations, checking of criminal database records, identifying a person from surveillance cameras at a public place, etc. While recognition using static images are common, face recognition from videos has become an active topic in the field of object recognition and computer vision. Video-based face recognition techniques have gained widespread interest primarily based on the idea expressed by psychologists from their studies that humans recognize faces through motion especially in most cases when the spatial image quality is low. It has always been the aim of researchers to make the computer behave like a human being and therefore, to make the computer recognize faces like humans do has been one of its goals. In order to do this, a robust face recognition algorithm is required and in this project a new feature set called difference theoretic texture feature set along three orthogonal planes (DTTF-TOP) is proposed which will help extract the facial features of a person from videos and thus further use it for recognition. The challenge of change in face appearance due to the different face expressions showing emotions such as anger, sad, happy, surprise, etc is taken up in this project. So, a dataset called the Extended Cohn-Kanade (CK+) database containing videos of person showing different emotions is chosen and the one nearest neighbor and SVM classifiers are used for the classification purpose in the experiments. Results from the newly proposed feature set are compared with the highly efficient local binary pattern along three orthogonal planes (LBP-TOP). Further comparisons are made with a template based cross correlation (TBCC) method and a face feature weighted fusion method based on fuzzy membership degree for video based face recognition. Face recognition done using the proposed DTTF-TOP is found to give better performance than the other techniques used for comparison in the experiments.

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CHAPTER-1
INTRODUCTION

The fundamental task in identity management is to establish the association between an individual and his personal identity. For person recognition, one must be able to determine a person's identity or verify the identity claim of an individual whenever required. Facial recognition technology has emerged as an attractive solution to address many contemporary needs for identification and the verification of identity claims. Face recognition is a challenging problem because faces vary highly in shape, size, color and texture. The appearance of a person may be affected by lighting conditions, facial expressions, occlusions or facial features, such as beard, mustaches and glasses. The orientation (upright, rotated) of the face also poses a challenging task.

Face recognition from videos has become an active topic in the field of object recognition and computer vision. The development of a robust face recognition system has been the aim of many researchers. While face recognition from static images have been widely used and developed, face recognition from videos has gained interest of researchers. By fusing information from multiple frames and temporal information of faces from the videos, the accuracy of face recognition in videos can be improved.

1.1 OBJECTIVE

The main objective of this project is to develop a robust feature set which will help in the recognition of face from videos. A novel feature set called the difference theoretic feature set along three orthogonal planes (DTTF-TOP) is proposed here. The DTTF-TOP is compared to a very efficient feature extraction technique called the local binary pattern along three orthogonal planes (LBP-TOP). The experimental analysis is carried out on the extended Cohn-Kanade database (CK+). The results obtained from face recognition using the DTTF-TOP feature set are also compared with a template based cross correlation (TBCC) method and a face feature weighted fusion based on fuzzy membership degree for video face recognition. Comparison of our DFFT-TOP feature set results with other existing video based face recognition techniques will help us to analyze the efficiency of our feature set.

The drastic changes in the appearance of a person caused by facial expressions may be considered a challenge in face recognition. Therefore, our objective is to use the proposed DTTF-TOP feature set to work on such situations and correctly recognize faces using videos. The extended Cohn-Kanade database is used as it consists of several videos of subjects with different expressions such as surprise, anger, sad, happy, etc.

CHAPTER-2
LITERATURE REVIEW

Earlier, the recognition of faces was a considered a very challenging task. But now researchers have come up with solutions to built face recognition systems which could capture, detect, extract and recognize a person's face efficiently. Due to the practical importance of the subject as well as theoretical interest from cognitive scientists, face recognition has always been a topic of interest among researchers. The need of making a system that would recognize a face just as a human does have always intrigued the researchers to come up with better systems which will be robust and efficient in every aspect.

Even though methods of identification such as fingerprints, iris scans, etc can give more accurate results, a major focus of research has been placed on face recognition as the method is non-invasive in nature and also it is one of the primary methods of identifying a person[11].

Face recognition has many practical applications such as checking criminal records, verification area, and identification of a person at a highly secured place, detection of a criminal at a public place, etc. A face recognition system can operate in either or both of two modes: (i) Face verification (or authentication) (ii) Face identification (or recognition)[6]. Face verification involves a one-to-one match where a query face image is compared against all the other stored template images in the database [6].

Face recognition from videos has become an active topic in the field of object recognition and computer vision. While face recognition from static images have been widely used and developed, face recognition from videos has gained interest of researchers. By fusing information from multiple frames and temporal information of faces from the videos, the accuracy of face recognition in videos can be improved[6]. In [5], the experiments indicate that static image-based systems are more sensitive to image quality than their spatio-temporal representation counterpart.

Categorization of face recognition can be made into anyone of the three following scenarios on the basis of the characteristics of images the images to be matched:- i) Still-to-Still recognition, ii) Video-to-Image recognition iii) Video-to-Video recognition[6]. Still-to-Still recognition involves matching of a still image against a database of other still images, for example mug shots, id cards, etc [6]. In Video-to-Image recognition a sequence video frames is matched against a database of still images [6]. It can be considered as an extension of face recognition using based on still images. Video-to-Video recognition involves matching of video sequence against a database of other video sequences [6].

2.1 VIDEO-BASED FACE RECOGNITION

There has been an increased interest in Video-based face recognition techniques primarily based on the idea expressed by psychologists from their studies that humans recognize faces through motion especially in most cases when the spatial image quality is low[6]. The traditional recognition algorithms are mostly based on static images but video-based face recognition has been gaining attention for decades. It is categorized into two approaches (i) Set-based and (ii) Sequential-based approaches [6]. Set-based approaches consider videos as unordered collections of images and take advantage of the multitude of observations where as sequential-based approaches explicitly use temporal information to increase efficiency or enable recognition in poor viewing conditions.

Face recognition system consists of three modules: (i) Face detection module (ii) Face Extraction module (iii) Face Recognition module [6].

Face Detection Module: The face detection module detects a face from every frame of the video sequence. This module operates on both static as well as dynamic images. When working on static images the procedure is called face localization and when working on dynamic images it is called face tracking [7]. The main purpose of this module is to localize and extract the face area from the background.

Feature Extraction Module: After detection of the face and separation from the background, the features of the face are extracted. The two types of features that can be extracted are (i) Geometric features and (ii) Appearance features [6]. Geometric features are those that represent shape and location of facial components such as eyes, noses, eyebrows, mouth, etc. Appearance based features present the skin texture changes of the face, such as furrows, wrinkles, etc.

Face Recognition Module: The face recognition module uses the extracted features of the face and compare it against the features present in the database. The features of the training and test subjects are compared with one another and then classified into different classes using an appropriate classifier.

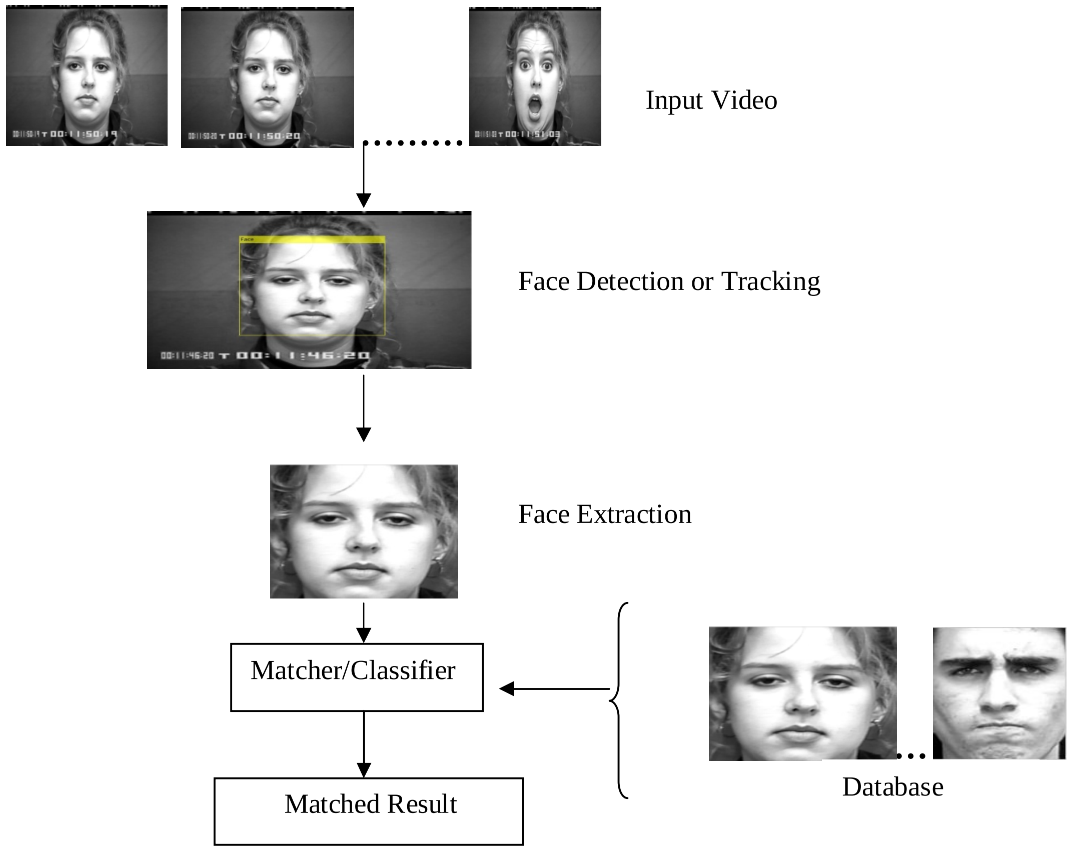


Figure 2.1.1Example of a Video-Based Face Recognition System

2.2 FEATURE EXTRACTION AND MATCHING

The matching of detected faces follows mainly follows three approaches: i) Texture-based ii) Appearance-based and iii) Model-Based techniques[11].

Texture-Based Techniques: The texture-based techniques are used to find local features which are robust and invariant to lighting or pose variations. LBP-TOP is an example of such technique[11].

Appearance-Based Techniques: These techniques map the high dimensional face image into a lower dimensional sub-space. A training set of images are used for learning to form a set of representative basic vectors which defines the subspace. Examples are Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), etc[11].

Model-Based Techniques: These techniques facilitate matching of face images by attempting to build 2D or 3D face models in the presence of pose variations. Example Face Bunch Graphs, etc[11].

2.3 LOCAL BINARY PATTERNS ALONG THREE ORTHOGONAL PLANES (LBP-TOP)

The Local Binary patterns (LBP) is used in the field of computer vision as a type of feature for classification. In texture classification it is considered as a powerful feature. The LBP feature set can be constructed using the following steps [8]:

- The examined window is divided into cells.
- Each pixel in the cells is compared with each of its 8 neighbors. The comparison is done in a circular manner (clockwise or anti clockwise) .
- If the value of center pixel is greater than the neighboring value, value "1" is assigned or else assign the value"0". With this we get a 8-digit binary number.
- The histogram of the frequency of occurrence of each number is computed
- The histogram is normalized if required.
- The feature vector for the window is formed by concatenation of histogram of all the cells.

The value of the LBP code of a pixel is given by:

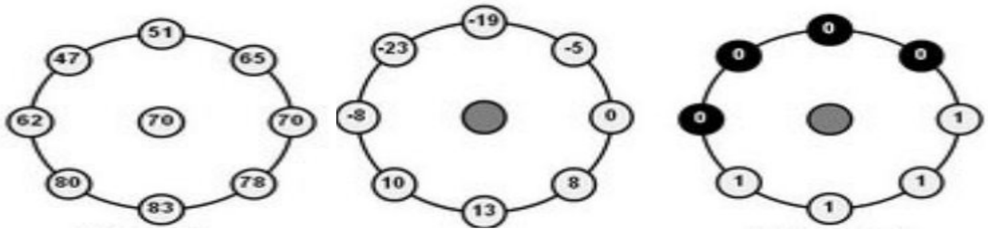
$$LBPp,r = \sum_{p=0}^{p-1} s(gp - gc)2^{p} \quad , \quad s(x) = \begin{cases} 1, if & x >= o \\ 0, & otherwise \end{cases} \tag{2.3.1}$$

Where, r = radius of the circle,

p = number of sampling points on the circle,

gc =gray value of center pixel and

gp =gray value of pixels on the circle.



1. Sample **2. Difference** **3. Threshold**

1*1+1*2+1*4+1*8+0*16+0*32+0*64+0*128=15

4. Multiply by powers of two and sum

Figure 2.3.1: An example of LBP computation

In order to reduce the size of the feature vector and for a simple rotation-invariant descriptor to be implemented, uniform patterns [10] are used. If the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa on circular traversal of the pattern, then it is called a uniform pattern[9]. For example, if we consider patterns 00000000, 01110000 and 11001111, they are uniform as they have 0, 2 and 2 transitions respectively. In case of patterns 11001001 and 01010010, they are non-uniform as they have 4 and 6 transitions respectively. A separate label is assigned for each pattern in case of uniform patterns and a single label is assigned for the remaining non-uniform patterns in order to compute the LBP labels. For example, when we use a neighborhood of (8, R) , we have 256 patterns where 58 of them are uniform and this will give us 59 different labels [9].

LBP-TOP (Three Orthogonal Planes) considers XY, XT and YT as the three orthogonal planes and concatenates the co-occurrence statistics of the local binary pattern in each of the three directions. The spatial coordinates are denoted by X and Y, and the frame index (time) is denoted by T. LBP-TOP considers the feature distributions from each separate plane and concatenates them together to form the feature vector.

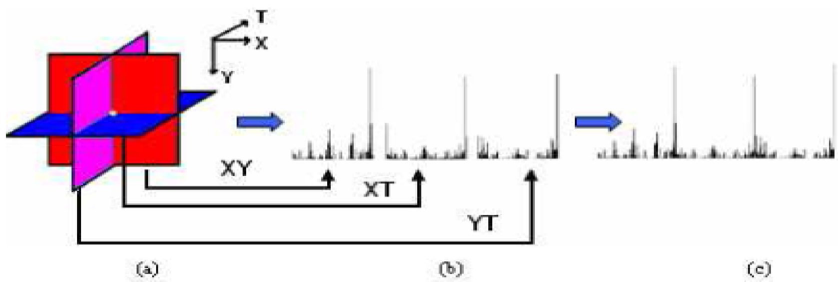


Figure 2.3.2: (a) The three orthogonal planes. (b)LBP histogram from each plane (c) Concatenated feature histogram.

An example of images from the three planes is shown in Fig 2.3.2 (a, b & c). The appearance information is represented by XY plane, a visual impression of one row changing in time is represented by the XT plane and the motion of one column in temporal space is represented by YT plane. For all the XY, XT and YT planes, the LBP codes are computed and are denoted as XY-LBP, XT-LBP and YT-LBP respectively. For each plane, the histograms are computed and concatenated into a single histogram [2].

2.4 AUTOMATIC FACE RECOGNITION FROM VIDEO SEQUENCES USING A TEMPLATE BASED CROSS-CORRELATION

This method of face recognition from video sequences uses a template based cross correlation technique [12]. The method involves the three major steps: i) Preprocessing ii)Template Generation(using Viola-Jones Detector) and iii) TBCC based face recognition[12].

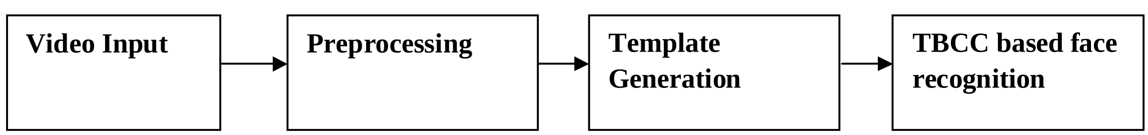


Figure 2.4.1: The processing diagram of TBCC method

Preprocessing Step: Before the proposed TBCC based recognition is carried out, first the preprocessing must be performed to ensure no variations between videos. The number of frames is taken to be 10 per video sequence.

Template Generation: The template generation for face recognition purpose is done using the Viola-Jones detector. The detector detects the face from each frame of the input video sequence and then the detected faces are extracted and stacked together for further computation.

TBCC for face recognition: The proposed method involves the transforming and concatenating of frames to an X*Y*P matrix, to obtain a discriminant feature representation for face recognition in a video sequence. X and Y are the original sizes of the matrix and P is the total frames used.

The TBCC utilizes the correlation between the convolution of complex functions in order to obtain the correlations between the training and test data samples[12]. The TBCC for the testing and training data can be computed using eqn 2.4.1,

$$\gamma(u,v) = \frac{\sum_{x,y}[f(x,y) - f_{u,v}][t(x-u, y-v) - \bar{t}]}{\sqrt{\sum_{x,y}[f(x,y) - \bar{f}u,v]^2 \sum_{x,y}[t(x-u,y-v) - \bar{t}]^2}} \quad (2.4.1)$$

Where, (u,v) are the shifts for (x,y) in time domain,

f(x,y) and t(x,y) represents the two matrices from testing and training data,

$\bar{f}$ and $\bar{t}$ are the average facial templates for f and t respectively,

$\gamma(u,v)$ is the result of the correlated matrices.

The correlation is computed for each data sample with other samples. For the final decision, the average values of every subject are used. The category c to which a testing sample f' belongs to is determined using eqn 2.4.2,

$$c = \arg\max_{c_i}(\gamma, f', t_i) \quad (2.4.2)$$

Where, c_i are the subjects in the training database and t_i is the training feature vectors.

2.5 FACE WEIGHTED FUSION TECHNIQUE BASED ON FUZZY MEMBERSHIP DEGREE FOR VIDEO FACE RECOGNITION

A new video face recognition method based on weighted fusion approach is used [4]. It aims at bringing a significant improvement of face recognition accuracy by adaptively fusing the features extracted from the multiple face images. In order to compute the optimal weights of face features to be fused, a weight determination method based on fuzzy membership function and quality measurements for face images is used. The proposed weight determination method has three sequential steps: (i) Face rejection (ii) Selection of Prototype face images and (iii) Using fuzzy membership function to compute weights[4].

The face rejection step is used to reject misaligned faces images which are incorrectly rotated or scaled. Here, the prototype images are those face images with small deviation from frontal pose and frontal lighting with high sharpness. The weight determination solution takes advantage of the fuzzy membership function based on the similarity view theory where membership is a notion of being similar to the prototype of the category. $F=\{I_m\}^{M}_{m=1}$ represents the face sequence after the face rejection procedure. Let $\{\tilde{I}_n\}_{n=1}^{K}$ denote a set of K prototype face images selected, where, $\tilde{I}_n \varepsilon F$, $\{\tilde{f}_n\}_{n=1}^{K}$ be face features corresponding to the nth prototype face image. The distance metric L_p (Minkowski metric) between face features f_m and $\tilde{f}_n$ of I_m and $\tilde{I}_n$ is used to measure the distance defined by

$$d_p(m,n) = (\sum_{k=1}^{D} | f_m^{(k)} - \tilde{f}_n^{(k)} |^p)^{1/p} \qquad (2.5.1)$$

Where, $f_m^{(k)}$ denotes K^{th} element of the feature vector f_m

D denotes dimension of the considered feature vectors.

The sum of distances with all the selected prototype features is the distance criterion for the f_m under consideration. It is defined by

$$d_p(m,n) = \sum_{n=1}^{k} d_p(m,n) \qquad (2.5.2)$$

The membership value for I_m is calculated by

$$\mu_m = \exp(-d_p(m)^r / \beta) \qquad (2.5.3)$$

Where, the parameters r and β are to be determined. The adjustment of the weighting effect of the membership function is done by the value r, and β is a weight threshold.

Within a face sequence, the weight which has to be assigned to each image is computed by

$$w_m = \frac{\mu_m}{\sum_{m=1}^{M} \mu_m} \qquad (2.5.4)$$

Several feature extraction techniques such as FLDA(Fischer’s Linear Discriminant Analysis), RLDA(Regularized Linear Discriminant Analyisis), etc can be used for construction of feature extractors for computing face features[4].

2.6 THE BASIC FACE EMOTIONS

The facial expression of a person is brought about by different emotions that a person feels. Some of the basic face emotions[3] that a person displays are:

i) Sad: A person feeling a sad emotion would usually have the brow raised and depression of the lip corner.

ii) Happy: A happy expression is easily recognizable with the lip corner being pulled up which indicates a smile.

iii) Surprise: A surprised expression is usually characterized by high rise of the eyebrows and opening of the mouth for an instantaneous reaction.

iv) Angry: People with an angry expression usually have the lips pressed or tightened.

v) Mild Surprise: A mild surprise expression is hard to distinguish as the reaction is usually mild.

vi) Disgust: A person showing disgust would usually have the lips pressed and the nose wrinkled.

vii) Fear: A fearful expression is usually characterized by a slightly open mouth and slanted brows.

The examples of the subjects showing different face emotions are:

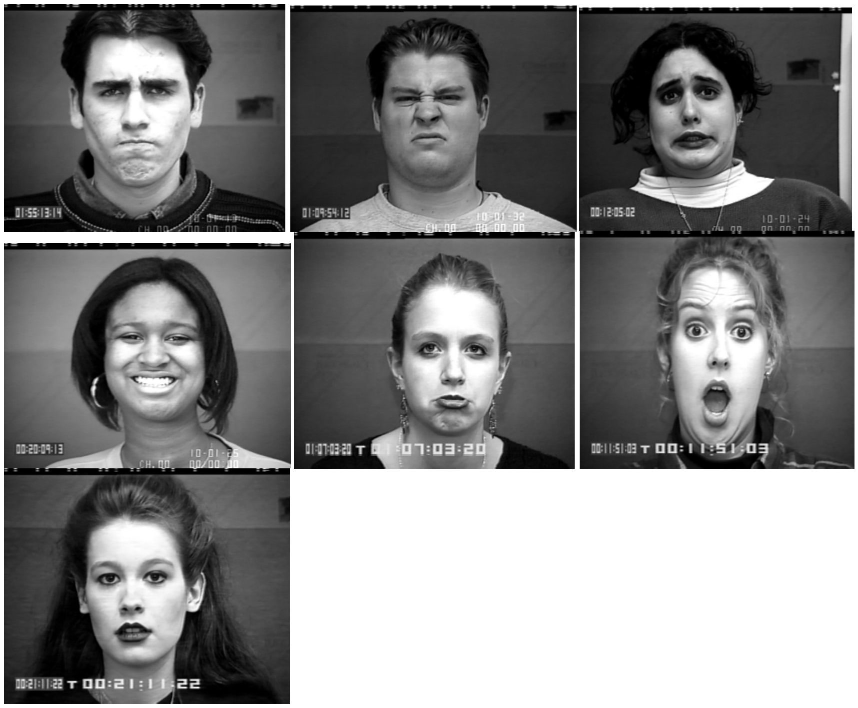


Fig 2.6.1: Images of Subjects expressing different emotions. (a)Angry, (b) Disgust, (c) Fear, (d) Happy, (e) Sad, (f) Surprise, (g) Mild Surprise

CHAPTER-3
INTRODUCTION TO THE DIFFERENCE THEORETIC FEATURES (DTTF)

3.1 INTRODUCTION

The difference theoretic texture feature set for scale, illumination and rotation invariant texture classification was proposed by Seba Susan and Madasu Hanmandlu[1]. Using this feature set experiments were performed on different texture samples of varying scale, orientation and brightness. The feature set proposed by Seba Susan and Madasu Hanmandlu has 11 features and was implemented on static textures.

The feature set is derived using the differences of the local and global intensities and their histograms which are invariant for a texture class. The feature set takes into consideration that there exists a correlation between the local pattern associated with a pixel and the actual pixel intensity[1]. The local pattern here is defined by the grey level difference of a pixel with its next immediate neighbor in the horizontal (H), vertical (V) and diagonal (D) directions taken separately to preserve the orientation information of the texture [1]. The global information regarding pixel intensity is global contrast, which is equal to the difference of pixel intensity with mean luminance of the image [1]. A higher value of correlation between local and global grey level differences in the texture would mean that the texture is more regular.

The difference theoretic texture feature set is given by

$$D = \frac{1}{M*N}[AD_H, AD_V, AD_D, \mathrm{B_H}, \mathrm{B_V}, \mathrm{B_D}, \mathrm{E}, \mathrm{C}, \mathrm{A_H}, \mathrm{A_V}, \mathrm{A_D}] \qquad (3.1.1)$$

Equation (1) can be rewritten as

D=[absdiffH,absdiffV,absdiffD,pdiffH,pdiffV,pdiffD,absY,pY,pdiffHY,pdiffVY, pdiffDY]

(3.1.2)

The difference theoretic feature set has been computed using the following steps:

Step 1: The absolute differences between a pixel and its immediate neighbor are computed for the horizontal, vertical and diagonal directions. These absolute differences for each direction are then summed up and their average taken. Local differences with value as zero indicates the same grey level intensities and therefore zero information from those pixels of the image[1].

In an M*N image, with pixels(i,j) where, i=1,…,M and j=1,….,N , the features obtained are

$$absdiffH = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} |f(i,j) - f(i,j+1)|}{M * N} \quad (3.1.3)$$

$$absdiffV = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} |f(i,j) - f(i+1,j)|}{M * N} \quad (3.1.4)$$

$$absdiffD = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} |f(i,j) - f(i+1,j+1)|}{M * N} \quad (3.1.5)$$

Step 2: The number of times a local difference repeats along the Horizontal (H), Vertical (V) and Diagonal directions is computed. The regularity of a texture will be higher if the number of occurrences of a specific difference pattern along H, V, and D directions is greater. The mean probability of occurrence of patterns along the H, V and D directions is obtained by first plotting the histograms of the signed grey level differences along H, V and D directions for the entire image[1].

Let h, v and d represent random variables which denote signed grey level differences computed in H, V and D directions and quantized to Q=128 bins. The probability values p_h, p_v, p_d from the h ,v ,d histograms are mapped back to each pixel in the image by matching the indices of the histogram with actual h ,v, d values at the pixel, and then these probabilities are averaged over all the pixels in the video sequence. The resulting feature vector is capable of discriminating the regular textures from the irregular ones. The features are computed from

$$pdiffH = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} p_h((f(i,j) - f(i,j+1))_Q)}{M * N} \quad (3.1.6)$$

$$pdiffV = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} p_v((f(i,j) - f(i+1,j))_Q)}{M * N} \quad (3.1.7)$$

$$pdiffD = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} p_d((f(i,j) - f(i+1,j+1))_Q)}{M * N} \quad (3.1.8)$$

Step 3: Here, the global contrast of a pixel with mean luminance of the image and the number of times it occurs in the image are measured. The information about local pattern mentioned in Steps 1 and 2 does not reflect the role that the intensity of the pixel plays in the global image scenario[1]. Therefore, we incorporate mean global contrast of the pixels in an image with respect to the mean luminance of the entire texture patterns, absY is defined by

$$absY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} | f(i, j) - \mu |}{M * N} \quad (3.1.9)$$

The mean luminance of the image is given by

$$\mu = \frac{1}{M * N} \sum_{i=1}^{M} \sum_{j=1}^{N} f(i, j) \quad (3.1.10)$$

Let g represent the random variable for denoting signed global differences in an image. Then, the mean frequency of occurrence of global differences throughout the video sequence pY , is obtained by mapping back to each pixel the probability values p_g from the histogram of the global differences quantized to Q=128 bins[1], and averaging the probabilities over all pixels as shown in (3.1.11).

$$pY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} p_g(f(i, j) - \mu)_Q)}{M * N} \quad (3.1.11)$$

Step 4: The number of times a specific global contrast is associated with a specific local pattern in the H, V and D directions is computed. The steps from 1-3 represent both local pattern information and pixel intensity taken separately; however, some measure is required to evaluate the number of times they occur together in the image[1]. This leads to the calculation of joint probability of local differences and the global contrasts which are averaged over the H,V and D directions to form the features below:

$$pdiffHY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} p_{hg}((f(i, j) - f(i, j+1))_Q, (\mathrm{f(i, j)} - \mu)_Q)}{M * N} \quad (3.1.12)$$

$$pdiffVY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} p_{vg}((f(i, j) - f(i+1, j))_Q, (\mathrm{f(i, j)} - \mu)_Q)}{M * N} \quad (3.1.13)$$

$$pdiffDY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} p_{dg}((f(i, j) - f(i+1, j+1))_Q, (\mathrm{f(i, j)} - \mu)_Q)}{M * N} \quad (3.1.14)$$

CHAPTER-4
INTRODUCTION TO THE PROPOSED DIFFERENCE THEORETIC TEXTURE FEATURES ALONG THREE ORTHOGONAL PLANES (DTTF-TOP)

4.1 INTRODUCTION

The feature set called the Difference Theoretic Texture Features along three orthogonal planes is derived from the Difference Theoretic Texture Features Set (DTTF) proposed by Seba Susan and Madasu Hanmandlu [1]. The DTTF-TOP works similar to the LBP-TOP features where the Three Orthogonal Planes (TOP) are considered for dynamic textures[3]. But unlike the LBP-TOP which considers the circular neighborhood around a pixel for computation, the DTTF-TOP considers the immediate vertical, horizontal and diagonal neighbors of the pixel along the three orthogonal planes similar to the DTTF.

From the DTTF feature set, we derive the new DTTF-TOP feature set which has 20 features. In DTTF-TOP, depth of the video is considered. Here, apart from the vertical (V), horizontal (H) and diagonal (D) neighbors, three additional variables R1, R2 and R3 are taken to incorporate the neighbors along the three orthogonal planes.

The DTTF-TOP feature set is given by

$$D = \frac{1}{M * N}[AD_H, AD_V, AD_D, AD_{R1}, AD_{R2}, AD_{R3}, B_H, B_V, B_D, B_{R1}, B_{R2}, B_{R3}, E, C, A_H, A_V, A_D, A_{R1}, A_{R2}, A_{R3}] \quad (4.1.1)$$

Equation (4.1.1) can be rewritten as

D=[absdiffH,absdiffV,absdiffD,absdiffR1,absdiffR2,absdiffR3,pdiffH,pdiffV, pdifD,pdiffR1,pdiffR2,pdiffR3,absY,pY,pdiffHY,pdiffVY,pdiffDY,pdiffR1, pdiffR2, pdifR3]
(4.1.2)

Step 1: The absolute differences between a pixel and its immediate neighbor are computed for the horizontal, vertical and diagonal directions. These absolute differences for each direction are then summed up and their average taken. Local differences with value as zero indicates the same grey level intensities and therefore zero information from those pixels of the image. Here, the length/depth of the video (length, l) is considered in order to get the temporal features of the video.

In an M*N image, with pixels(i,j,l) where, i=1,…,M , j=1,….,N and l=1,….,L(depth of video) the features obtained are

$$absdiffH = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} |f(i,j,l) - f(i,j+1,l)|}{M * N} \tag{4.1.3}$$

$$absdiffV = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} |f(i,j,l) - f(i+1,j,l)|}{M * N} \tag{4.1.4}$$

$$absdiffD = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} |f(i,j,l) - f(i+1,j+1,l)|}{M * N} \tag{4.1.5}$$

$$absdiffR1 = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} |f(i,j,l) - f(i,j,l+1)|}{M * N} \tag{4.1.6}$$

$$absdiffR2 = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} |f(i,j,l) - f(i+1,j,l+1)|}{M * N} \tag{4.1.7}$$

$$absdiffR3 = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} |f(i,j,l) - f(i,j+1,l+1)|}{M * N} \tag{4.1.8}$$

Step 2: The number of times a local difference repeats along the Horizontal (H), Vertical (V) and Diagonal directions is computed. The regularity of a texture will be higher if the number of occurrences of a specific difference pattern along H, V, and D directions is greater. The mean probability of occurrence of patterns along the H, V and D directions is obtained by first plotting the histograms of the signed grey level differences along H, V and D directions for the entire image.

Let h, v, d, r1,r2 and r3 represent random variables which denote signed grey level differences computed in H, V and D directions and quantized to Q=128 bins. The probability values p_h, p_v, p_d, p_{r1}, p_{r1}, p_{r2}, and p_{r3} from the h,v,d ,r1,r2 and r3 histograms are mapped back to each pixel in the image by matching the indices of the histogram with actual h,v,d,r1,r2 and r3 values at the pixel, and then these probabilities are averaged over all the pixels in the video sequence. The resulting feature vector is capable of discriminating the regular textures from the irregular ones. The features are computed from

$$pdiffH = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_h((f(i,j,l) - f(i,j+1,l))_Q)}{M * N} \tag{4.1.9}$$

$$pdiffV = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_v((f(i,j,l) - f(i+1,j,l))_Q)}{M * N} \tag{4.1.10}$$

$$pdiffD = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_d((f(i,j,l) - f(i+1, j+1, l))_Q)}{M*N} \tag{4.1.11}$$

$$pdiffR1 = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{r1}((f(i,j,l) - f(i,j,l+1))_Q)}{M*N} \tag{4.1.12}$$

$$pdiffR2 = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{r2}((f(i,j,l) - f(i+1, j, l+1))_Q)}{M*N} \tag{4.1.13}$$

$$pdiffR3 = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{r3}((f(i,j,l) - f(i, j+1, l+1))_Q)}{M*N} \tag{4.1.14}$$

Step 3: Here, the global contrast of a pixel with mean luminance of the image and the number of times it occurs in the image are measured. The information about local pattern mentioned in Steps 1 and 2 does not reflect the role that the intensity of the pixel plays in the global image scenario. Therefore, we incorporate mean global contrast of the pixels in an image with respect to the mean luminance of the entire texture patterns, absY is defined by

$$absY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} |f(i,j,l) - \mu|}{M*N} \tag{4.1.15}$$

The mean luminance of the image is given by

$$\mu = \frac{1}{M*N} \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} f(i,j,l) \tag{4.1.16}$$

Let g represent the random variable for denoting signed global differences in an image. Then, the mean frequency of occurrence of global differences throughout the video sequence pY , is obtained by mapping back to each pixel the probability values p_g from the histogram of the global differences quantized to Q=128 bins, and averaging the probabilities over all pixels as shown in (32).

$$pY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_g(f(i,j,l) - \mu)_Q)}{M*N} \tag{4.1.17}$$

Step 4: The number of times a specific global contrast is associated with a specific local pattern in the H, V and D directions is computed. The steps from 1-3 represent both local pattern information and pixel intensity taken separately; however, some measure is required to evaluate the number of times they occur together in the image. This leads to the calculation of joint probability of local differences and the global contrasts which are averaged over the H,V and D directions to form the features below:

$$pdiffHY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{hg}((f(i,j,\mathrm{l}) - f(i,j+1,l))_{\mathrm{Q}}, (\mathrm{f(i,j,l)} - \mu)_{\mathrm{Q}})}{M*N} \quad (4.1.18)$$

$$pdiffVY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{vg}((f(i,j,\mathrm{l}) - f(i+1,j,l))_{\mathrm{Q}}, (\mathrm{f(i,j,l)} - \mu)_{\mathrm{Q}})}{M*N} \quad (4.1.19)$$

$$pdiffDY = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{dg}((f(i,j,\mathrm{l}) - f(i+1,j+1,l))_{\mathrm{Q}}, (\mathrm{f(i,j,l)} - \mu)_{\mathrm{Q}})}{M*N} \quad (4.1.20)$$

$$pdiffR1Y = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{r1g}((f(i,j,\mathrm{l}) - f(i,j,l+1))_{\mathrm{Q}}, (\mathrm{f(i,j,l)} - \mu)_{\mathrm{Q}})}{M*N} \quad (4.1.21)$$

$$pdiffR2Y = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{r2g}((f(i,j,\mathrm{l}) - f(i+1,j,l+1))_{\mathrm{Q}}, (\mathrm{f(i,j,l)} - \mu)_{\mathrm{Q}})}{M*N} \quad (4.1.22)$$

$$pdiffR3Y = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{l=1}^{L} p_{r3g}((f(i,j,\mathrm{l}) - f(i,j+1,l+1))_{\mathrm{Q}}, (\mathrm{f(i,j,l)} - \mu)_{\mathrm{Q}})}{M*N} \quad (4.1.23)$$

CHAPTER-5
IMPLEMENTATION DETAILS

The aim of this project implementation is face recognition through the comparison of facial features of test subjects from among the facial features of training subjects stored in the database. Since DTTF-TOP is a newly proposed feature set, our main focus is to check its efficiency and compare it with other existing video based face recognition techniques.

The DTTF-TOP features are first extracted from the face images and its results compared with that of results from LBP-TOP Features. The results of both these features are then compared to check for better performance. The DTTF-TOP results are also compared with two other video based face recognition techniques. The video based face recognition techniques used for comparison with our proposed method are-i) the automatic face recognition from video sequences using a template based cross-correlation method and ii)the face feature weighted fusion based on fuzzy membership degree for video face recognition.

The face of every subject present in the video sequences are detected and extracted using the Viola-Jones Detector[13]. The detection of face in the video is automated using this method of face acquisition.

The Extended-Cohn Kanade(CK+) Database is the facial database used which consists of several video sequences of different subjects showing emotions such as sad, anger, surprise, etc [3]. Within the past decade, significant effort has occurred in developing methods of facial feature tracking and analysis. This analysis includes both measurement of facial motion and recognition of expression [7]. Researchers work on several images in order to develop robust systems for proper facial expression recognition. However, such systems can be said to work well only if testing is done on a dataset consisting of images of subjects from different age groups and ethnic background [7]. A common dataset is used so that multiple laboratories can determine the relative strengths and weaknesses of their approaches. The Cohn-Kanade(CK) database is one such database which is made available for research work. For our experimental purpose we have considered subjects which have more than one video sequence each. On the basis of this, we selected 107 subjects and a total of 575 videos are used.

Subjects from Extended Cohn-Kanade(CK+) with consent for publication:

1. S52
2. S55
3. S74
4. S106
5. S111
6. S113
7. S121
8. S124
9. S125
10. S130
11. S132

In this thesis, pictures of only those subjects are shown who gave their consent for publication. Every subject has a number of sequences (ranging from 1 to 9 sequences) and each sequence has a number of image frames (ranging from 8 to 45 frames per sequence). An example of the frame composition of a video sequence of 11 subjects is shown in table 5.1.

Table 5.1: Number of frames in each video sequence for 11 subjects

Sequence No. **Subject No.**	**001**	**002**	**003**	**004**	**005**	**006**	**007**	**008**	**009**	**010**	**011**	**012**	**013**
S52	15	22	19	33	-	13	-	-	-	-	-	-	-
S55	12	25	9	28	45	8	-	-	-	-	-	-	-
S74	20	16	15	18	43	-	-	-	-	-	-	-	-
S106	18	16	12	8	35	11	16	-	-	-	-	-	-
S111	14	15	12	10	11	10	14	-	-	-	-	-	-
S113	12	19	15	23	8	21	42	23	-	-	-	-	-
S121	16	17	18	11	14	-	-	-	-	-	-	-	-
S124	14	17	11	29	43	11	24	-	-	-	-	-	-
S125	14	17	8	14	13	22	9	10	-	-	-	-	-
S130	18	30	28	19	9	32	20	19	19	-	-	11	15
S135	11	18	23	15	16	23	19	10	-	-	-	-	-

5.1 CLASSIFIER USED

The one-nearest neighbor classifier is used where the Euclidean distance between the training and test features is considered. The Support Vector Machine is also used for better classification results.

5.2 METHODS USED FOR IMPLEMENTATION

Initially, the DTTF-TOP was tested on a small dataset (i.e., only those subjects who gave their consent for publication) of the CK+ database. 11 subjects in total were used and for each subject two video sequences were taken as test samples and the remaining as training samples. The LBP-TOP and TBCC methods are also implemented for comparison on the small dataset.

The Grid-based partition method is then implemented to increase the recognition rate of the face recognition system. In [15], the LBP face image is partitioned into grids and LBP histograms are computed over each grid cell. Here, we compute the features over every grid cell and are combined together to form one single feature set for that face. In our experiments a 6*7 grid partitioning is used.

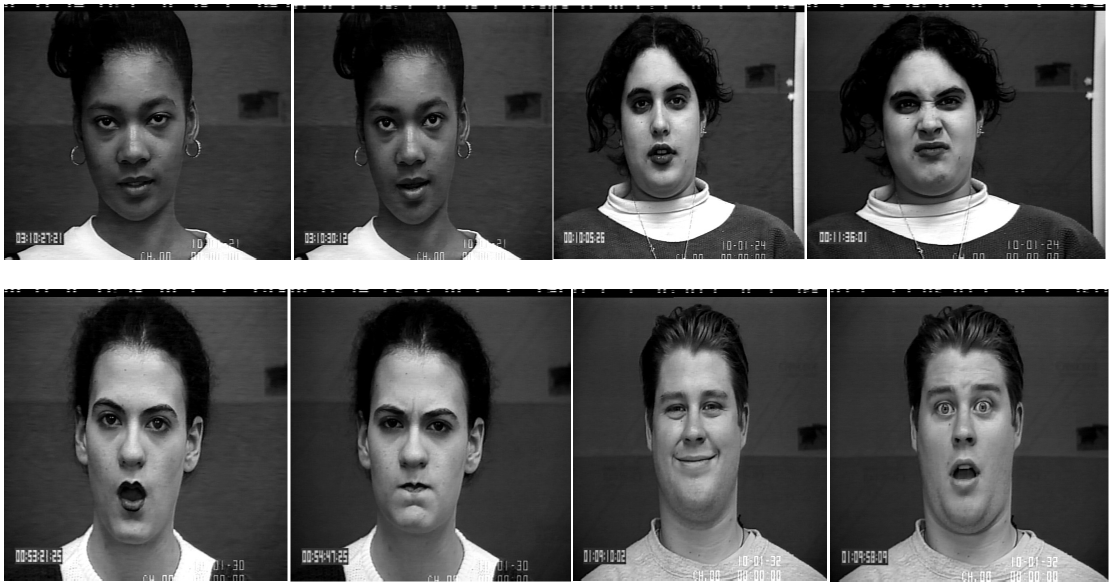
The DTTF-TOP and LBP-TOP features are also tested for the entire CK+ database and the results compared. Since the time taken for TBCC method was very high, this method is ignored for the larger dataset. The face feature weighted fusion based on fuzzy membership degree is also implemented for the video based face recognition and its results compared with that of our proposed DFFT-TOP feature set.

5.3 IMPLEMENTATION STEPS

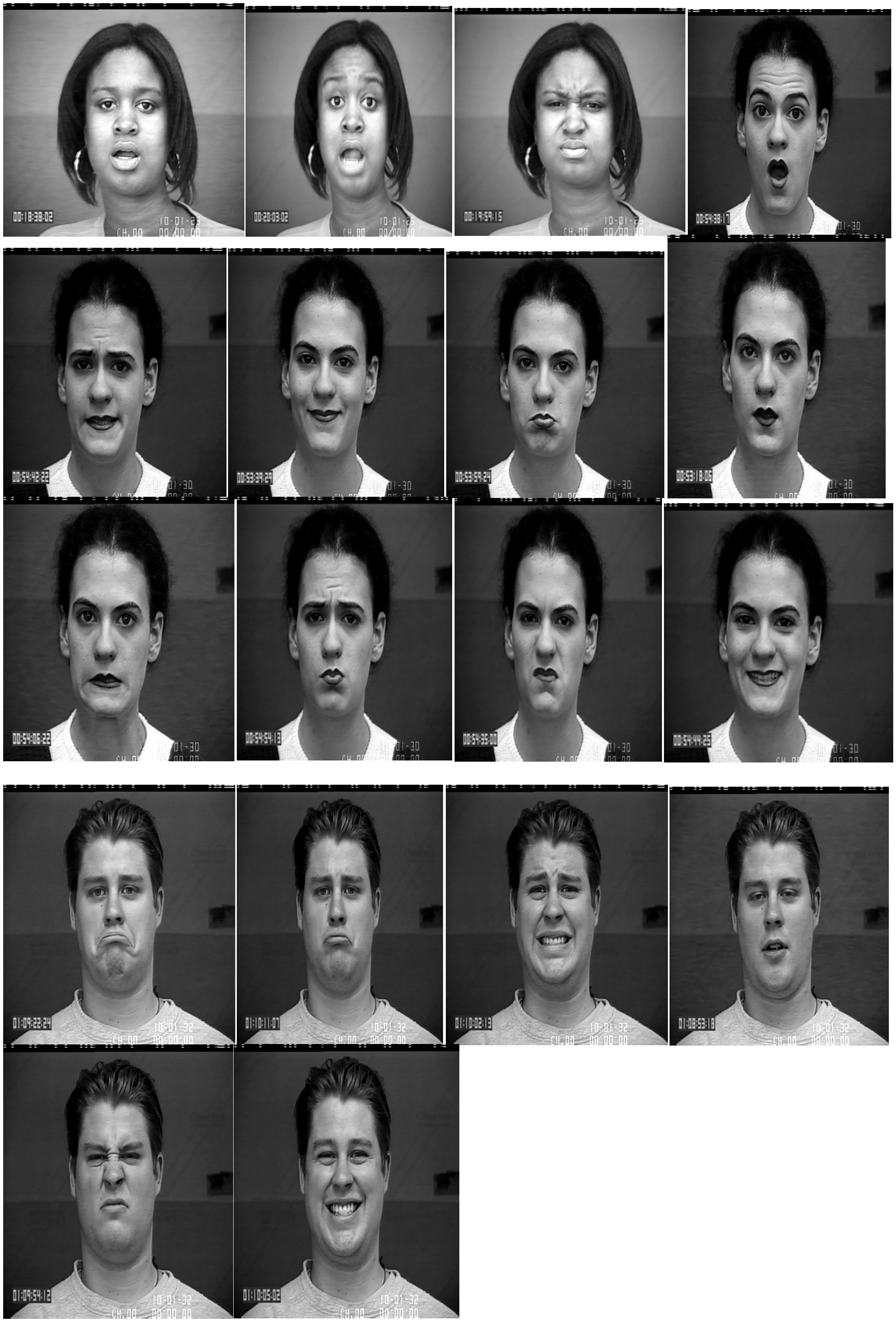
5.3.1 Implementing the DTTF-TOP and LBP-TOP on a small dataset of CK+ database

Step 1: Select two video sequences of each subject which are to be used for feature extraction. These two sequences from each subject will be used as test samples and the remaining will be used as the training samples. The facial features of these training subjects will be standard features against which the features of other test subjects will be measured.

The 22 subjects chosen as test subjects are shown below:



The remaining subjects (55) are taken as the training set and are shown below:



Step 2: Use the Viola-Jones detector on the video to detect the face of the subject.

Fig 5.3.1.1: An example of Face Detection using Viola-Jones Detector

Step 3: Extract the detected faces from the videos and resize them to 292*292 for uniformity throughout the frames in the videos and stack them together.

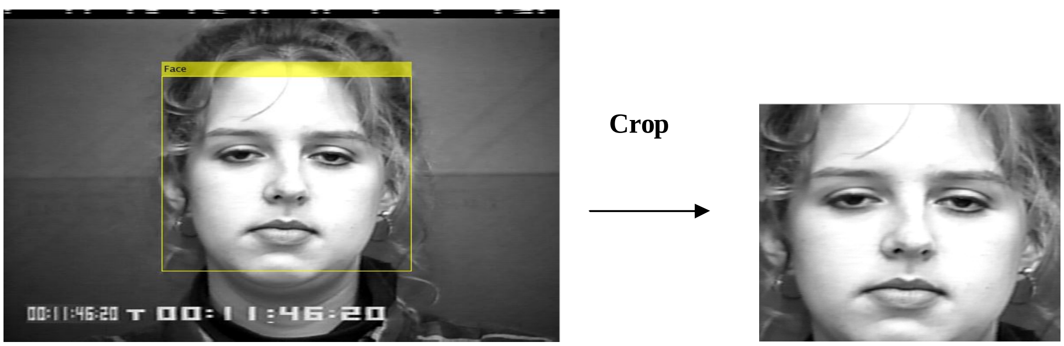


Fig 5.3.1.2: An example of Cropping the detected face

Step 4: Features of the training subjects and test subjects are extracted using the DTTF-TOP and LBP-TOP features, and stored separately. The one-nearest neighbor classifier is used and the distance calculated using the Euclidean distance.

Step 5:. The results of the DTTF-TOP and LBP-TOP features are compared and analyzed. Validation test is performed using the test and training feature set.

Step 6: The cross-validation is then carried out using the training set as the test set and the test set as the training set.

5.3.2 Implementing the Grid-based Partitioning Method for DTTF-TOP and LBP-TOP

Step1: Use the Viola-Jones detector on the video to detect the face of the subject.

Step 2: Extract the detected faces from the videos and resize them to 292*292 for uniformity throughout the frames in the videos and stack them together.

Step 3: Divide each video into 6*7 grids (i.e,42 cells).

Fig 5.1.2.1: 42 cells of the 6*7 Grid

Step 4: Calculate the DTTF-TOP and LBP-TOP features for every cell and store them in a matrix of size 1*840 and 1*7434 respectively.

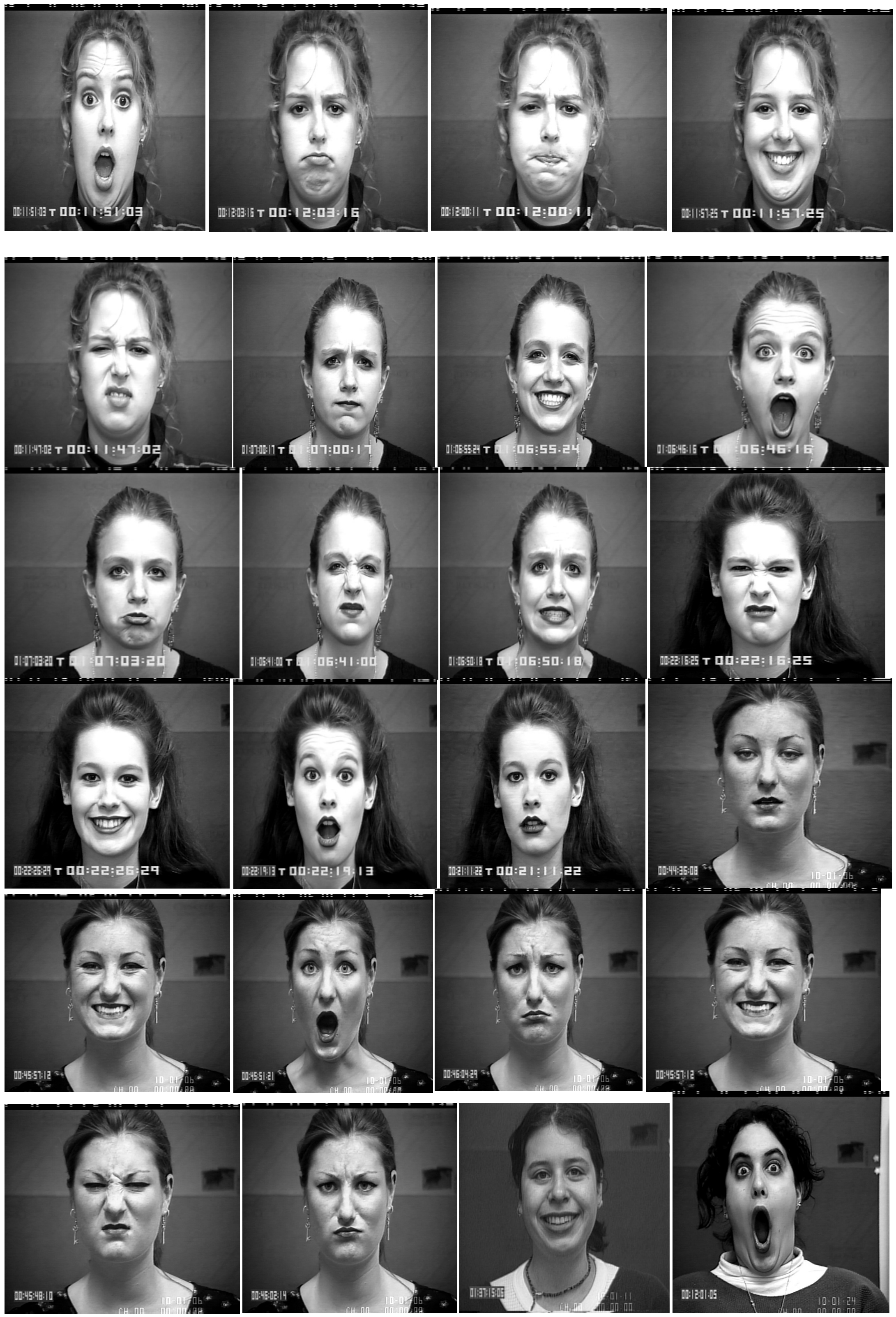
Step 5: Repeat from Step 1 till the features of all the 77 videos have been gathered.

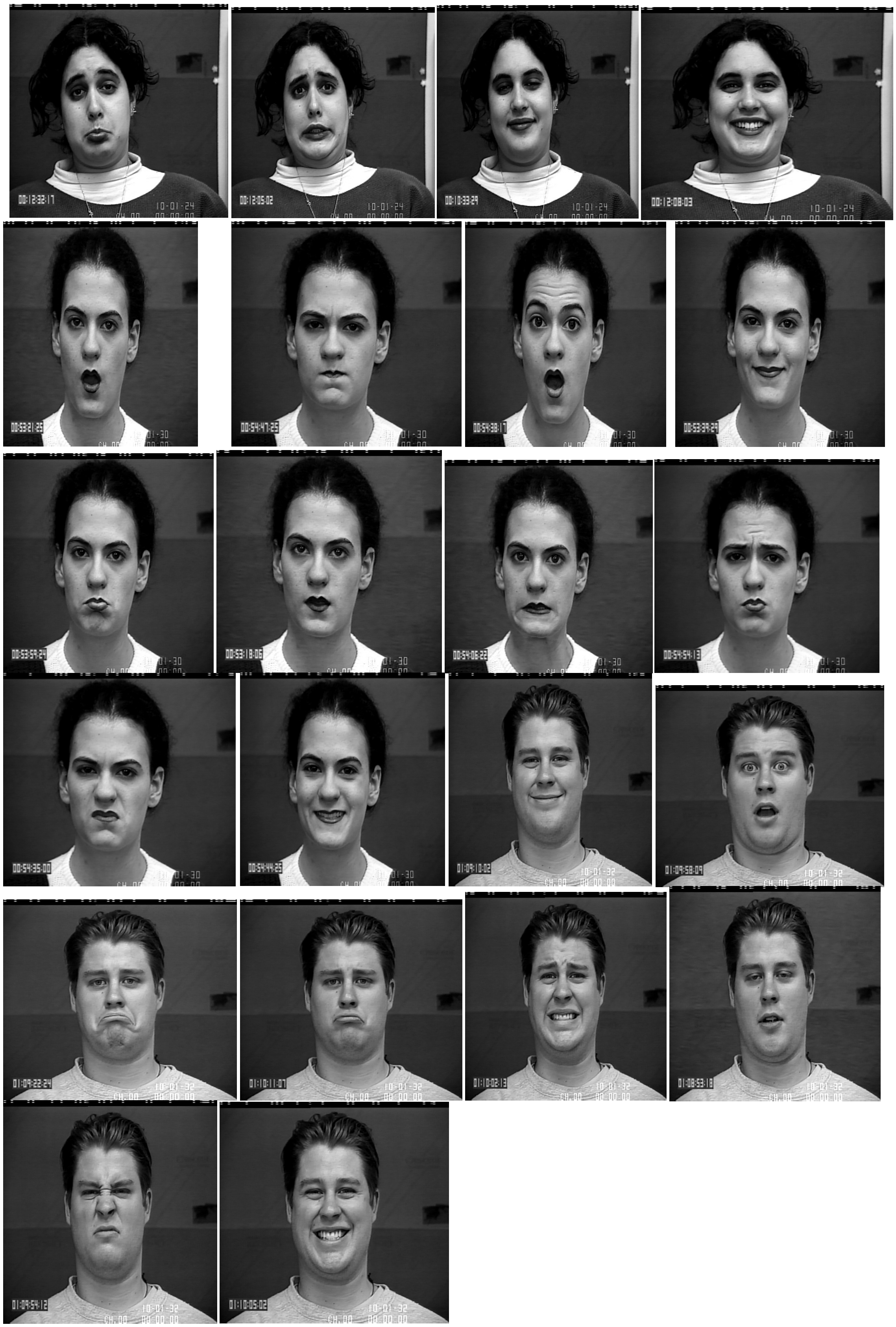
Step 6: Store the final DTTF-TOP and LBP-TOP features in a matrix of size 77*840 and 77*7434 respectively. The one nearest neighbor classifier is used for classification.

Step 7: Validation of the faces are carried out by taking the features in the odd indexes of both the matrices as training features and those at the even indexes as the testing features.

Step 8: Cross Validation test is carried out by taking the features in the even indexes as training features and those at the odd indexes as the testing features.

The 77 sequences of subjects for which features are extracted:





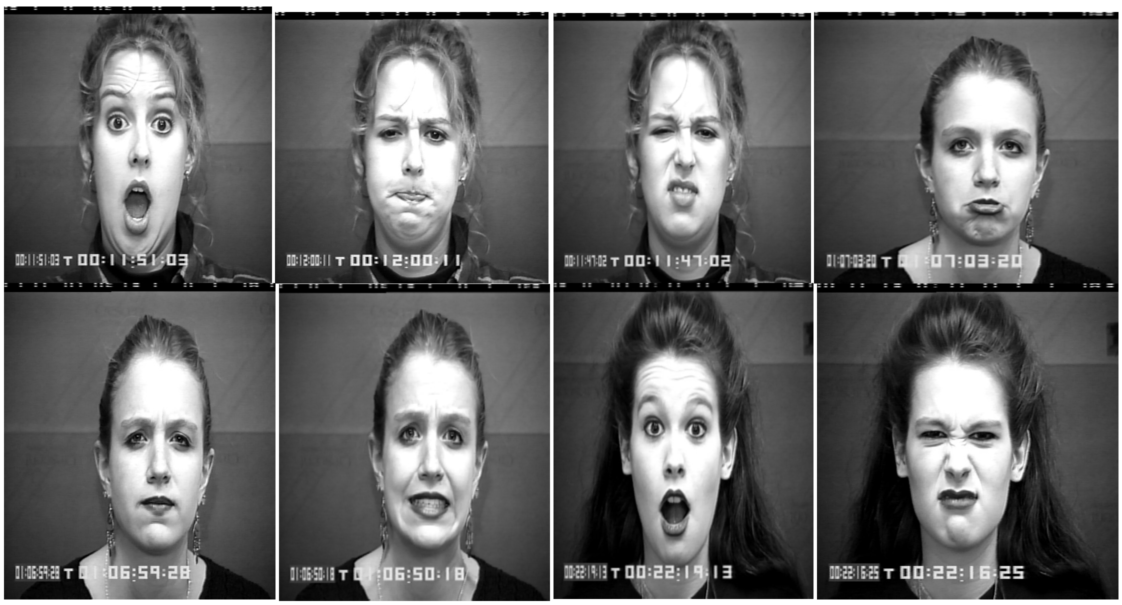
5.3.3 Implementing the TBCC method on a small CK+ dataset

Step1: Use the Viola-Jones detector on the video to detect the face of the subject.

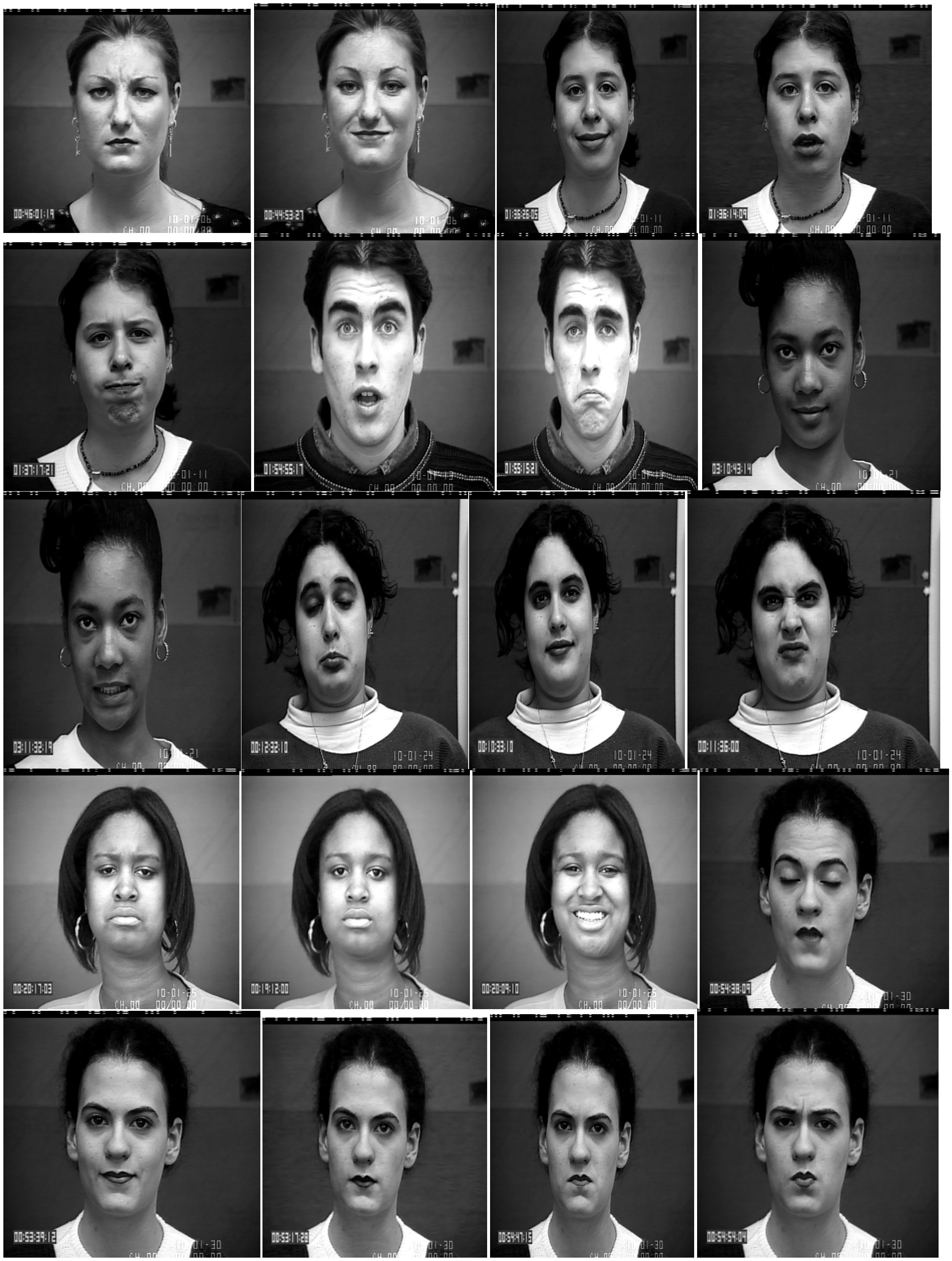
Step 2: Extract the detected faces from the videos and resize them to 292*292 for uniformity throughout the frames in the videos and stack them together.

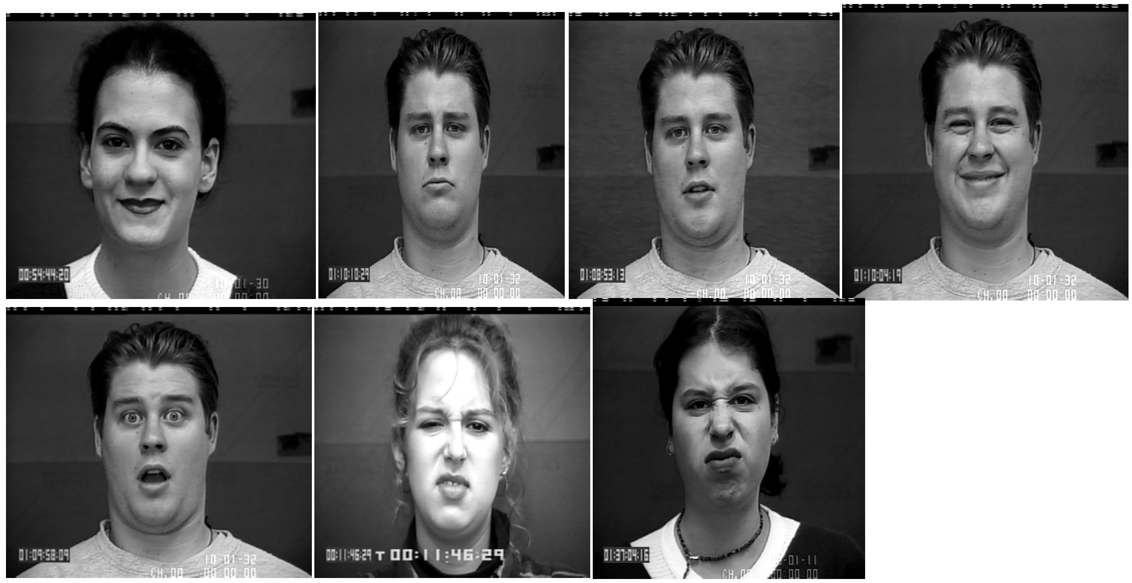
Step 3: Divide the video sequences into training and testing samples. For each video sequence 10 frames are taken for further computation in this method. Therefore, we select only those videos whose frame count is 10 or more (a total of 70 videos are selected).

The 35 video sequences used as training samples are:



The 35 video sequences used as test samples are:





Step 4: Apply the Template Based Cross-Correlation method (eqn 2.4.1) for face recognition and compute the correlated matrices.

Step 5: Using eqn 2.4.2, get the index of the training sample corresponding to the highest value in the correlation matrix.

Step 6: Carry out validation and cross-validation test of the test samples against the training samples. Note down the results.

Step 7: Compare the TBCC computed results with the DTTF-TOP and LBP-TOP results.

5.3.4 Implementing the DTTF-TOP and LBP-TOP on the entire CK+ database

Step1: Use the Viola-Jones detector on each video to detect the face of the subject.

Step 2: Extract the detected faces from the videos and resize them to 292*292 for uniformity throughout the frames in the videos and stack them together.

Step 3: Divide the video sequences into training and testing samples.

Step 4: Calculate the DTTF-TOP and LBP-TOP features for every cell and store them in a matrix of size 1*20 and 1*177 respectively.

Step 5: Repeat from Step 1 till the features of all the 575 videos have been gathered. Keep on storing the final DTTF-TOP and LBP-TOP features in a matrix of size 575*20 and 575*177respectively.

Step 6: The one nearest neighbor classifier as well as the SVM classifier are used for the classification purpose. In SVM classifier we consider two groups of classes. First group is the class of the subject to be recognized. The second group consists of all the remaining classes of subjects in the database. Using this method, average percentage performances for DTTF-TOP and LBP-TOP are computed.

5.3.5 Implementing the face feature weighted fusion based on fuzzy membership degree for video face recognition (using the entire CK+ dataset)

Step 1: Divide the video sequences into test and training samples. For every video sequence 10 frames are considered in this method and so we use only those videos whose frame count is 10 or more (a total of 533 videos are selected).

Step 2: Since in our experimental analysis we are using the extended Cohn-Kanade database where all the faces are properly aligned, we leave out the face rejection step.

Step 3: Viola-Jones face detector is used to detect faces throughout the frames in the video sequence.

Step 4: The DTTF method is used for feature extraction from the face images. For every video sequence 1*110 features are extracted and stored.

Step 5: Select the first frame of the video sequence as the prototype face image.

Step 6: Using eqn 2.5.1, compute the distance between the prototype image and the frames of the video sequence. Consider the value of p as 1.

Step 7: Using eqn 2.5.2, compute the sum of distances with the prototype image for every frame of the video sequence considered.

Step 8: Using eqn 2.5.3, calculate the membership value for every frame of the video sequence. Set the parameters r and β to 1.5 and 1 respectively(as mentioned in the proposed method).

Step 9: Using eqn 2.5.4, the weight to be assigned to each frame of the video sequence is computed.

Step 10: The one nearest neighbor classifier as well as the SVM classifier are used for the classification purpose. In SVM classifier we consider two groups of classes. First group is the class of the subject to be recognized. The second group consists of all the remaining classes of subjects in the database.

Steps 11: The results are then compared with the DTTF-TOP and LBP-TOP results

CHAPTER-6

EXPERIMENTAL RESULTS AND DISCUSSIONS

6.1 EXPERIMENTAL SETUP

The system configurations used while carrying out the experiments are given below:

Hardware Configuration

Processor:	Intel(R) Core(TM)2 Duo CPU
Clock Speed:	2.10GHz
Main Memory:	3GB
Hard Disk Capacity:	300GB

Software Configuration

Operating System:	Windows 7
Software Used:	MATLAB R2013a

The Extended Cohn-Kanade (CK+) database is the facial database used which consists of videos of several subjects displaying facial expressions of different emotions. We have considered only those subjects who had more than one video sequence each. So a total of 107 subjects were selected. 11 subjects who had given permission for publication were used when performing experiments on the small dataset. When experiments were performed on the whole dataset all the 107 subjects were used.

The one nearest neighbor classifier and the Support Vector Machines are used as the classifiers for classification purpose.

In the experimental analysis, the dataset is divided into two parts: 1) Test Samples 2) Training Samples. The test samples are the query videos containing the persons whose identities are to be determined and the training samples are those videos containing persons whose identities are known.

Two types of methods are performed: 1) Validation 2) Cross-Validation. In validation, the test samples are compared against the training samples and the results of the recognition rate are computed. In cross-validation, the training samples earlier considered are now taken as the test samples and the earlier test samples are now taken as the training samples and further results for recognition rate are computed.

There are two feature extraction methods considered for our experimentation purpose: 1) DTTF-TOP and 2) LBP-TOP. The method of Grid- based partitioning is also used to improve the results of recognition rate. The DTTF-TOP results are also compared with two other video based face recognition techniques-i) Automatic face recognition from video sequences using a template based cross-correlation(TBCC) method and ii) Face feature weighted fusion based on fuzzy membership degree for video face recognition. Due to the large amount of time taken for grid-based partition and TBCC method, they are implemented only for a small dataset.

The computation of results is divided into 5 parts according to the method of experiments performed:

1) Using DTTF-TOP and LBP-TOP on 11 subjects (i.e, a small dataset of CK+.)
2) Using the Grid-based partitioning method for DTTF-TOP and LBP-TOP on 11 subjects
3) Implementing the TBCC method on 11 subjects.
4) Using the DTTF-TOP and LBP-TOP on 107 subjects (i.e, the whole CK+ dataset).
5) Implementing the face feature weighted fusion based on fuzzy membership degree for video face recognition (using the entire CK+ dataset)

6.2 COMPARISON OF RESULTS

Table 6.2.1: Results for DTTF-TOP on 11 subjects of CK+ Dataset using one nearest neighbor classifier

Subject No.	TestFeatures	Cross Validation Results	Training Features	Validation Results
1-(S52)	Surprise, Sad, Angry	2/3	Happy, Disgust	2/2
2-(S55)	Surprise, Sad, Disgust, Fear	2/4	Angry, Happy	2/2
3-(S74)	Fear, Surprise, Mild Surprise	3/3	Disgust, Happy	2/2
4-(S106)	Surprise, Sad, Happy, Disgust, Anger	3/5	Mild Surprise, Happy	2/2
5-(S111)	Surprise, Mild Surprise, Happy, Mild Surprise, Disgust	1/5	Happy, Anger	2/2
6-(S113)	Surprise, Fear, Sad, Happy, Sad, Mild Surprise	3/6	Mild Surprise, Anger	2/2
7-(S121)	Happy, Fear, Fear	3/3	Mild Surprise, Mild Surprise	2/2
8-(S124)	Surprise, Sad, Fear, Happy, Happy	3/5	Mild Surprise, Disgust	2/2
9-(S125)	Sad, Happy, Sad, Mild Surprise, Surprise, Disgust	3/6	Happy, Fear	2/2
10-(S130)	Surprise, Fear, Happy, Sad, Mild Surprise, Fear , Sad, Disgust, Happy	6/9	Mild Surprise, Anger	2/2
11-(S132)	Sad, Sad, Fear, Mild Surprise, Disgust, Happy	3/6	Happy, Surprise	2/2
Recognition Rate		58.18%		100%

Table 6.2.2: Results for LPB-TOP on 11 subjects of CK+ Dataset using one nearest neighbor classifier

Subject No.	**TestFeatures**	**Cross Validation Results**	**Training Features**	**Validation Results**
1-(S52)	Surprise, Sad, Angry	2/3	Happy, Disgust	2/2
2-(S55)	Surprise, Sad, Disgust, Fear	2/4	Angry, Happy	0/2
3-(S74)	Fear, Surprise, Mild Surprise	0/3	Disgust, Happy	1/2
4-(S106)	Surprise, Sad, Happy, Disgust, Anger	3/5	Mild Surprise, Happy	2/2
5-(S111)	Surprise, Mild Surprise, Happy, Mild Surprise, Disgust	2/5	Happy, Anger	0/2
6-(S113)	Surprise, Fear, Sad, Happy, Sad	1/6	Mild Surprise, Anger	0/2
7-(S121)	Happy, Fear, Fear	0/3	Mild Surprise, Mild Surprise	0/2
8-(S124)	Surprise, Sad, Fear, Happy, Happy	0/5	Mild Surprise, Disgust	0/2
9-(S125)	Sad, Happy, Sad, Mild Surprise, Surprise, Disgust	2/6	Happy, Fear	0/2
10-(S130)	Surprise, Fear, Happy, Sad, Mild Surprise, Fear , Sad, Disgust, Happy	6/9	Mild Surprise, Anger	2/2
11-(S132)	Sad, Sad, Fear, Mild Surprise, Disgust, Happy	2/6	Happy, Surprise	1/2
Recognition Rate		36.36%		36.36%

Table 6.2.3: Validation Results for Grid Partitioning on 11 subjects of CK+ Dataset using one nearest neighbor classifier

Feature Index	Subject	DTTF-TOP	LBP-TOP
2	S52-002	Yes	Yes
4	S52-004	Yes	Yes
6	S55-001	Yes	No
8	S55-003	Yes	Yes
10	S55-005	Yes	Yes
12	S74-001	Yes	Yes
14	S74-003	No	No
16	S74-005	No	Yes
18	S106-002	Yes	Yes
20	S106-004	Yes	Yes
22	S106-006	Yes	Yes
24	S111-001	Yes	Yes
26	S111-003	Yes	Yes
28	S111-005	Yes	Yes
30	S111-007	Yes	Yes
32	S113-002	Yes	Yes
34	S113-004	Yes	Yes
36	S113-006	Yes	Yes
38	S113-008	Yes	Yes
40	S121-002	Yes	Yes
42	S121-004	Yes	Yes
44	S124-001	Yes	No
46	S124-003	Yes	Yes
48	S124-005	No	No
50	S124-007	Yes	Yes
52	S125-002	Yes	Yes
54	S125-004	Yes	Yes
56	S125-006	Yes	Yes
58	S125-008	Yes	Yes
60	S125-002	Yes	Yes
62	S125-004	Yes	Yes
64	S125-006	Yes	Yes
66	S125-008	Yes	Yes
68	S125-012	Yes	Yes
70	S132-001	Yes	Yes
72	S132-003	Yes	Yes
74	S132-005	Yes	Yes
76	S132-007	Yes	Yes

Table 6.2.4: Cross-Validation Results for Grid Partitioning on 11 subjects of CK+ Dataset using one nearest neighbor classifier

Feature Index	Subject	DTTF-TOP	LBP-TOP
1	S52-001	Yes	Yes
3	S52-003	Yes	Yes
5	S52-006	Yes	Yes
7	S55-002	No	Yes
9	S55-004	Yes	Yes
11	S55-006	Yes	Yes
13	S74-002	Yes	Yes
15	S74-004	Yes	Yes
17	S106-001	Yes	Yes
19	S106-003	Yes	No
21	S106-005	Yes	Yes
23	S106-007	Yes	Yes
25	S111-002	No	No
27	S111-004	Yes	Yes
29	S111-006	Yes	Yes
31	S113-001	Yes	Yes
33	S113-003	Yes	Yes
35	S113-005	Yes	Yes
37	S113-007	Yes	Yes
39	S121-001	Yes	Yes
41	S121-003	Yes	Yes
43	S121-005	Yes	Yes
45	S124-002	Yes	Yes
47	S124-004	Yes	Yes
49	S124-006	Yes	Yes
51	S125-001	Yes	Yes
53	S125-003	Yes	Yes
55	S125-005	Yes	Yes
57	S125-007	Yes	Yes
59	S130-001	Yes	Yes
61	S130-003	Yes	Yes
63	S130-005	Yes	Yes
65	S130-007	Yes	Yes
67	S130-009	Yes	Yes
69	S130-013	Yes	Yes
71	S132-002	Yes	Yes
73	S132-004	Yes	No
75	S132-006	Yes	Yes
77	S132-008	Yes	Yes

Table 6.2.5: TBCC Validation Test Results on small CK+ dataset using one nearest neighbor classifier

SL. No.	Sequence No.	Test Result
1	S52-002	Yes
2	S52-004	Yes
3	S55-001	No
4	S55-003	Yes
5	S55-005	Yes
6	S74-001	Yes
7	S74-003	Yes
8	S106-001	No
9	S106-003	No
10	S106-005	No
11	S106-007	Yes
12	S111-002	No
13	S111-004	Yes
14	S111-006	No
15	S113-001	Yes
16	S113-003	Yes
17	S121-001	No
18	S121-003	No
19	S121-005	No
20	S124-002	Yes
21	S124-004	Yes
22	S124-006	Yes
23	S125-001	Yes
24	S125-003	Yes
25	S125-005	Yes
26	S130-001	Yes
27	S130-003	Yes
28	S130-005	Yes
29	S130-007	Yes
30	S130-009	Yes
31	S130-013	Yes
32	S132-002	Yes
33	S132-004	Yes
34	S132-006	Yes
35	S132-008	Yes

Table 6.2.6: TBCC Cross Validation Test Results on small CK+ dataset using one nearest neighbor classifier

SL. No.	Sequence No.	Test Result
1	S52-001	No
2	S52-003	No
3	S52-006	Yes
4	S55-002	No
5	S55-004	Yes
6	S74-002	Yes
7	S74-004	Yes
8	S106-002	Yes
9	S106-004	Yes
10	S106-006	Yes
11	S111-001	No
12	S111-003	Yes
13	S111-005	Yes
14	S111-007	Yes
15	S113-004	No
16	S113-006	Yes
17	S113-008	Yes
18	S121-002	Yes
19	S121-004	Yes
20	S124-001	Yes
21	S124-003	Yes
22	S124-007	Yes
23	S125-002	Yes
24	S125-004	No
25	S125-006	No
26	S125-008	Yes
27	S130-002	Yes
28	S130-004	Yes
29	S130-006	Yes
30	S130-008	Yes
31	S132-012	Yes
32	S132-001	Yes
33	S132-003	Yes
34	S132-005	Yes
35	S132-007	No

Table 6.2.7: Validation results for DTTF-TOP, LBP-TOP and Face feature weighted fusion based on fuzzy membership degree for video face recognition of whole CK+Dataset using SVM Classifier

SL.NO.	Subject No.	%performance for DTTF_TOP	%performance for LBP_TOP	%performance for Face feature weighted fusion method
1	S010	94.3182	95.8333	89.7727
2	S011	96.5909	98.1061	85.9848
3	S014	95.8333	97.3485	96.7805
4	S022	98.1061	97.3485	98.7805
5	S026	100	97.3485	85.9848
6	S032	98.4848	98.1061	89.7727
7	S034	99.2424	95.8333	85.9848
8	S035	98.4848	97.7273	98.7805
9	S037	98.4848	96.9697	98.7805
10	S042	96.9697	98.1061	98.3740
11	S044	95.8333	95.0758	85.9848
12	S045	98.8636	98.1061	89.7727
13	S046	97.3485	97.7273	95.9350
14	S050	99.2424	97.7273	98.3740
15	S051	100	96.9697	89.7727
16	S052	97.7273	96.2121	98.7805
17	S053	98.4848	96.9697	98.7805
18	S054	99.6212	94.6970	98.7805
19	S055	85.6061	81.8182	98.7805
20	S056	96.5909	97.7273	89.7727
21	S057	98.8636	95.0758	85.9848
22	S058	92.0455	92.0455	97.9675
23	S059	92.0455	95.4545	98.3740
24	S060	96.9697	97.3485	98.7805
25	S061	100	96.2121	85.9848
26	S062	90.1515	97.3485	95.9350
27	S063	98.4848	97.7273	85.9848
28	S064	94.6970	94.3182	99.1870
29	S065	99.6212	94.3182	97.1545
30	S066	100	95.8333	75.7042
31	S067	89.0152	81.8182	98.3740
32	S068	97.7273	95.8333	89.7727
33	S069	100	97.7273	97.5610
34	S070	99.6212	93.5606	99.1870

SL.NO.	Subject No.	%performance for DTTF_TOP	%performance for LBP_TOP	%performance for Face feature weighted fusion method
35	S071	79.5455	97.3485	95.1220
36	S072	97.3485	93.9394	97.9675
37	S073	100	97.3485	91.4634
38	S074	97.3485	95.8333	95.8333
39	S075	81.8182	96.2121	96.2121
40	S076	97.3485	98.1061	85.9848
41	S077	99.6212	97.7273	92.8030
42	S078	92.8030	95.0758	75.0758
43	S079	99.2424	97.3485	97.3485
44	S080	98.8636	85.9848	85.9848
45	S081	98.4848	95.8333	92.8030
46	S082	92.4242	97.3485	97.3485
47	S083	97.3485	96.9697	96.9697
48	S084	99.6212	98.1061	98.1061
49	S085	98.8636	98.1061	92.8030
50	S086	99.2424	97.7273	95.8333
51	S087	100	98.1061	89.7727
52	S088	99.2424	96.9697	96.9697
53	S089	99.6212	98.1061	89.7727
54	S090	100	97.7273	97.7273
55	S091	89.7727	85.9848	94.3182
56	S092	93.5606	98.1061	94.3182
57	S093	94.6970	95.4545	95.8333
58	S094	98.8636	97.3485	97.3485
59	S095	98.4848	94.3182	85.9848
60	S096	96.5909	96.5909	85.9848
61	S097	97.3485	96.2121	94.3182
62	S098	99.6212	95.8333	95.8333
63	S099	96.9697	93.1818	89.7727
64	S100	95.4545	95.4545	95.4545
65	S101	98.4848	97.3485	89.7727
66	S102	98.8636	97.7273	97.3485
67	S103	96.9697	97.7273	97.7273
68	S104	98.1061	97.7273	85.9848
69	S105	96.2121	89.7727	89.7727
70	S106	97.3485	97.7273	85.9848

SL.NO.	**Subject No.**	**%performance for DTTF_TOP**	**%performance for LBP_TOP**	**%performance for Face feature weighted fusion method**
71	S107	95.8333	97.7273	94.3182
72	S108	97.3485	94.3182	94.6970
73	S109	96.2121	97.3485	96.9697
74	S110	99.2424	96.2121	96.2121
75	S111	93.5606	95.8333	85.9848
76	S112	95.4545	96.5909	85.9848
77	S113	97.7273	96.2121	96.2121
78	S114	89.7727	96.9697	96.9697
79	S115	91.667	85.9848	89.7727
80	S116	92.8030	94.3182	94.3182
81	S117	94.3182	96.5909	90.1515
82	S118	96.5909	95.4545	95.4545
83	S119	87.5000	95.8333	85.9848
84	S120	99.2424	94.3182	94.3182
85	S121	99.6212	97.7273	97.7273
86	S122	95.4545	97.3485	90.1515
87	S124	95.8333	85.9848	90.1515
88	S125	95.4545	85.9848	89.7727
89	S126	93.5606	94.6970	94.6970
90	S127	95.4545	96.9697	93.9394
91	S128	93.1818	96.5909	92.8030
92	S129	85.9848	92.8030	82.1970
93	S130	87.8788	97.3485	85.9848
94	S131	82.1970	93.9394	93.9394
95	S132	94.6970	94.3182	90.1515
96	S133	95.8333	97.3485	96.5909
97	S134	96.2121	96.2121	96.9697
98	S135	95.4545	95.4545	97.3485
99	S136	98.1061	98.1061	97.3485
100	S137	98.8636	98.8636	90.1515
101	S138	98.1061	98.1061	97.3485
102	S502	97.7273	97.7273	90.1515
103	S503	97.7273	99.6212	96.5909
104	S504	96.5909	99.6212	96.5909
105	S505	96.5909	98.1061	96.9697
106	S506	96.9697	96.9697	96.9697
107	S999	98.4848	97.3485	90.1515

Table 6.2.8: Cross Validation results for DTTF-TOP, LBP-TOP and Face feature weighted fusion based On fuzzy membership degree for video face recognition of whole CK+ Dataset using SVM Classifier

SL.NO.	Subject No.	%performance for DTTF_TOP	%performance for LBP_TOP	%performance for Face feature weighted fusion method
1	S010	97.7492	94.5338	96.1268
2	S011	91.3183	81.3505	97.5352
3	S014	98.0707	97.4277	73.5915
4	S022	98.3923	98.7138	97.1831
5	S026	98.0707	97.4277	78.5211
6	S032	98.3923	98.3923	83.0986
7	S034	98.0707	99.3569	80.2817
8	S035	91.3183	97.4277	79.2254
9	S037	81.3505	98.0707	82,3944
10	S042	96.7846	98.3923	83.8028
11	S044	99.0354	96.4630	81.6901
12	S045	98.7138	98.3923	99.2958
13	S046	94.5338	98.3923	83.3028
14	S050	98.7138	97.1061	98.5915
15	S051	99.6785	98.1061	80.2817
16	S052	98.0707	97.1061	83.0986
17	S053	98.3923	81.3505	78.1690
18	S054	99.6707	98.0707	81.6901
19	S055	91.6399	97.7492	74.2958
20	S056	98.0707	97.4277	83.8028
21	S057	98.3923	95.8199	98.1061
22	S058	99.0354	96.7846	98.1061
23	S059	95.1768	98.0707	97.3485
24	S060	92.6045	97.7492	95.0758
25	S061	99.6785	97.7492	85.9848
26	S062	97.7492	97.7492	94.3182
27	S063	98.7138	95.4984	96.5909
28	S064	96.7846	95.4984	96.2121
29	S065	100	91.3183	95.8333
30	S066	99.6785	91.3183	86.2676
31	S067	100	97.7492	79.9296
32	S068	96.4630	97.1061	80.9859
33	S069	99.0354	81.3505	96.9697
34	S070	99.3569	98.3923	98.3740

SL.NO.	Subject No.	%performance for DTTF_TOP	%performance for LBP_TOP	%performance for Face feature weighted fusion method
35	S071	90.6752	98.0707	96.3415
36	S072	100	96.1415	98.7805
37	S073	99.0354	96.7846	96.1268
38	S074	95.4984	96.7846	75.7042
39	S075	99.0354	97.1061	95.8333
40	S076	99.0354	98.3923	97.7273
41	S077	99.0354	98.0707	96.2121
42	S078	97.4277	96.4630	94.6970
43	S079	98.3923	98.3923	95.8333
44	S080	94.2122	94.8553	97.7273
45	S081	100	94.8553	96.2121
46	S082	96.1415	97.4277	94.6970
47	S083	98.0707	97.4277	81.8182
48	S084	98.3923	97.7492	95.8333
49	S085	97.1061	98.0707	97.7273
50	S086	99.3569	98.3923	93.5606
51	S087	99.3569	91.3183	95.8333
52	S088	96.7846	98.3923	97.7273
53	S089	99.6785	98.3923	96.2121
54	S090	100	98.3923	94.6970
55	S091	98.7138	98.0707	81.8182
56	S092	92.2830	97.1061	95.8333
57	S093	92.9260	95.1768	97.7273
58	S094	99.0354	98.0707	93.5606
59	S095	98.3923	96.4630	75.7042
60	S096	99.3569	93.8907	98.3740
61	S097	95.1768	96.4630	89.7727
62	S098	91.9614	93.8907	85.9848
63	S099	91.9614	93.8907	95.0758
64	S100	100	93.2476	95.0758
65	S101	97.1061	81.3505	85.9848
66	S102	97.7492	98.3923	95.8333
67	S103	97.4277	98.3923	94.6970
68	S104	96.7846	95.1768	96.2121
69	S105	96.7846	95.1768	97.7273
70	S106	97.7492	97.4277	90.1515

SL.NO.	Subject No.	%performance for DTTF_TOP	%performance for LBP_TOP	%performance for Face feature weighted fusion method
71	S107	99.0354	95.4984	75.7042
72	S108	96.4630	96.7846	98.3740
73	S109	91.6399	96.4630	89.7727
74	S110	92.6045	92.6045	85.9848
75	S111	90.9968	96.1415	95.0758
76	S112	96.1415	93.8907	89.7727
77	S113	96.7846	96.4630	85.9848
78	S114	99.3569	97.7492	95.8333
79	S115	93.5691	97.1061	94,6970
80	S116	91.6399	93.8907	96.2121
81	S117	97.7492	81.3505	97.7273
82	S118	99.0354	97.4277	90.1515
83	S119	99.0354	97.4277	75.7042
84	S120	98.7138	97.4277	98.3740
85	S121	98.0707	98.3907	89.7727
86	S122	93.2476	93.8907	85.7727
87	S124	96.7846	96.4630	95.0758
88	S125	95.4984	98.3923	89.7727
89	S126	95.1768	96.7846	85,9848
90	S127	97.7492	97.7492	95.8333
91	S128	90.3537	91.3183	94.6970
92	S129	97.1061	75.8842	96.2121
93	S130	95.4984	81.3505	97.7273
94	S131	81.0289	91.3183	90.1515
95	S132	90.0322	96.7846	75.7042
96	S133	96.7846	98.3923	98.3740
97	S134	97.7492	97.7492	89.7727
98	S135	92.2830	98.3923	85.9848
99	S136	97.1061	97.7492	95.0758
100	S137	94.5338	97.4277	89.7727
101	S138	98.3923	91.3183	95.8333
102	S502	100	98.3923	94.6970
103	S503	100	98.3923	96.2121
104	S504	99.3569	98.0707	97.7273
105	S505	98.3923	97.7492	97.7273
106	S506	97.4277	91.3183	90.1515
107	S999	99.0354	97.7492	99.2958

Table 6.2.9: Validation Results for DTTF-TOP, LBP-TOP and Face feature weighted fusion based on fuzzy membership degree method of whole CK+ Dataset using one nearest neighbor Classifier

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
2	Yes	Yes	No
4	Yes	Yes	Yes
6	No	Yes	Yes
8	Yes	Yes	Yes
10	Yes	No	No
12	Yes	No	Yes
14	No	No	No
16	Yes	Yes	Yes
18	No	No	Yes
20	No	Yes	Yes
22	Yes	Yes	No
24	No	No	No
26	Yes	No	Yes
28	Yes	No	Yes
30	Yes	Yes	Yes
32	Yes	Yes	Yes
34	No	Yes	Yes
36	Yes	Yes	Yes
38	Yes	Yes	Yes
40	Yes	Yes	Yes
42	Yes	No	Yes
44	No	No	Yes
46	No	No	Yes
48	No	Yes	Yes
50	Yes	No	Yes
52	Yes	No	Yes
54	No	Yes	Yes
56	No	Yes	Yes
58	No	Yes	Yes
60	Yes	Yes	Yes
62	No	Yes	Yes
64	No	Yes	No
66	Yes	Yes	Yes
68	Yes	No	Yes
70	No	Yes	Yes
72	No	Yes	Yes
74	Yes	Yes	No
76	Yes	No	No

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
78	Yes	No	No
80	Yes	No	No
82	Yes	No	Yes
84	Yes	Yes	No
86	Yes	No	No
88	No	No	Yes
90	No	No	No
92	Yes	Yes	No
94	No	No	Yes
96	Yes	Yes	No
98	Yes	Yes	No
100	No	No	Yes
102	Yes	Yes	No
104	Yes	Yes	No
106	Yes	Yes	No
108	No	Yes	No
110	No	Yes	No
112	No	No	Yes
114	Yes	Yes	No
116	Yes	Yes	No
118	No	No	No
120	Yes	Yes	Yes
122	No	No	Yes
124	No	No	No
126	Yes	Yes	Yes
128	Yes	Yes	No
130	Yes	Yes	No
132	Yes	Yes	Yes
134	Yes	Yes	No
136	No	No	Yes
138	No	Yes	No
140	Yes	No	No
142	No	Yes	No
144	Yes	Yes	Yes
146	Yes	No	No
148	No	No	No
150	Yes	Yes	Yes
152	No	No	Yes

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
154	Yes	No	No
156	Yes	Yes	Yes
158	No	No	No
160	Yes	No	Yes
162	No	Yes	No
164	Yes	Yes	Yes
166	Yes	Yes	Yes
168	No	No	Yes
170	No	Yes	No
172	No	Yes	Yes
174	Yes	Yes	Yes
176	No	No	No
178	No	No	Yes
180	Yes	Yes	Yes
182	No	Yes	Yes
184	No	No	No
186	Yes	Yes	No
188	Yes	Yes	No
190	Yes	Yes	No
192	No	Yes	Yes
194	No	No	Yes
196	Yes	Yes	No
198	Yes	Yes	Yes
200	Yes	Yes	Yes
202	Yes	Yes	No
204	Yes	Yes	Yes
206	Yes	Yes	No
208	Yes	Yes	Yes
210	No	No	No
212	No	No	No
214	No	No	No
216	Yes	Yes	Yes
218	Yes	Yes	Yes
220	No	No	No
222	Yes	Yes	Yes
224	Yes	No	No
226	Yes	No	No
228	Yes	Yes	Yes

Feature Index	**DTTF-TOP**	**LBP-TOP**	**Face Feature weighted fusion based on fuzzy membership degree method**
230	No	Yes	Yes
232	Yes	No	Yes
234	Yes	Yes	Yes
236	No	No	No
238	No	No	No
240	Yes	No	No
242	No	No	Yes
244	Yes	Yes	Yes
246	Yes	No	Yes
248	Yes	Yes	No
250	No	No	No
252	No	No	No
254	Yes	Yes	No
256	No	Yes	No
258	Yes	Yes	Yes
260	Yes	Yes	Yes
262	No	Yes	Yes
264	Yes	No	Yes
266	Yes	Yes	Yes
268	Yes	Yes	Yes
270	Yes	Yes	No
272	No	No	Yes
274	Yes	Yes	Yes
276	Yes	Yes	No
278	Yes	Yes	Yes
280	Yes	Yes	Yes
282	No	No	No
284	No	No	No
286	Yes	Yes	No
288	Yes	Yes	No
290	No	No	No
292	No	No	Yes
294	No	No	No
296	Yes	Yes	Yes
298	No	No	Yes
300	No	No	No
302	No	Yes	No
304	No	No	Yes

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
306	Yes	No	Yes
308	Yes	Yes	No
310	Yes	No	Yes
312	Yes	No	Yes
314	Yes	Yes	No
316	Yes	Yes	Yes
318	Yes	Yes	No
320	Yes	Yes	Yes
322	Yes	Yes	No
324	Yes	Yes	No
326	No	Yes	Yes
328	Yes	Yes	No
330	Yes	Yes	Yes
332	Yes	Yes	No
334	Yes	No	No
336	Yes	No	No
338	Yes	Yes	Yes
340	No	Yes	No
342	Yes	Yes	No
344	Yes	Yes	No
346	Yes	Yes	No
348	Yes	No	No
350	Yes	No	Yes
352	No	No	No
354	Yes	Yes	Yes
356	No	No	Yes
358	Yes	Yes	No
360	Yes	Yes	No
362	Yes	Yes	No
364	Yes	Yes	Yes
366	No	No	No
368	Yes	NO	No
370	No	No	Yes
372	Yes	Yes	Yes
374	Yes	Yes	No
376	Yes	Yes	No
378	No	No	No
380	No	Yes	No

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
382	Yes	Yes	No
384	Yes	No	Yes
386	Yes	Yes	No
388	Yes	Yes	No
390	No	No	Yes
392	Yes	Yes	Yes
394	Yes	Yes	Yes
396	Yes	No	No
398	Yes	Yes	No
400	Yes	Yes	Yes
402	Yes	Yes	Yes
404	Yes	Yes	Yes
406	Yes	Yes	Yes
408	No	No	No
410	Yes	Yes	No
412	Yes	Yes	Yes
414	Yes	Yes	No
416	Yes	No	No
418	Yes	Yes	No
420	Yes	No	Yes
422	Yes	Yes	No
424	No	Yes	Yes
426	No	No	No
428	Yes	Yes	No
430	Yes	Yes	Yes
432	Yes	Yes	Yes
434	Yes	Yes	Yes
436	Yes	Yes	No
438	No	Yes	No
440	No	Yes	No
442	No	Yes	Yes
444	Yes	Yes	No
446	Yes	No	Yes
448	Yes	Yes	Yes
450	Yes	Yes	Yes
452	Yes	Yes	No
454	Yes	Yes	Yes
456	No	No	Yes

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
458	Yes	Yes	No
460	Yes	Yes	Yes
462	Yes	Yes	No
464	Yes	Yes	Yes
466	No	Yes	Yes
468	Yes	Yes	Yes
470	No	Yes	Yes
472	Yes	Yes	No
474	Yes	Yes	Yes
476	Yes	Yes	No
478	Yes	Yes	Yes
480	Yes	Yes	Yes
482	No	Yes	Yes
484	No	Yes	No
486	Yes	No	Yes
488	No	Yes	Yes
490	No	Yes	No
492	Yes	No	Yes
494	No	Yes	No
496	Yes	No	Yes
498	Yes	Yes	No
500	Yes	Yes	Yes
502	Yes	No	Yes
504	No	Yes	No
506	Yes	Yes	Yes
508	Yes	Yes	Yes
510	Yes	Yes	Yes
512	Yes	Yes	No
514	Yes	Yes	Yes
516	Yes	Yes	No
518	Yes	Yes	Yes
520	Yes	Yes	No
522	Yes	Yes	No
524	Yes	No	Yes
526	Yes	No	No
528	Yes	No	Yes
530	Yes	No	No

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
532	Yes	Yes	-
534	Yes	Yes	-
536	Yes	Yes	-
538	No	Yes	-
540	Yes	Yes	-
542	Yes	Yes	-
544	Yes	Yes	-
546	Yes	Yes	-
548	Yes	No	-
550	Yes	Yes	-
552	Yes	Yes	-
554	Yes	Yes	-
556	Yes	Yes	-
558	Yes	Yes	-
560	Yes	No	-
562	Yes	Yes	-
564	Yes	Yes	-
566	Yes	Yes	-
568	Yes	Yes	-
570	No	Yes	-
572	Yes	Yes	-
574	No	Yes	-

Table 6.2.10: Cross Validation Results for DTTF-TOP, LBP-TOP and Face feature weighted fusion based on fuzzy membership degree method on whole CK+ Dataset using one nearest neighbor classifier

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
1	No	Yes	No
3	Yes	Yes	Yes
5	No	Yes	Yes
7	Yes	Yes	No
9	No	No	Yes
11	Yes	Yes	Yes
13	No	No	Yes
15	No	Yes	No
17	Yes	No	No
19	Yes	No	Yes
21	Yes	Yes	Yes
23	Yes	Yes	Yes
25	No	No	No
27	Yes	No	Yes
29	Yes	No	Yes
31	Yes	Yes	No
33	Yes	Yes	No
35	Yes	Yes	No
37	Yes	Yes	Yes
39	Yes	Yes	No
41	No	Yes	Yes
43	Yes	Yes	Yes
45	No	No	Yes
47	Yes	Yes	No
49	Yes	Yes	No
51	No	Yes	Yes
53	Yes	Yes	Yes
55	Yes	Yes	Yes
57	Yes	Yes	Yes
59	Yes	Yes	Yes
61	Yes	Yes	Yes
63	No	Yes	Yes
65	No	No	No
67	Yes	Yes	Yes
69	Yes	Yes	No
71	No	No	Yes
73	Yes	Yes	Yes
75	No	No	No

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
77	Yes	Yes	Yes
79	Yes	Yes	No
81	Yes	Yes	Yes
83	Yes	No	No
85	No	No	Yes
87	Yes	Yes	Yes
89	Yes	Yes	No
91	Yes	Yes	No
93	No	No	Yes
95	No	No	No
97	Yes	Yes	No
99	Yes	Yes	Yes
101	No	Yes	No
103	Yes	Yes	Yes
105	Yes	Yes	No
107	No	No	Yes
109	No	Yes	Yes
111	Yes	Yes	Yes
113	No	Yes	No
115	No	Yes	No
117	Yes	Yes	No
119	Yes	Yes	No
121	Yes	Yes	Yes
123	No	Yes	Yes
125	Yes	Yes	Yes
127	Yes	Yes	No
129	No	Yes	Yes
131	No	Yes	No
133	Yes	Yes	No
135	No	No	Yes
137	No	No	Yes
139	No	Yes	No
141	Yes	Yes	No
143	Yes	Yes	Yes
145	Yes	No	No
147	Yes	Yes	Yes
149	No	No	Yes
151	Yes	Yes	Yes

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
153	No	Yes	Yes
155	Yes	No	No
157	Yes	Yes	Yes
159	No	Yes	No
161	No	No	Yes
163	Yes	Yes	Yes
165	Yes	Yes	Yes
167	Yes	No	Yes
169	No	No	Yes
171	Yes	Yes	Yes
173	Yes	Yes	Yes
175	No	Yes	Yes
177	Yes	No	Yes
179	Yes	No	Yes
181	Yes	Yes	No
183	Yes	Yes	No
185	Yes	Yes	No
187	Yes	Yes	Yes
189	No	Yes	Yes
191	Yes	Yes	Yes
193	No	No	Yes
195	No	No	Yes
197	Yes	Yes	Yes
199	Yes	Yes	Yes
201	Yes	Yes	No
203	Yes	Yes	No
205	No	No	Yes
207	No	No	No
209	Yes	Yes	Yes
211	Yes	No	No
213	No	No	Yes
215	No	No	Yes
217	No	No	Yes
219	No	No	No
221	Yes	No	Yes
223	Yes	No	No
225	No	No	Yes
227	No	No	Yes
229	Yes	Yes	Yes

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
231	No	No	No
233	Yes	Yes	Yes
235	Yes	Yes	Yes
237	Yes	No	No
239	Yes	No	Yes
241	Yes	Yes	Yes
243	No	No	Yes
245	No	Yes	No
247	Yes	No	Yes
249	Yes	Yes	Yes
251	No	No	No
253	No	No	Yes
257	No	No	No
259	Yes	No	Yes
261	Yes	Yes	No
263	No	Yes	No
265	No	Yes	No
267	Yes	No	No
269	Yes	No	No
271	Yes	Yes	Yes
273	No	No	Yes
275	No	No	No
277	No	No	No
279	No	No	Yes
281	No	No	No
283	Yes	No	No
285	Yes	Yes	Yes
287	Yes	Yes	Yes
289	Yes	No	Yes
291	No	No	Yes
293	Yes	No	Yes
295	No	No	No
297	No	No	No
299	No	No	Yes
301	No	No	Yes
303	No	No	No
305	No	No	No
307	Yes	No	Yes
309	No	No	Yes
311	Yes	Yes	Yes

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
313	No	Yes	Yes
315	No	No	Yes
317	No	No	Yes
319	Yes	No	Yes
321	No	No	No
323	No	No	Yes
325	No	No	Yes
327	Yes	No	Yes
329	Yes	Yes	Yes
331	Yes	Yes	No
333	No	No	Yes
335	No	No	Yes
337	Yes	No	Yes
339	No	Yes	No
341	No	No	No
343	No	No	No
345	No	Yes	No
347	No	No	Yes
349	Yes	No	Yes
351	Yes	Yes	No
353	Yes	No	Yes
355	Yes	Yes	No
357	Yes	Yes	Yes
358	No	No	Yes
359	No	No	No
361	No	No	No
363	No	No	Yes
365	Yes	Yes	Yes
367	No	No	Yes
369	No	No	Yes
371	Yes	No	Yes
373	No	No	No
375	No	No	No
377	No	Yes	No
379	Yes	Yes	Yes
381	No	Yes	Yes
383	No	No	Yes
385	Yes	No	No
387	No	No	No

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
389	No	Yes	Yes
391	Yes	Yes	Yes
393	No	No	Yes
395	Yes	No	Yes
397	Yes	Yes	No
399	Yes	No	No
401	Yes	Yes	Yes
403	No	No	Yes
405	Yes	No	No
407	Yes	Yes	Yes
409	No	No	Yes
411	No	No	Yes
413	Yes	No	No
415	No	No	Yes
417	No	No	Yes
419	Yes	No	Yes
421	Yes	No	Yes
423	No	No	Yes
425	No	No	Yes
429	Yes	No	No
431	Yes	No	Yes
433	Yes	Yes	Yes
435	No	No	Yes
437	No	No	No
439	Yes	Yes	No
441	No	Yes	Yes
443	No	Yes	Yes
445	No	No	Yes
447	Yes	Yes	No
449	No	No	No
451	Yes	Yes	Yes
453	Yes	Yes	Yes
455	Yes	Yes	Yes
457	No	No	No
459	Yes	Yes	No
461	Yes	Yes	Yes
463	Yes	Yes	No
465	Yes	No	Yes
467	Yes	Yes	Yes

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
469	Yes	Yes	No
471	Yes	Yes	No
473	Yes	Yes	Yes
475	Yes	Yes	No
477	No	No	No
479	Yes	Yes	Yes
481	Yes	Yes	No
483	Yes	No	Yes
485	Yes	No	Yes
487	Yes	Yes	Yes
489	No	Yes	No
491	Yes	Yes	Yes
493	Yes	No	No
495	Yes	Yes	Yes
497	No	Yes	No
499	Yes	Yes	Yes
501	Yes	Yes	Yes
503	Yes	Yes	No
505	No	No	Yes
507	Yes	Yes	No
509	Yes	No	Yes
511	Yes	No	Yes
513	Yes	No	Yes
515	Yes	Yes	No
517	Yes	No	Yes
519	Yes	No	No
521	Yes	No	No
523	Yes	Yes	No
525	No	Yes	Yes
527	No	Yes	Yes
529	No	Yes	No
531	No	Yes	Yes
533	No	Yes	No

Feature Index	DTTF-TOP	LBP-TOP	Face Feature weighted fusion based on fuzzy membership degree method
535	No	Yes	-
537	Yes	Yes	-
539	No	No	-
541	Yes	No	-
543	No	No	-
545	Yes	Yes	-
547	Yes	No	-
549	Yes	Yes	-
551	Yes	Yes	-
553	Yes	Yes	-
555	No	Yes	-
557	Yes	No	-
559	Yes	No	-
561	No	No	-
563	Yes	No	-
565	Yes	No	-
567	Yes	No	-
569	Yes	No	-
571	No	No	-
573	Yes	No	-
575	Yes	No	-

Table 6.2.11: Comparison of DTTF-TOP, LBP-TOP and TBCC results on 11 subjects of CK+ dataset using one nearest neighbor classifier

Methods Used	Validation Test Result	Cross Validation Test Result
Face recognition from videos using TBCC Method	74.28%	77.14%
Face recognition from videos using LBP-TOP Features with grid-based partitioning	89.47%	92.30%
Face recognition from videos using DTTF-TOP Features with grid-based partitioning	92.105%	94.87%

Table 6.2.12: Comparison of DTTF-TOP, LBP-TOP and Face feature weighted fusion based on fuzzy membership degree for video face recognition on the whole CK+ dataset using SVM Classifier

Methods Used	Validation Test Result	Cross Validation Test Result
Face feature weighted fusion based on fuzzy membership degree for video face recognition	93.6248%	90.9839%
Face recognition from videos using LBP-TOP Features	95.7130%	95.564%
Face recognition from videos using DTTF-TOP Features	96.1732%	96.9318%

Table 6.2.13: Comparison of DTTF-TOP, LBP-TOP and Face feature weighted fusion based on fuzzy membership degree for video face recognition on the whole CK+ dataset using one nearest neighbor Classifier

Methods Used	Validation Test Result	Cross Validation Test Result
Face feature weighted fusion based on fuzzy membership degree for video face recognition	50.936%	63.157%
Face recognition from videos using LBP-TOP Features	69.337%	51.736%
Face recognition from videos using DTTF-TOP Features	67.944%	59.027%

*In Table 6.2.3, 6.2.4, 6.2.5, 6.2.6, 6.2.9 and 6.2.10, Yes:-Indicates correct recognition and No :-Indicates incorrect recognition.

Initially, the DTTF-TOP and LBP-TOP results computed on a small CK+ dataset did not give good recognition results and so the grid-based partitioning method is used to improve the recognition rate. Earlier, for validation DTTF-TOP features gave a recognition rate of 100% and LBP-TOP features gave 36.36%. For cross-validation DTTF-TOP features gave a recognition rate of 58.18% and LBP-TOP features gave 36.36%. After the grid-based partitioning method is used, for validation DTTF-TOP features gave a recognition rate of 92.105% and LBP-TOP gave a recognition rate of 89.47%. For cross-validation DTTF-TOP features gave a recognition rate of 94.87% and LBP-TOP gave a recognition rate of 92.30%. Thus, the grid-based method implemented increased the recognition rate. The one nearest neighbor classifier is used for this classification purpose.

From Table 6.2.11, we can see that DTTF-TOP features gives better results than the LBP-TOP and TBCC methods. However, due to the high computation time taken by the grid-based partitioning and TBCC method, they are implemented only on a small part of CK+ dataset.

Further experiments are carried out on the whole CK+ dataset. At first we used the one nearest neighbor classifier and on performing validation test, we got a recognition rate of for 67.944% DTTF-TOP, 69.337% for LBP-TOP and 50.926% for face feature weighted fusion based on fuzzy membership degree method.

In order to improve the classification accuracy, the support vector machine is again used for the classification purpose on the whole CK+ dataset. On performing Validation Test, the average percentage performance using DTTF-TOP is 96.1732% and using that of LBP-TOP is 95.7130%. Cross Validation test gives an average percentage performance of 96.9318 % using DTTF-TOP and 95.5645% using LBP-TOP. The face feature weighted fusion based on fuzzy membership degree for video face recognition on the whole CK+ dataset gave a recognition rate of 93.6248% during validation test and 90.9839% during cross validation test. For this experiment, we observe that the one nearest neighbor classifier did not give good results and so the support vector machine was used which gave much better classification results. On comparing the recognition rates of the three methods used, we can say that our proposed DTTF-TOP feature set gives better recognition results and can be considered an ideal feature set to perform face recognition from videos.

CHAPTER-7
CONCLUSION AND FUTURE SCOPE

There are several face recognition techniques from videos that have been introduced so far. From the experimental results and comparisons performed we can see that the newly proposed DTTF-TOP feature set we have introduced in this thesis performs well for face recognition from videos and outperforms some other good existing methods as well. The small feature vector of the DTTF-TOP feature set is an added advantage to the face recognition system and it is observed to perform well even with changes in the facial expression of a person.

The experiments performed in this project used the CK+ dataset where all the faces of the subjects are aligned properly with frontal poses and the videos were captured under proper lighting conditions. Further experiments can be performed to check whether the feature set works well for rotation and illumination variant conditions. Here, each frame of the video sequence contained only one subject and so the future scope of this work can include solving the multiple persons per frame problem. The problem of identification due to the changes brought about by age on a person’s face can also be a challenge taken up in future work.

REFERENCES

[1] Susan, Seba, and Madasu Hanmandlu. "Difference theoretic feature set for scale-, illumination- and rotation-invariant texture classification." *IET Image Processing* 7.8 (2013): 725-732.

[2] Zhao, Guoying, and Matti Pietikainen. "Dynamic texture recognition using local binary patterns with an application to facial expressions." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 29.6 (2007): 915-928.

[3] Lucey, Patrick, et al. "The Extended Cohn-Kanade Dataset (CK+): A complete dataset for action unit and emotion-specified expression." *Computer Vision and Pattern Recognition Workshops (CVPRW), 2010 IEEE Computer Society Conference on*. IEEE, 2010.

[4] Choi, Jae Young, Konstantinos N. Plataniotis, and Yong Man Ro. "Face feature weighted fusion based on fuzzy membership degree for video face recognition."*Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*42.4 (2012): 1270-1282.

[5] Hadid, Abdenour, and M. Pietikainen. "From still image to video-based face recognition: an experimental analysis." *Automatic Face and Gesture Recognition, 2004. Proceedings. Sixth IEEE International Conference on*. IEEE, 2004.

[6] A Suneetha, J. "A survey on Video-based Face Recognition Approaches."

[7] Barr, Jeremiah R., et al. "Face recognition from video: A review." *International Journal of Pattern Recognition and Artificial Intelligence* 26.05 (2012).

[8] http://www.scholarpedia.org/article/Local_Binary_Patterns- Local Binary Patterns

[9] Ahonen, Timo, Abdenour Hadid, and Matti Pietikainen. "Face description with local binary patterns: Application to face recognition." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 28.12 (2006): 2037-2041.

[10] Ojala, Timo, Matti Pietikainen, and Topi Maenpaa. "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 24.7 (2002): 971-987.

[11] Jain, Anil K, Arun Ross and Karthik Nandakumar, “An Introduction to Biometrics”.

[12] Rosales, Edward, et al. "Automatic face recognition from video sequences using a template based cross correlation method." *Electrical and Computer Engineering (CCECE), 2013 26th Annual IEEE Canadian Conference on*. IEEE, 2013.

[13] Jensen, Ole Helvig. *Implementing the Viola-Jones face detection algorithm*. Diss. Technical University of Denmark, DTU, DK-2800 Kgs. Lyngby, Denmark, 2008.

[14] Jain, Anil K., Arun Ross, and Salil Prabhakar. "An introduction to biometric recognition." *Circuits and Systems for Video Technology, IEEE Transactions on* 14.1 (2004): 4-20.

[15] Maturana, Daniel, Domingo Mery, and Alvaro Soto. "Face recognition with local binary patterns, spatial pyramid histograms and naive Bayes nearest neighbor classification." *Chilean Computer Science Society (SCCC), 2009 International Conference of the*. IEEE, 2009.

[16] Nanni, Loris, Alessandra Lumini, and Sheryl Brahnam. "Survey on LBP based texture descriptors for image classification." *Expert Systems with Applications*39.3 (2012): 3634-3641.

[17] Tistarelli, Massimo, Manuele Bicego, and Enrico Grosso. "Dynamic face recognition: From human to machine vision." *Image and Vision Computing* 27.3 (2009): 222-232.

[18] Belhumeur, Peter N., João P. Hespanha, and David J. Kriegman. "Eigenfaces vs. fisherfaces: Recognition using class specific linear projection." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 19.7 (1997): 711-720.

[19] Jiang, Xudong, Bappaditya Mandal, and Alex Kot. "Eigenfeature regularization and extraction in face recognition." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 30.3 (2008): 383-394.

[20] Aggarwal, Gaurav, Amit K. Roy Chowdhury, and Rama Chellappa. "A system identification approach for video-based face recognition." *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*. Vol. 4. IEEE, 2004.

[21] Hadid, Abdenour, and Matti Pietikäinen. "From still image to video-based face recognition: an experimental analysis." *Automatic Face and Gesture Recognition, 2004. Proceedings. Sixth IEEE International Conference on*. IEEE, 2004.

[22] Tie, Yun, and Ling Guan. "Automatic face detection in video sequences using local normalization and optimal adaptive correlation techniques." *Pattern Recognition* 42.9 (2009): 1859-1868.

[23] Yun, Tie, and Ling Guan. "Local Normalization with Optimal Adaptive Correlation for Automatic and Robust Face Detection on Video Sequences."*Multimedia, 2008. ISM 2008. Tenth IEEE International Symposium on.* IEEE, 2008.

[24] Aggarwal, Gaurav, Amit K. Roy Chowdhury, and Rama Chellappa. "A system identification approach for video-based face recognition." *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*. Vol. 4. IEEE, 2004.

[25] Chen, Yi-Chen, et al. "Video-based face recognition via joint sparse representation." *Automatic Face and Gesture Recognition (FG), 2013 10th IEEE International Conference and Workshops on*. IEEE, 2013.

[26] Saisan, Payam, et al. "Dynamic texture recognition." *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*. Vol. 2. IEEE, 2001.

[27] Topkaya, Ibrahim Saygin, and Nilgun Guler Bayazit. "Improving face recognition from videos with preprocessed representative faces." *2008 23rd International Symposium on Computer and Information Sciences*. 2008.

[28] Best-Rowden, Lacey, et al. "Video-to-video face matching: Establishing a baseline for unconstrained face recognition." *Biometrics: Theory, Applications and Systems (BTAS), 2013 IEEE Sixth International Conference on*. IEEE, 2013.

[29] Chin, Tat-Jun, et al. "Face recognition from video by matching image sets."*Digital Image Computing: Techniques and Applications, 2005. DICTA'05. Proceedings 2005.* IEEE, 2005.

[30] Bhatt, Himanshu S., Rajdeep Singh, and Mayank Vatsa. "On recognizing faces in videos using clustering-based re-ranking and fusion." *Information Forensics and Security, IEEE Transactions on* 9.7 (2014): 1056-1068.

[31] Faggian, Nathan, Andrew Paplinski, and Tat-Jun Chin. "Face recognition from video using active appearance model segmentation." *Pattern Recognition, 2006. ICPR 2006. 18th International Conference on*. Vol. 1. IEEE, 2006.

[32] Haralick, Robert M., Karthikeyan Shanmugam, and Its' Hak Dinstein. "Textural features for image classification." *Systems, Man and Cybernetics, IEEE Transactions on* 6 (1973): 610-621.

[33] Kashyap, Rangasami L., and Alireza Khotanzad. "A model-based method for rotation invariant texture classification." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 4 (1986): 472-481.

[34] Leung, Michael M., and Allen M. Peterson. "Scale and rotation invariant texture classification." *Signals, Systems and Computers, 1992. 1992 Conference Record of The Twenty-Sixth Asilomar Conference on*. IEEE, 1992.

[35] Introna, Lucas, and Helen Nissenbaum. "Facial Recognition Technology A Survey of Policy and Implementation Issues." (2010).

[36] Jozer, Ban, et al. "Face recognition under partial occlusion and noise."*EUROCON, 2013 IEEE*. IEEE, 2013.

[37] Poh, Norman, et al. "An evaluation of video-to-video face verification."*Information Forensics and Security, IEEE Transactions on* 5.4 (2010): 781-801.

[38] Majumdar, Angshul, and Panos Nasiopoulos. "Frontal face recognition from video." *Advances in Visual Computing*. Springer Berlin Heidelberg, 2008. 297-306.

[39] Lee, Kuang-Chih, et al. "Video-based face recognition using probabilistic appearance manifolds." *Computer Vision and Pattern Recognition, 2003. Proceedings. 2003 IEEE Computer Society Conference on*. Vol. 1. IEEE, 2003.

[40] Roy-Chowdhury, Amit K., and Yilei Xu. "Pose and illumination invariant face recognition using video sequences." *Face Biometrics for Personal Identification*. Springer Berlin Heidelberg, 2007. 9-25.

[41] Assadi, Atefe, and Alireza Behrad. "A new method for human face recognition using texture and depth information." *Neural Network Applications in Electrical Engineering (NEUREL), 2010 10th Symposium on*. IEEE, 2010.

[42] Haralick, Robert M., Karthikeyan Shanmugam, and Its' Hak Dinstein. "Textural features for image classification." *Systems, Man and Cybernetics, IEEE Transactions on* 6 (1973): 610-621.

[43] Kanade, Takeo, Jeffrey F. Cohn, and Yingli Tian. "Comprehensive database for facial expression analysis." *Automatic Face and Gesture Recognition, 2000. Proceedings. Fourth IEEE International Conference on*. IEEE, 2000.

[44] Saber, Eli, and A. Murat Tekalp. "Frontal-view face detection and facial feature extraction using color, shape and symmetry based cost functions." *Pattern Recognition Letters* 19.8 (1998): 669-680.

[45] Tan, Xiaoyang, and Bill Triggs. "Enhanced local texture feature sets for face recognition under difficult lighting conditions." *Image Processing, IEEE Transactions on* 19.6 (2010): 1635-1650.

[46] Saisan, Payam, et al. "Dynamic texture recognition." *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*. Vol. 2. IEEE, 2001.

[47]Lu, Xiaoguang. "Image analysis for face recognition." *personal notes, May* 5 (2003).

[48] Péteri, Renaud, and Dmitry Chetverikov. "Dynamic texture recognition using normal flow and texture regularity." *Pattern Recognition and Image Analysis*. Springer Berlin Heidelberg, 2005. 223-230.

[49] Zhao, Guoying, and Matti Pietikäinen. "Dynamic texture recognition using volume local binary patterns." *Dynamical Vision*. Springer Berlin Heidelberg, 2007. 165-177.

[50] Ergin, Semih, and M. Bilginer Gulmezoglu. "A novel framework for partition-based face recognition." *International Journal of Innovative Computing Information and Control* 9.5 (2013): 1819-1834.

.