CHAPTER 1

INTRODUCTION

FACE recognition attracts extensive attention recently in real-world applications [1]–[4]. In the scope of face recognition, it is admitted that face feature description significantly affects the recognition performance. More specifically, the three critical issues for developing a good face descriptor are: (1) maximize the margin between inter-persons, (2) minimize the correlation between intra-person, and (3) can be extracted with low computational cost from original input data. However, a good recognition result cannot be anticipated by using unsatisfactory face features, even though adopting the optimum classifier. The existing face descriptions attempt to incorporate and balance the above criteria to produce more prominent recognition results.

A **face Recognition System** is a computer application for automatically identifying and verifying a person from a digital image. One of the ways to do this is by comparing selected facial features from the image and a Facial database. Face recognition has many applications ranging from security and surveillance to biometric identification to access secure devices and in face image database management and criminal investigations. The methods of Face Recognition are Local Binary Pattern, Local Derivative Pattern, Local Vector Pattern. **Face Recognition** technique records face images through a digital camera and analyses facial characteristics like the distance between eyes, nose, mouth, and jaw edges. These measurements are broken into facial planes and retained in a database, further used for comparison.

Face Recognition System Block Diagram

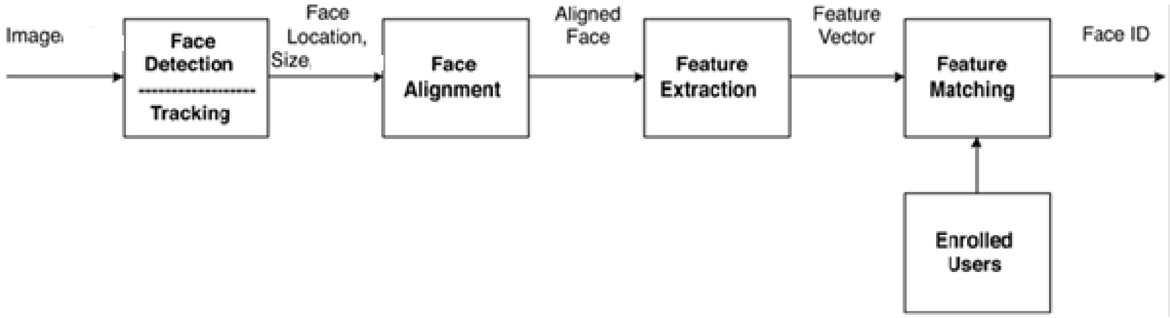


Figure:1 Face recognition system block diagram

Face detection:

Given a single image, an ideal face detector must be able to identify and locate all the present faces regardless of their position, scale, orientation, age, and expression.

1.1BENEFITS OF FACE RECOGNITION

It has long been known that each person has a unique face. The way a person's parts of their face can be used to prove a person's identity. Face recognition is a biometric technology that is used to positively identify a person. This form of identification captures the behavioral biometrics of a person rather than the physical biometrics. The dynamic face recognition technology confirms the identity of the user by analyzing the shape, place of each part. It is used in face database management and also criminal investigations.In criminal investigations a face from a video are captured and it is compared with the features of faces in the database so that the person can be identified.

Face recognition is a part of a wide area of pattern recognition technology. Recognition and especially face recognition covers a range of activities from many walks of life. Face recognition is something that humans are particularly good at and science and technology have brought many similar tasks to us. Face recognition in general and the recognition of moving people in natural scenes in particular, require a set of visual tasks to be performed robustly. That process includes mainly three-task a*cquisition, normalisation and recognition. By the term acquisition we mean* the detection and tracking of face-like image patches in a dynamic scene. *Normalisation is* the segmentation, alignment and normalisation of the face images, and finally r*ecognition that is* the representation and modelling of face images as identities, and the association of novel face images with known models.

Why Face Recognition?: Given the requirement for determining people's identity, the obvious question is what technology is best suited to supply this information? The are many ways that humans can identify each other, and so is for machines. There are many different identification technologies available, many of which have been in commercial use for years. The most common person verification and identification methods today are Password/PIN known as Personal Identification Number, systems. The problem with that or other similar techniques is that they are not unique, and is possible for somebody to forget loose or even have it stolen for somebody else. In order to overcome these problems there has developed considerable interest in "biometrics" identification systems, which use pattern recognition techniques to identify people using their characteristics. Some of those methods are fingerprints and retina and iris recognition. Though these techniques are not easy to use. For example in bank transactions and entry into secure areas, such technologies have the disadvantage that they are intrusive both physically and socially. The user must position the body relative to the sensor, and then pause for a second to declare himself or herself. That doesn't mean that face recognition doesn't need specific positioning. As we are going to analyse later on the poses and the appearance of the image taken is very important.

While the pause and present interaction are useful in high-security, they are exactly the opposite of what is required when building a store that recognise its best customers, or an information kiosk that remembers you, or a house that knows the people who live there. Face recognition from video and voice recognition have a natural place in these next generation smart environments, they are unobtrusive, are usually passive, do not restrict user movement, and are now both low power and inexpensive. Perhaps most important, however, is that humans identify other people by their face and voice, therefore are likely to be comfortable with systems that use face and voice recognition.

History of Face Recognition: Face recognition rises from the moment that machine started to become more and more "intelligent" and had the advance of fill in, correct or help the lack of human abilities and senses. The subject of face recognition is as old as computer vision and both because of the practical importance of the topic and theoretical interest from cognitive science. Face recognition is not the only method of recognising other people. Even humans between each other use senses in order to recognise others. Machines have a wider range for recognition purposes, which use thinks such as fingerprints, or iris scans. Despite the fact that these methods of identification can be more accurate, face recognition has always remains a major focus of research because of its non-invasive nature and because it is people's primary method of person identification.

Since the start of that field of technology there were two main approaches. The two main approaches to face recognition are

1. Geometrical approach

2. Pictorial approach.

The geometrical approach uses the spatial configuration of facial features. That means that the main geometrical features of the face such as the eyes, nose and mouth are first located and then faces are classified on the basis of various geometrical distances and angles between features. On the other hand, the pictorial approach uses templates of the facial features. That method is using the templates of the major facial features and entire face to perform recognition on frontal views of faces. Many of the projects that where based on those two approaches have some common extensions that handle different poses backgrounds. Apart from these two techniques we have other recent template-based approaches, which form templates from the image gradient, and the principal component analysis approach, which can be read as a sub-optimal template approach. Finally we have the deformable template approach that combines elements of both the pictorial and feature geometry approaches and has been applied to faces at varying pose and expression.

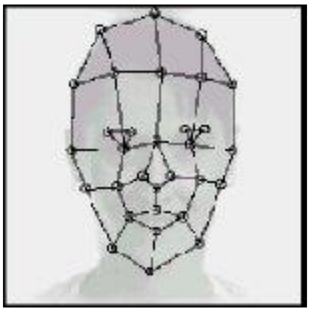


Fig.2 Sample face recognition

Since the early start of face recognition there is a strong relation and connection with the science of neural networks. Neural networks are going to be analyses in more detail later on. The most famous early example of a face recognition "system", using neural networks is the Kohonen model. That system was a simple neural network that was able to perform face recognition for aligned and normalised face images. The type of network he employed computed a face description by approximating the eigenvectors of the face image's auto-correlation matrix;

these eigenvectors are now known as "eigenfaces".

After that there were more other methods that where developed based on older techniques. If we want to summarise the methods that the "idea" of face recognition is based we have a geometrical approach or pictorial approach, and after that we have methods like eigenfaces, Principal Component Analysis, or other methods that process images in combination with neural networks or other expert systems.

In the recognition stage, the input is compared against all selected model views of each person. To compare the input against a particular model view, the face is first geometrically aligned with the model view. An affine transform is applied to the input to bring the facial features automatically located by the system into correspondence with the same features on the model. A technique based on the optical flow between the transformed input and the model is used to compensate for any remaining small transformation between the two. Templates from the model are then compared with the image using normalised correlation. Both the model and input images are pre-processed with a differential operator such the ones mentioned just above. Here, we address the problem of recognizing faces when only one view of the face is available. The key to making this work will be an example-based learning system that uses multiple images of prototype faces undergoing changes in pose to learn, with the help of neural networks. The system will apply this knowledge to synthesise new virtual views of the person's face.

The present: With the rapid evolution of the technology and the commercialization of technological achievements, face recognition became more and more popular, not only for research but also for the use of security systems. That gave the motive to many researchers, and also companies in order to develop techniques for automatically recognising faces that would find many applications, including security and human-computer interaction. For instance, a face recognising machine could allow automated access control for buildings or enable a computer to recognise the person sitting at the console. Most existing face recognition systems, however, work only for frontal or nearly frontal images of faces. By recognising faces under varying pose, one makes the conditions under which face recognition systems operate less rigid.

Face recognition and Face detection: As mentioned above face recognition is technique of recognising faces but it is not necessary to "freeze" the user in order to take a picture. Though there is a problem with recognising faces when the pose of the face is different, but in particular, there is a limit on face rotations in depth, which include left and right and up and down rotations. Face recognition itself is difficult because it is a fine discrimination task among similar objects, once we can find faces, which are quite similar. Adding pose variation naturally makes the problem more difficult. This is because the appearance of a person's face changes under rotation since the face has a complex 3D structure. At this point we have to distinguish face recognition for face detection. Many people thing that these two terms are the same. Thought even they have many similar techniques, are based on the same idea and algorithms, are two different, systems. The main difference is the fact that face recognition is detecting faces and search through a dataset in order to find an exact match but on the other have face detection is looking for any match and as soon as one is found then the search stops.

This task of face recognition seems to be sequential and have traditionally often been treated as such. However, it is both computationally and psychophysically more appropriate to consider them as a set of co-operative visual modules with closed-loop feedback. In order to realise such a system, an integrated approach has been adopted which will perform acquisition, normalisation and recognition in a coherent way. Images of a dynamic scene are processed in real-time to acquire normalise and aligned face sequences. In essence, this process is a closed-loop module that includes the computation and fusion of three different visual cues: motion, colour and face appearance models. Face tracking based upon motion and a face appearance model has been addressed in greater detail elsewhere.

In general much research effort has been concentrated on face recognition tasks in which only a single image or at most a few images of each person are available. A major concern has been scalability to large databases containing thousands of people. However, large intra-subject variability casts doubt upon the possibility of scaling face recognition, at least in this form, to very large. Databases are mentioned in detail in another part of the report.

The tasks of face recognition mostly require recognition to be performed using sequences acquired and normalise automatically in poorly constrained dynamic scenes. These are characterised by low resolution, large-scale changes, variable illumination and occasionally inaccurate cropping and alignment. Recognition based upon isolated images of this kind is highly inconsistent and unreliable. However, accumulating recognition scores over time can compensate the poor quality of the data.

Face recognition is an active research area involving different fields such as physics, psychology, biology, mathematics, computer science and several others. A wide range of problems has been approached, resulting in many interesting applications. In the research presented here, we look at one of the core problems in a face identification system.

1.2Applications of Face Recognition

Better tools for law enforcement. After the Boston Marathon bombing, the Boston police commissioner said that facial recognition software had not helped them identify Dzhokhar and Tamerlan Tsarnaev, despite the fact that the two were in public records databases—and photographed at the scene. Only, those images were taken from far away, the brothers were wearing sunglasses and caps, and many shots of them were in profile — all things that make facial recognition difficult. Experts say that technology can overcome these difficultiesIn a fascinating article via Yahoo, Paul Schuepp of the company Animetrics shares a more specific advance: software that turns 2D images into a simulated 3D model of a person's face. In a single second, it can turn an unidentifiable partial snapshot into a very identifiable headshot. He claims the software can boost identification rates from 35 percent to 85 percent.

2 **Full body recognition?** Allyson Rice of the University of Texas at Dallas has an idea for how facial recognition software could become even more accurate for law enforcement purposes — by becoming *body* recognition software. In a study published this month in *Psychological Science*, Rice and her fellow researchers asked college students to discern whether two photos — which had stumped facial recognition software — were indeed of the same person. They used eye-tracking equipment to discern how the participants were making the call. In the end, they found that students were far more accurate in their answers when the face *and* body of the subject was shown. And while participants reported judging based on facial features, their eyes were spending more time examining body build, stance, and other body features. "Psychologists and computer scientists have concentrated almost exclusively on the role of the face in person recognition," Rice tells *The Telegraph*. "But our results show that the body can also provide important and useful identity information for person recognition."

3 **A face scan for your phone. "**Face Unlock" is a feature that allows you to unlock Android

smartphones using your "faceprint," i.e. a map of the unique structure of your face. This is just the beginning of face-as-security measure. In June, according to eWeek.com, Google patented a technology that would turn goofy facial expressions — a wink, a scrunched nose, a smile, a stuck-out tongue — into a code to unlock devices. The hope: that this would be harder to spoof than a faceprint. Turns out, apps such as FastAccess Anywhere, which uses your face as a password, can reportedly be fooled with a simple photo, says USA Today.

4 **Facial recognition as advertising.** Could facial recognition technology be used to influence what we buy? Very likely. In 2012, an interactive ad for Choice for Girls was launched at bus stops in London. These billboards were able to scan passersby, judge their gender and show them appropriate content. Girls and women got a video, while boys and men got statistics on a subject. This ad was for a good cause, but this technology will no doubt expand — and could allow corporations and organizations to tap into our personal lives in unpredictable ways. Personalized ads as we walk down the street, a la the classic scene in *Minority Report*, yes. Ads can identify us and our two favorite friends on Facebook. From there, it's a snap to create a composite image of a person who'll star in an ad targeted just to us. For more in what's coming in the facial recognition advertising realm, check out Leslie Stahl's 60 Minutes segment "A Face in the Crowd: Say goodbye to anonymity." Among other fascinating tidbits, it introduces us to FaceDeals — which notes when you've walked into an establishment, mines your Facebook likes and text messages a deal created just for you.

5 **Shattered Glass**. The fact that someone's face can be used to find out private information is especially disconcerting given Google Glass' emergence on the scene. In June, US

lawmakers questioned Google about the privacy implications of the device and, in response, Google stressed that they "won't be approving any facial recognition Glassware at this time." But of course, it's not completely up to them. In July, Stephen Balaban announced to NPR and the world that he had hacked Glass in order to give it facial recognition powers. "Essentially what I am building is an alternative operating system that runs on Glass but is not controlled by Google," he said. On a similar note, one Michael DiGiovanni created a program called Winky for Glass that lets the wearer take a photo with a wink, rather than using the voice command.

6 **Your face as currency.** In July, a Finnish company called Uniqul released a video of a project in the works, a pay-by-face authentication system. The idea? At a store, rather than paying with cash or a credit card, you give a "meaningful nod" to a scanner to make a purchase. A Huffington Post article describes this new tech, and also gives a peak at the Millennial ATM, which uses facial recognition as its primary security method.

1.3 Difficulties in Face Recognition

Recent public facial recognition benchmarks have shown that in general, the identification performance decreases linearly in the logarithm of number of people in the gallery database. Also, in a demographic point of view, it was found that the recognition rates for males were higher than for females, and that the recognition rates for older people were higher than for younger people. These tests also revealed that while the best recognition techniques were successful on large face databases recorded in well-controlled environments, their performance was seriously deteriorated in uncontrolled environments, mainly due to variations in illumination and head rotations. Such variations have proven to be one of the biggest problems of face recognition systems.

Several techniques have been proposed to recognize faces under varying pose. One approach is the automatic generation of novel views resembling the pose in the probe image. This is achieved either by using a face model (an active appearance model (AAM) or a deformable 3D model or by warping frontal images using the estimated optical flow between probe and gallery. Classification is subsequently based on the similarity between the probe image and the generated view. A different approach is based on building a pose varying eigenspace by recording several images of each person under varying pose. Representative techniques are the view-based subspace and the predictive characterized subspace. More recently, techniques that rely on 3D shape data have been proposed.

The problem of coping with illumination variations is increasingly appreciated by the scientific community and several techniques have been proposed that may be roughly classified into two main categories. The first category contains techniques seeking illumination insensitive representations of face images. Several representations were seen to be relatively insensitive to illumination variability, e.g. the direction of the image gradient or the sum of gradient of ratios between probe and gallery images.

The second approach relies on the development of generative appearance models, able to reconstruct novel gallery images resembling the illumination in the probe images. Some of these techniques utilize a large number of example images of the same person under different illumination conditions to reconstruct novel images. Other approaches utilize a 3D range image and albedo map of the person's face to render novel images under arbitrary illumination, while others are based on a combination of the above. Finally, a third more recent approach is based on computer graphics techniques for relighting the probe image so that it resembles the illumination in gallery images.

1.3 LITERATURE SURVEY

Primarily, the desirable components of well-recognized face features in face recognition system are comprised mainly of local pattern descriptors [5]–[11], Eigenface [12], Fisherface [13], and manifold-based learning methods[14]–[17]. These methods are inclined to effectively extract the representation and discriminate classes from original input images. In particular, the importance of local pattern descriptors has been well recognized in face recognition because they can successfully and effectively represent the spatial structure information of an input image to generate distinguishing local features, such as local binary pattern (LBP) [18]–[21] which has been successfully applied to facial application for achieving good recognition results permitted with computational simplicity as well as low-dimensional space requirements. Generally, a good local pattern descriptor is desired to extract discriminative and robust features from original input images. In face recognition, LBP achieves much better performance comparing with Eigenface and Fisherface. The idea of LBP is to divide a face image into sub-regions which include the compositions of micropatterns [21]. To generate a micropattern, each pixel is encoded based on the relationship between the referenced pixel and its neighborhoods, which can be modeled by the statistical histogram to represent the potential texture information (e.g., spots, lines, corners).

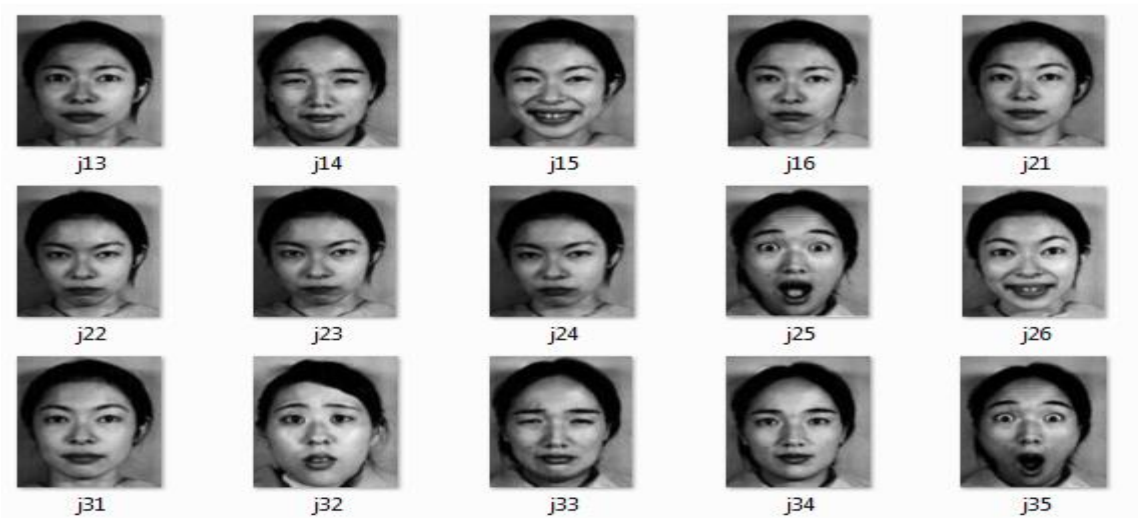
On the other hand, LBP can also be considered as the nondirectional first-order circular derivative local pattern which is used to concatenate binary comparative results for generating the micropatterns according to the extended definition from the local derivative pattern (LDP) [22]. Derived from the LBP, Zhang *et al*. proposed the high-order derivative descriptor for face representation that can more successfully capture the discriminative information than the LBP [22]. The reason is that the first-order derivative pattern fails to combine the relationship of neighborhoods to extract more detailed information. In the investigation, the LDP encodes the turning points or the monotonical ones to the two distinct values ("1" or "0") by comparing the derivative values between the referenced pixel and its local neighborhoods in a given high-order derivative direction. Different from LDP, Murala *et al*. proposed the local tetra pattern (LTrP) to extend the two distinct values to four distinct values by using the two high-order derivative direction patterns for generating more distinguishing information [23]. However, the LTrP encodes the four tetra patterns with the quadrant of the referenced pixel, while the other tetra patterns are encoded with "0" which possibly loses the potential texture information. It leads to both high redundancy and feature length increasing which are considered as critical issues for developing an effective local pattern descriptor. This observation hence motivates us to solve the problems of the LTrP to improve the performance for use in our face recognition application.

In this project, a novel pattern descriptor, called local vector pattern (LVP), for use in face recognition. We mainly aim at enhancing the proposed method with respect to the aforementioned problems (high redundancy and feature length increasing). To resolve these two problems, we develop a novel vector representation by calculating the various directions with diverse distances to represent the 1D direction and structure information of the face texture. Based on the vector representation, the LVP encodes various pairwise directions of vector as a facial descriptor to strengthen the structure of micropatterns. Moreover, we develop a novel coding scheme, comparative space transform (CST), in LVP encoding to encode a pairwise direction of vector for reducing the feature length and high redundancy resulting from LTrP. Furthermore, the proposed CST uses a designed dynamic linear decision function to suppress the slight noise influence, such as intensity change in a flat surface. In our work, the LVP can also be applied in various high-order derivative spaces to refine the vector representation for obtaining a more compact and discriminative local pattern descriptor. Hence, the first order LVP can be considered as the non-directional derivative local pattern, and the second-order LVP refines the vector to obtain 2D direction information of local structure in various first-order derivative spaces. Consequently, the *nth*-order LVP is a general form representing a local pattern descriptor which inherently generates more detailed information from a given local structure. According to our observation, like the LBP, the LVP can be modeled by statistical histogram to represent the generated spatial distribution of the LVP micropatterns. In addition, the use of more directional information makes the high-order LVP exhibit better performance in various experimental results comparing to a set of similar methods (the LBP, the LDP, and the LTrP).

1.4 DRAWBACKS OF EXISTING SYSTEMS

The coding schemes of the previous methods have several drawbacks in generating the specific code, especially under the illumination changes and noise influence in the face images. For example, LBP encodes the surrounding neighborhoods by using the grayscale value of the referenced pixel as a threshold function [20], [21]. If the grayscale values of the referenced pixel and its neighborhoods are similar, the threshold function is very sensitive to noise and will thereby encode different code that deteriorates the performance of accuracy immediately. Derived from the LBP, the LDP encodes the 1D spatial relationship between the referenced and its neighborhoods with single high-order derivative direction that can be considered as either the turning point or monotonically increasing or decreasing spatial relationship [22]. Extended from the LDP, the LTrP adopts both the horizontal and vertical high-order derivative directions to encode the 2D spatial relationship [23]. Similar to the problem occurring in LBP, the high-order derivative values of the neighborhoods are sensitive to the noise influence which will result in inconsistent bit string. Although the relating methods of LDP and LTrP explore the distinct information from neighborhoods and Gabor features to make the bit string more stable than the LBP [6], [31]–[33], they still encode the unexpected characteristics in a bit string as similar to the LBP. Consequently, certain effective coding schemes are derived to suppress the noise influence [10], [34]. For instance, the LDN encodes directional information from neighborhoods by using the prominent direction indices (directional numbers) to distinguish the different intensity transitions among the similar structural patterns [10]. The Color Angular Patterns (CAP) of LCVBP calculates the angle values of the referenced pixel and its neighborhoods between a pair of the spectral-band images where the angle values fall between 0° and 90° for extracting discriminative binary patterns [34]. For instance, the angle value at a pixel location between a pair of spectral-band images will be invariant even in the illuminated image region. It indicates that CAP can still encode the illumination invariant binary pattern by using the angle information for color facial images. However, the angle value calculated in CAP is no longer between 0° and 90° for the pairwise directions of vector at a pixel location from grayscale facial images in our LVPs.

1.5 DATA SET FOR FACE RECOGNITION WITH DIFFERENT EXPRESSIONS



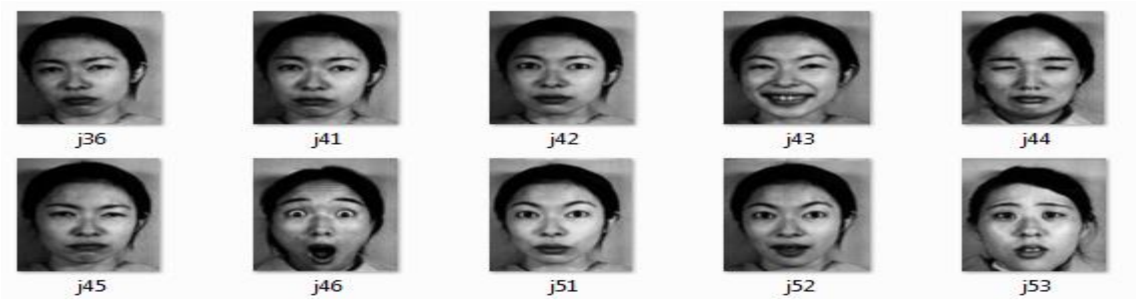


Figure.3 Dataset for face recognition with different expressions

1.6 OBJECTIVE OF THE WORK

Trying to find a face within a large database of faces. In this approach the system returns a possible list of faces from the database. The most useful applications contain crowd surveillance, video content indexing, personal identification (example: driver's license), mug shots matching, etc.

Real time face recognition: Here, face recognition is used to identify a person on the spot and grant access to a building or a compound, thus avoiding security hassles. In this case the face is compared against a multiple training samples of a person.

1.7 SCOPE OF THE WORK

First chapter, a brief introduction about the content Face analysis, Face Recognition, Face Recognition with different expressions and various methods are discussed under the literature survey. Chapter 2 describes the existing method LBP and how they can be implemented. Chapter 3 describes the existing method LDerP and how they can be implemented. Chapter 4 describes our developed method LVP and how they can be implemented and the conclusion is given in chapter 5.

CHAPTER 2

FACE RECOGNITIONUSING LOCAL BINARY PATTERNS

2.1 INTRODUCTION

The local binary pattern (LBP) operator is defined as a grey level invariant texture measure, derived from a general definition of texture in a local neighborhood, the centre of which is the pixel (x, y). Recent extensions of the LBP operator have shown it to be a really powerful measure of image texture, producing excellent results in many empirical studies .The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its invariance to monotonic grey level changes. Equally important is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.

2.2 LOCAL BINARY PATTERNS

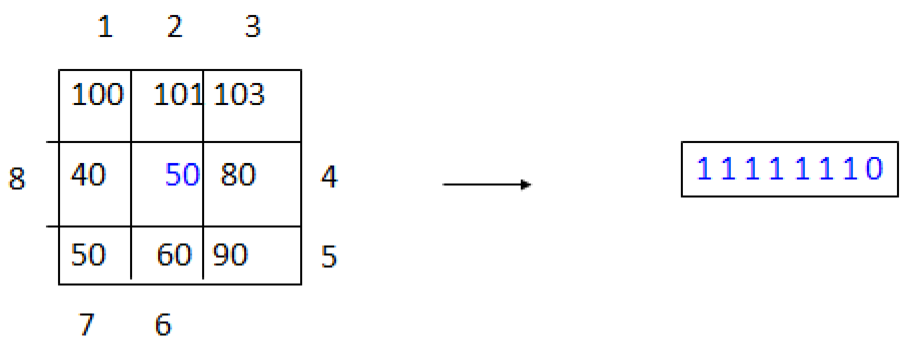
The local binary pattern operator describes the surroundings of the pixel(x, y) by generating a bit-code from the binary derivatives of a pixel as a complementary measure for local image contrast. The original LBP operator takes the eight neighboring pixels using the centre grey level value I(x, y) as a threshold. The operator generates a binary code 1 if the neighbor is greater than or equal to the central level, otherwise it generates a binary code 0. The eight neighboring binary codes can be represented by an 8-bit number .The LBP operator outputs for all the pixels in the image can be accumulated to form a histogram, which represents a measure of the image texture. The generalized LBP operator is derived on the basis of a circularly symmetric neighbor set of P members on a circle of radius R. The parameter P controls the quantization of the angular space and R determines the spatial resolution of the operator. The LBP code of central pixel (x, y) with P neighbors and radius R is defined as

$$LBP_{P,R}(G_c) = \{s_1(I(G_{1,R}), I(G_c)), s_1(I(G_{2,R}), I(G_c)), \ldots, s_1(I(G_{p,R}), I(G_c))\}|_{p=1,2,\ldots,P;R=1} \quad (1)$$

where Gp,R is one of 8-neighborhoods of the referenced pixel with unit-radius, and p is the index of the neighborhoods surrounding referenced pixel Gc in a given local sub-region I. The label of each neighborhood is decided by calculating the coding function s1(·,·) with both referenced pixel and neighborhood pixel, called threshold function, which can be formulated as

$$s_1(I(G_{p,R}), I(G_c)) = \begin{cases} 1, & \text{if } (I(G_{p,R}) - I(G_c)) \geq 0 \\ 0, & \text{else} \end{cases} \quad (2)$$

where the output of s1(·,·) represents the binary gradient direction. Furthermore, the local features of the distribution of local sub-region can be modeled as the edges, spots, corners, and other local features.



2.3 RESULTS AND DISCUSSIONS

The LBP is analyzed on the sample face image .The features of LBP are calculated .These parameters are evaluated with different classifiers such as k-nearest neighbor (KNNC). In experiment 2 sample faces are taken from FERET database and 20, 30 individual faces are from each sample total 50 faces are taken as training set.Training set is tested using LBP feature extraction. Each image is taken and its LBP image is found. After that the histogram is found of the image. Next the Euclidean Distance is calculated between the histogram of the images. Using this distance we see the difference between the any 2 images. Rows correspond to classes in the training set. Columns correspond to classes in the classification .The diagonal elements in the matrix represent the number of correctly classified pixels of each class, i.e. the number of training set with a certain class name that actually obtained the same class name during classification. Example of an LBP output is shown. Results are of classifiers are shown in table 1.The histogram is shown in below figure.

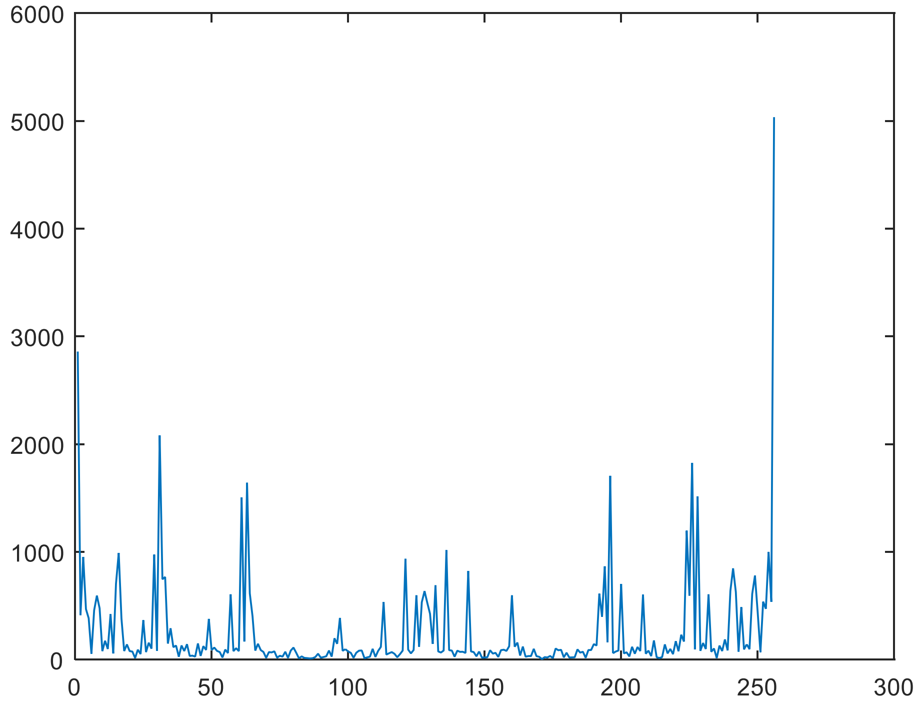


Figure4:Histogram using LBP features

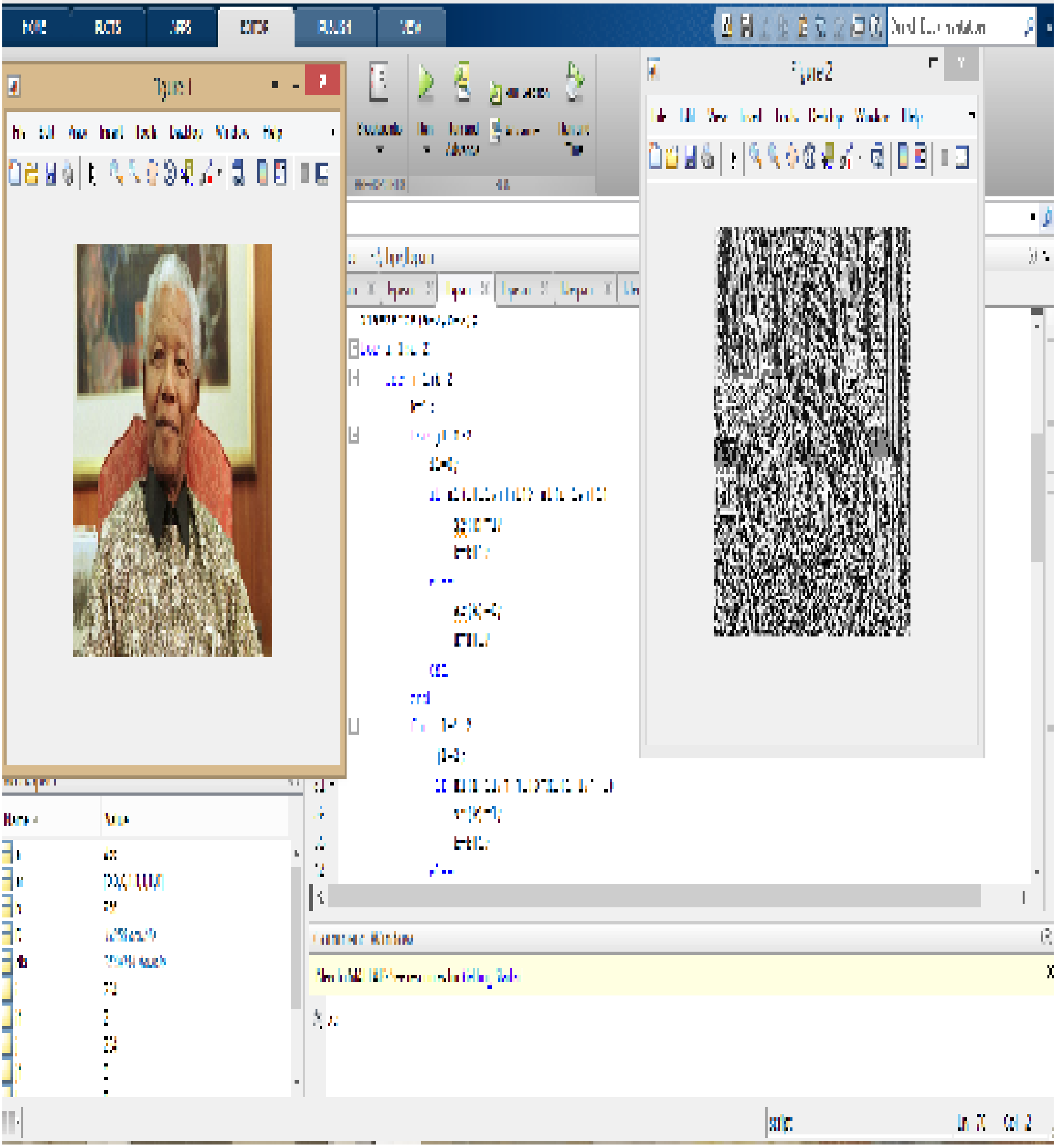


Figure 5: Example image and its LBP image

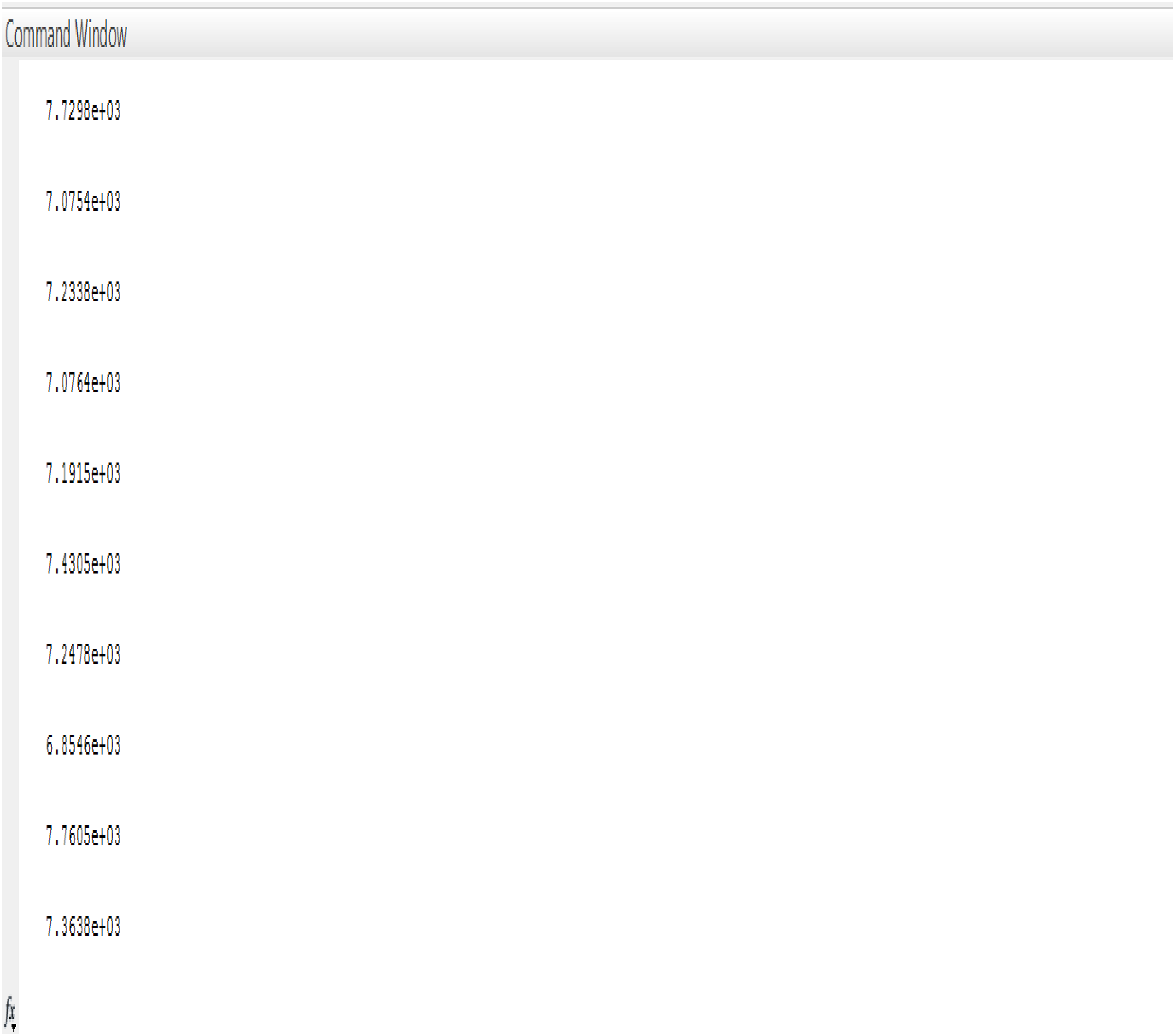


Figure 6: Euclidean distances found while using LBP

Table 1

Results of LBP with K-nearest neighbor Classifier (KNNC)

True Labels	1	2	Totals
1	13	7	20
2	7	23	30
Totals	20	30	50

CHAPTER 3

FACE RECOGNITION USING LOCAL DERIVATIVE PATTERN

3.1 INTRODUCTION

Local derivative patterns are a general framework to encode directional pattern features based on local derivative variations. Different from LBP encoding the relationship between the central point and its neighbors, the local derivative patterns templates extract high-order local information by encoding various distinctive spatial relationships contained in a given local region The high-order local derivative patterns consistently performs much better than LBP .

LBP actually encodes the binary result of the first-order derivative among local neighbours by using a simple threshold function which is incapable of describing more detailed information. An LDP operator is proposed, in which the n-1^{th}-order derivative direction variations based on a binary coding function. In this scheme, LBP is conceptually regarded as the no directional first-order local pattern operator, because LBP encodes all-direction first-order derivative binary result while LDP encodes the higher-order derivative information which contains more detailed discriminative features that the first-order local pattern (LBP) cannot obtain from an image.

3.2 LOCAL DERIVATIVE PATTERN

The nth-order LDP can be encoded by $(n\text{-}1)^{th}$-order local derivative various, to calculate second-order LDP must calculate first-order derivative various For encoding the nth-order LDP, the (n −1)th-order derivatives along0°, 45°,90° and135°directionsare denoted as In−1 α (Gc) where α = 0°, 45°, 90° and 135°, which are pre-calculated separately based on

$$I_{0^\circ}^{n-1}(G_c) = I_{0^\circ}^{n-2}(G_{1,R}) - I_{0^\circ}^{n-2}(G_c) \quad (3)$$
$$I_{45^\circ}^{n-1}(G_c) = I_{45^\circ}^{n-2}(G_{2,R}) - I_{45^\circ}^{n-2}(G_c) \quad (4)$$
$$I_{90^\circ}^{n-1}(G_c) = I_{90^\circ}^{n-2}(G_{3,R}) - I_{90^\circ}^{n-2}(G_c) \quad (5)$$
$$I_{135^\circ}^{n-1}(G_c) = I_{135^\circ}^{n-2}(G_{4,R}) - I_{135^\circ}^{n-2}(G_c). \quad (6)$$

Then, the nth-order LDP, LDPn P,R,α(Gc), inα derivative direction at Gc is encoded as

$$\begin{aligned} LDP_{P,R,\alpha}^{n}(G_c) = \{ & s_2(I_\alpha^{n-1}(G_{1,R}), I_\alpha^{n-1}(G_c)), \\ & s_2(I_\alpha^{n-1}(G_{2,R}), I_\alpha^{n-1}(G_c)), \ldots, \\ & s_2(I_\alpha^{n-1}(G_{p,R}), I_\alpha^{n-1}(G_c))\}|_{p=1,2,\ldots,P;R=1} \end{aligned} \quad (7)$$

Finally, the nth-order LDP, LDPn P,R(Gc) at Gc, is defined as the concatenation of the four directional LDPs

$$LDP_{P,R}^{n}(G_c) = \{LDP_{P,R,\alpha}^{n}(G_c) | \alpha = 0^\circ, 45^\circ, 90^\circ, 135^\circ\}. \quad (9)$$

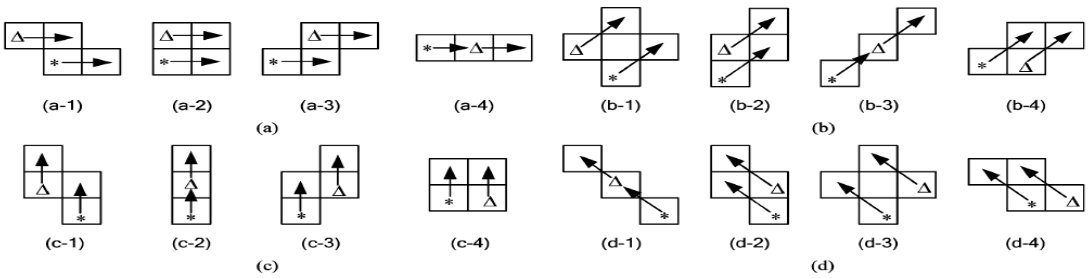


Fig.7 Local derivative pattern directions

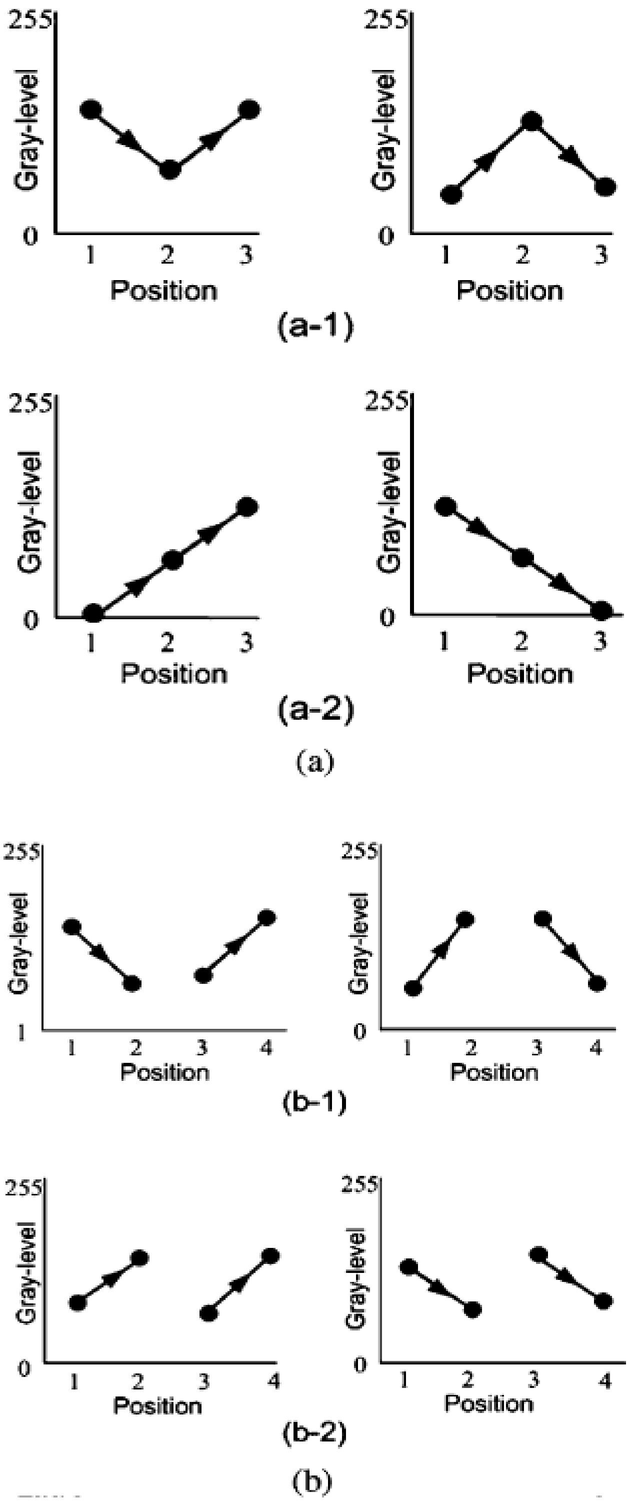


Figure.8. Meanings of “0” and “1” for the second-order LDP. ref. 1 is Z_0, and ref. 2 is one of the 8-neighbor of Z_0. The arrows mean the gradient in each point. (a-1) result in both cases are “1”. (a-2) result in both cases is “0”. (b-1) result in both cases is “1”. (b-2) result in both cases is “0”.

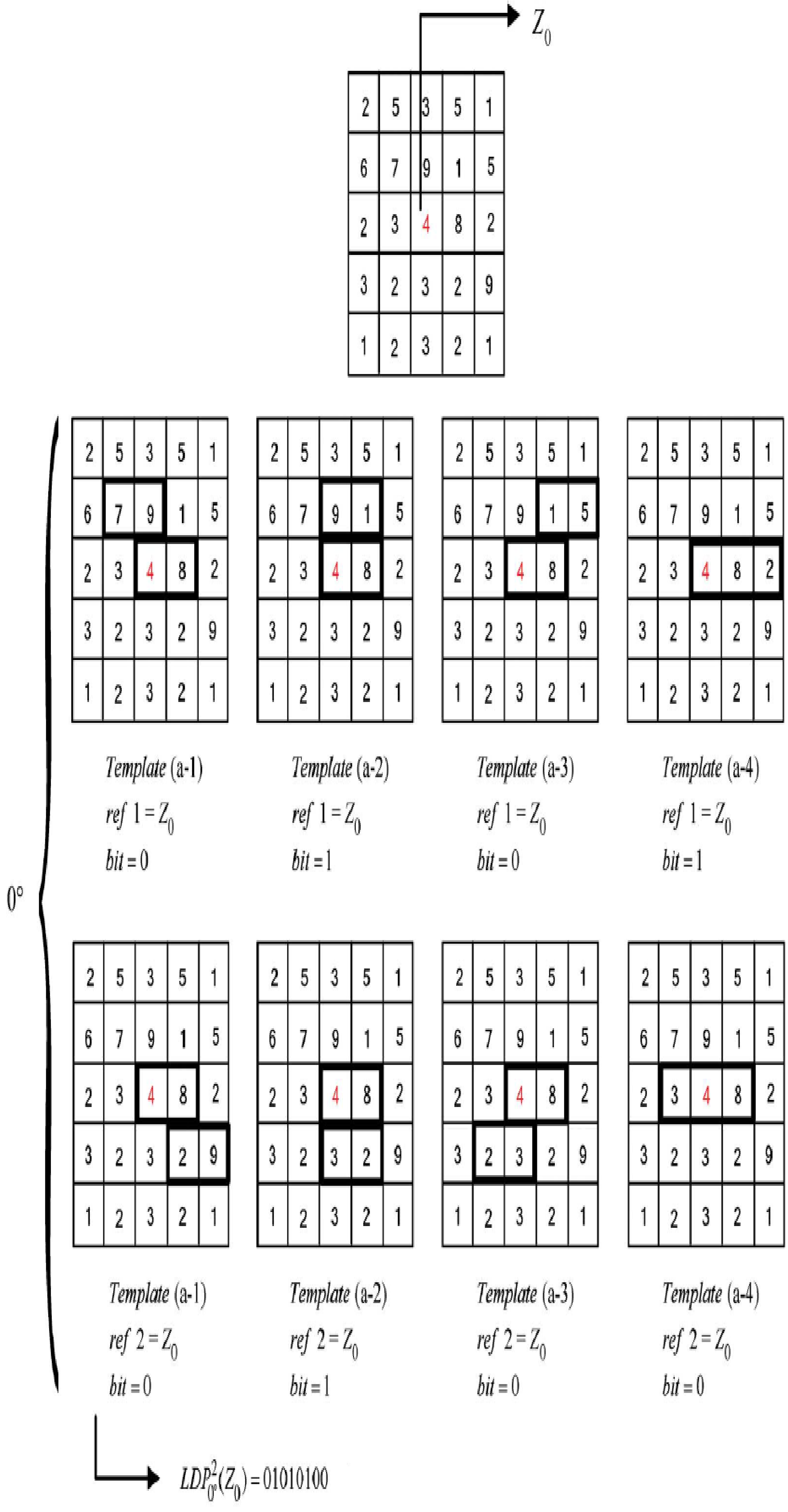


Fig.9 Local derivative pattern example

3.3 RESULTS AND DISCUSSIONS

The LDerivP is analyzed on the sample face image .The features of LDerivP are calculated .These parameters are evaluated with different classifiers such as k-nearest neighbor(KNNC). In experiment 2 sample faces are taken from FERET database and 20,30 individual faces are from each sample total 90 faces are taken as training set(some of the examples of signature samples in training set are shown above).Training set is tested using LDerivP feature extraction. Each image is taken and its LDerP image is found. After that the histogram is found of the image. Next the Euclidean Distance is calculated between the histogram of the images. Using this distance we see the difference between the any 2 images. Rows correspond to classes in the training set. Columns correspond to classes in the classification .The diagonal elements in the matrix represent the number of correctly classified pixels of each class, i.e. the number of training set with a certain class name that actually obtained the same class name during classification. Results are of classifiers are shown in table 3 .The histogram is shown in below figure 10.

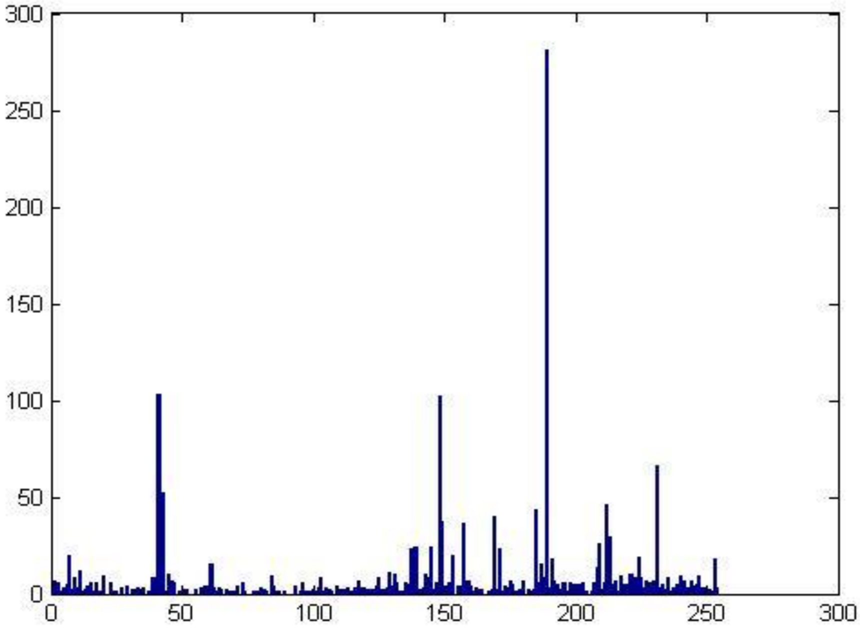


Figure10:Histogram using LderivP features

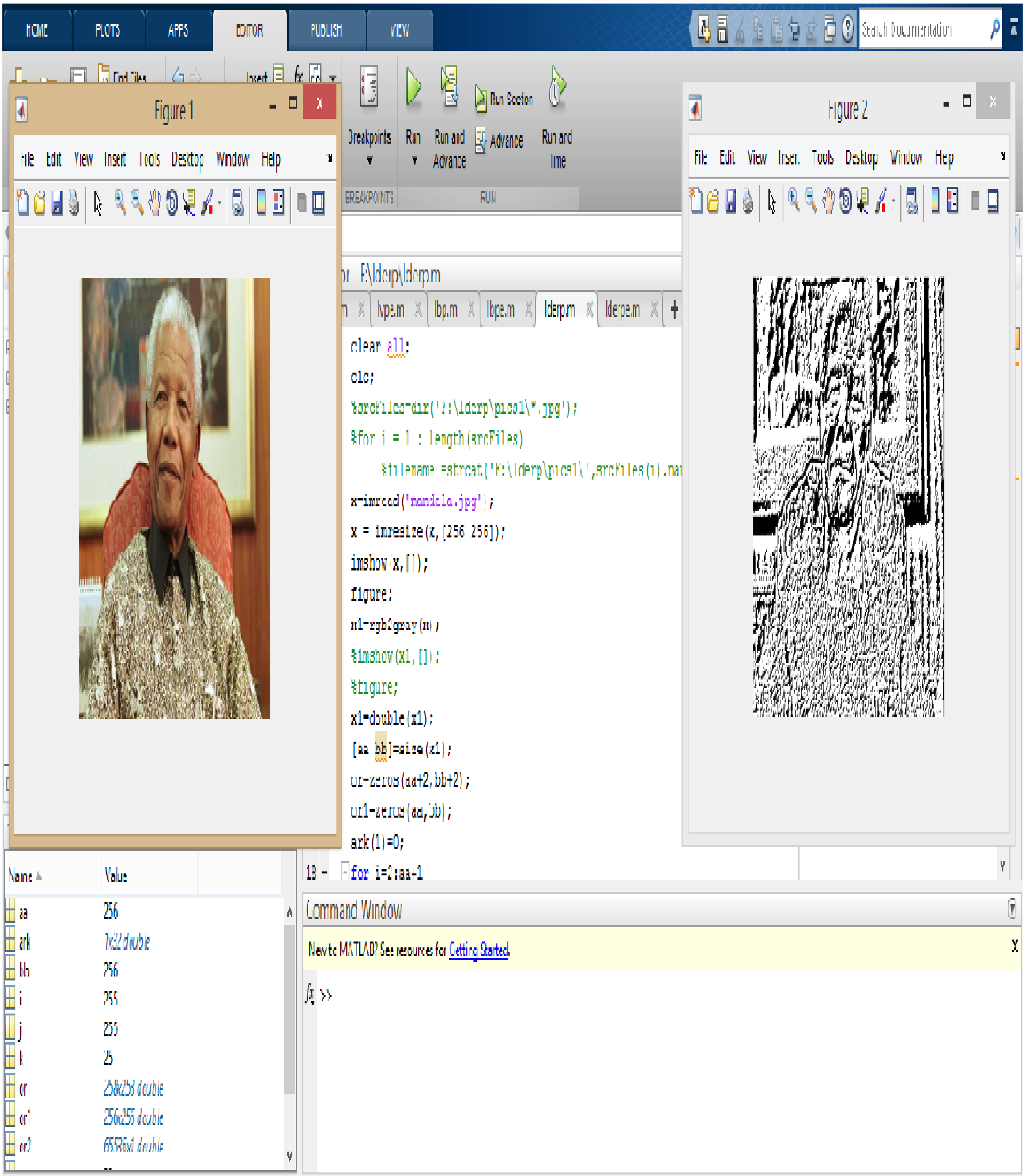


Figure 11: Example image and its LDerP image

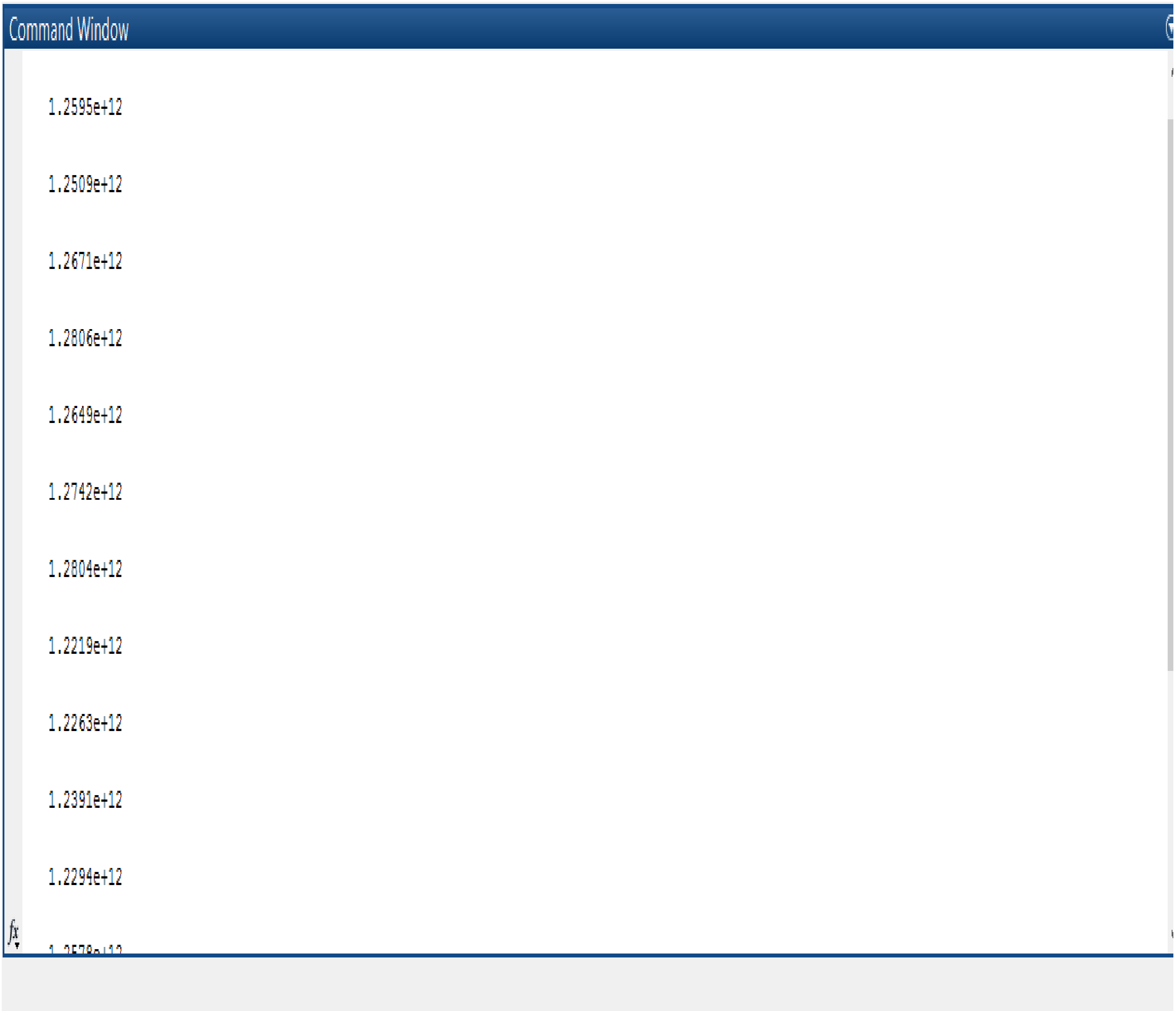


Figure 12: Euclidean distances found while using LDerP

Table 3

Results of LDerivP with K-nearest neighbor Classifier (KNNC)

True labels	1	2	Totals
1	17	3	20
2	3	27	30
Totals	20	30	50

CHAPTER 4

FACE RECOGNITION USING LOCAL VECTOR PATTERN

4.1 INTRODUCTION

According to the literature review in Section II, we observe that the LBP is a basic descriptor for extracting micropatterns without considering feasible neighboring relationship, the LDerP only adopts the single derivative direction and loses potential information between derivative directions, and the LTrP generates micropatterns by using both horizontal and vertical derivative directions so that it produces high redundancy and feature length increasing. In consequence, we propose a novel local pattern descriptor, called Local Vector Pattern (LVP), to remedy the drawbacks existing in current local pattern descriptors.

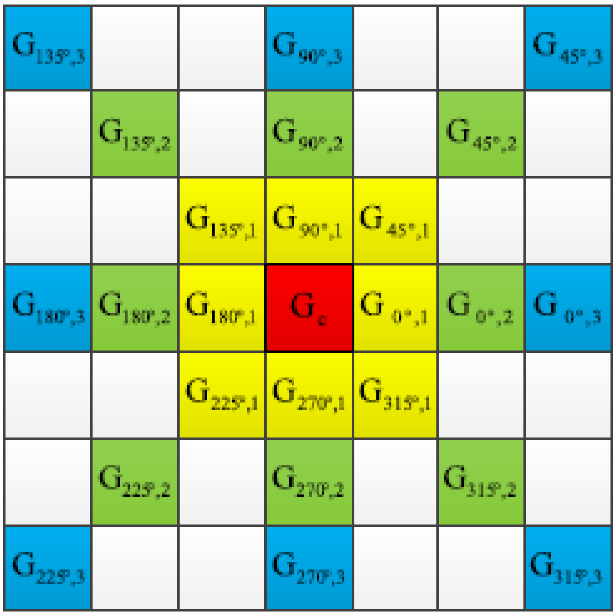


Fig.13. Adjacent pixels of Vβ,D(Gc) with different distances along each direction.

In our work, the key idea of the LTrP proposed in [23] is applied and improved to generate more discriminative features in our proposed LVP. Under the non-directional derivative preprocessing, the coding function of the LBP only considers the grayscale value of the referenced pixel and its neighborhoods and the LDP encodes the two distinct values

("1" or "0") by comparing the single high-order derivative direction between the referenced pixel and its neighborhoods. As a result, the horizontal and vertical high-order derivative directions are adopted for generating the four quadrants in LTrP. That is the LTrP extends the LDP to encode the tetra patterns of the surrounding neighborhoods with the quadrant of the referenced pixel.

4.2 LOCAL VECTOR PATTERN

In this project, a novel vector representation is developed to represent the 1D direction and structure information of local texture by calculating the values between the referenced pixel and the adjacent pixels with diverse distances from different directions. Based on the vector representation, the LVP descriptor is proposed to provide various 2D spatial structures of micropatterns with various pairwise directions of vector of the referenced pixel and its neighborhoods. Moreover, the coding functions of micropatterns in LBP, LDP, and LTrP are investigated for extracting more detailed discriminative features by encoding the various pairwise directions of vector of micropatterns through the proposed CST. The proposed CST here encodes the pairwise directions of vector with two distinct values by using dynamic linear decision function to extract discriminative features.

Given a local sub-region I, the direction value of a vector is denoted as Vβ,D(Gc) as illustrated in Fig. 2. Let Gc denote the referenced pixel marked with red in I, β be the index angle of the variation direction, and D be the distance between the referenced pixel and its adjacent pixels along the β direction. For illustration purpose, the distance D = 1 is marked with yellow, D = 2 is marked with green, and D = 3 is marked with blue. The direction value of a vector at the referenced pixel Gc can be defined as

$$V_{\beta,D}(G_c) = (I(G_{\beta,D}) - I(G_c)). \qquad (15)$$

When D =1, the vector can be considered as the first-order derivative values of LDP and LTrP. When D > 1,the implicit characteristics of 1D direction information can be acquired.

The LVP, LVPP,R,β(Gc), inβ direction of vector at Gc is encoded as

$$
\begin{aligned}
LVP_{P,R,\beta}(G_c) = \{ & s_5(V_{\beta,D}(G_{1,R}), V_{\beta+45^\circ,D}(G_{1,R}), V_{\beta,D}(G_c), \\
& V_{\beta+45^\circ,D}(G_c)), s_5(V_{\beta,D}(G_{2,R}), \\
& V_{\beta+45^\circ,D}(G_{2,R}), V_{\beta,D}(G_c), V_{\beta+45^\circ,D}(G_c)), \\
& \ldots, \\
& s_5(V_{\beta,D}(G_{p,R}), V_{\beta+45^\circ,D}(G_{p,R}), V_{\beta,D}(G_c), \\
& V_{\beta+45^\circ,D}(G_c))\}|_{p=1,2,\ldots,P;R=1} \qquad (16)
\end{aligned}
$$

where s5(·,·) adopts transform ratio which is calculated with a pairwise direction of vector of the referenced pixel to transform the β-direction value of neighborhoods to (β + 45°)-direction, which is used to compare with the original (β +45°)-direction value of neighborhoods for labeling the binary pattern of micropatterns. Therefore,

$$
\begin{aligned}
& s_5(V_{\beta,D}(G_{p,R}), V_{\beta+45^\circ,D}(G_{p,R}), V_{\beta,D}(G_c), V_{\beta+45^\circ,D}(G_c)) \\
& = \begin{cases} 1, & \text{if } V_{\beta+45^\circ,D}(G_{p,R}) - \left(\frac{V_{\beta+45^\circ,D}(G_c)}{V_{\beta,D}(G_c)} \times V_{\beta,D}(G_{p,R}) \right) \geq 0 \\ 0, & \text{else.} \end{cases}
\end{aligned} \qquad (17)
$$

Finally, the LVP, LVPP,R(Gc), at referenced pixel Gc is defined as the concatenation of the four 8-bit binary patterns LVPs.

$$LVP_{P,R}(G_c) = \{ LVP_{P,R,\beta}(G_c) | \beta = 0^\circ, 45^\circ, 90^\circ, 135^\circ \}. \quad (18)$$

In order to extract more discriminative 2D spatial structures of micropatterns, the proposed local pattern descriptor encodes the LVPs by using the four pairwise directions of vector of the referenced pixel and its neighborhoods. Especially, each pairwise direction of vector of the referenced pixel generates the transform ratio which is used to design the weight vector of dynamic linear decision function for encoding the distinct 8-bit binary pattern of each LVP. Different from the LTrP in encoding the 96 (4×3×8)-bit (three 8-bit binary patterns for each tetra pattern) binary pattern which uses both horizontal and vertical high-order derivative directions, the LVP reduces the feature length from 96-bit binary pattern to

8-bit binary pattern. More precisely, the LVP can extract more detailed texture information than the LTrP by using the four pairwise directions of vector. As a result, the LVPs are concatenated to form as a 32 (4 × 8)-bit binary pattern for each referenced pixel in the local sub-region.

4.3: RESULTS AND DISCUSSIONS

The LVP is analyzed on the sample face image. The features of LVP are calculated .These parameters are evaluated with different classifiers such as k-nearest neighbor(KNNC). In experiment 2 sample faces are taken from FERET database and 20,30 individual faces are from each sample total 90 faces are taken as training set(some of the examples of signature samples in training set are shown above).Training set is tested using LVP feature extraction. Each image is taken and its LVP image is found. After that the histogram is found of the image. Next the Euclidean Distance is calculated between the histogram of the images. Using this distance we see the difference between the any 2 images. Rows correspond to classes in the training set. Columns correspond to classes in the classification .The diagonal elements in the matrix represent the number of correctly classified pixels of each class, i.e. the number of training set with a certain class name that actually obtained the same class name during classification. Results are of classifiers are shown in table 3

.

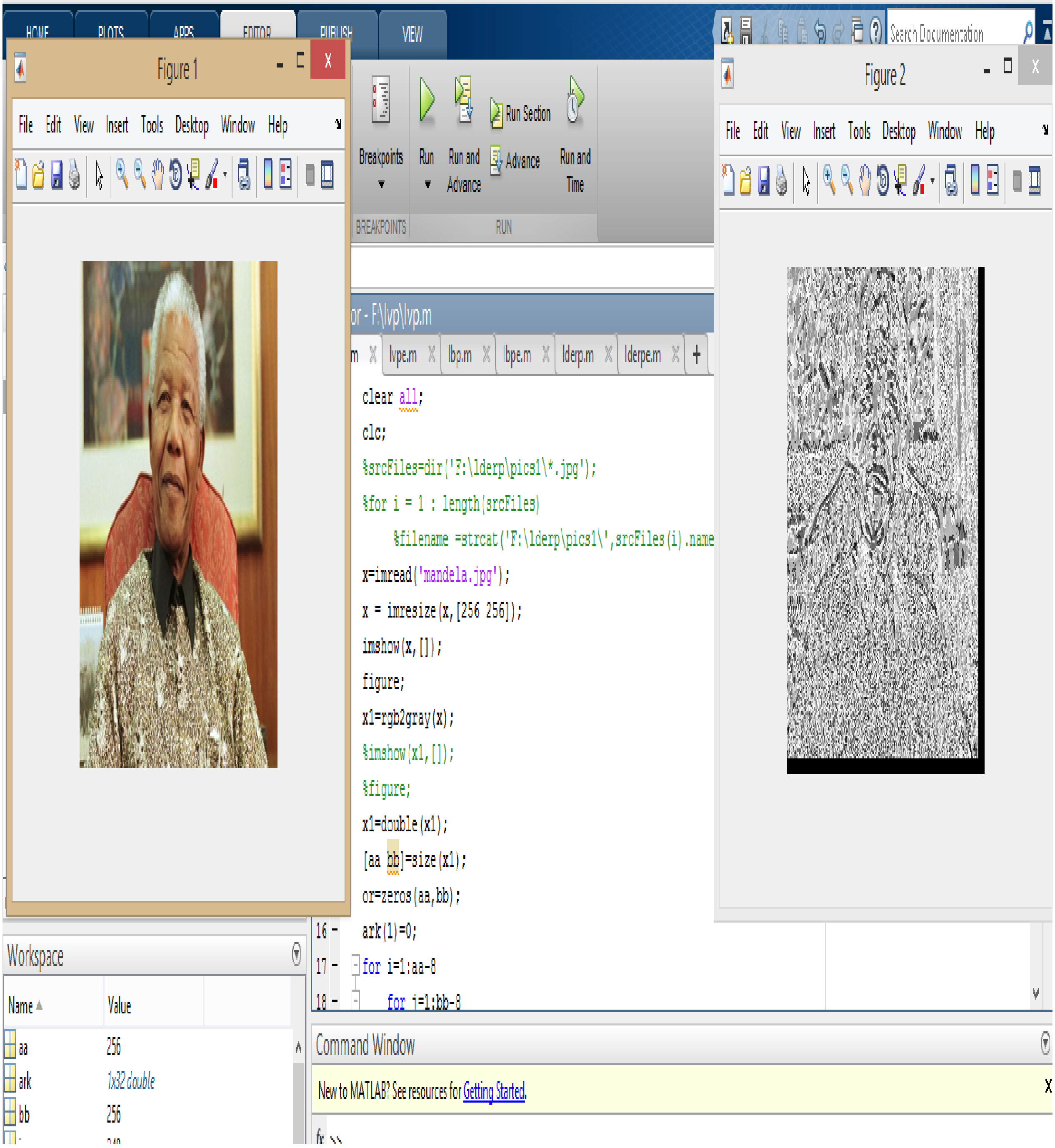


Figure 14: Example image and its LVP image

Figure 12: Euclidean distances found while using LDerP

4.4: OUTPUTS

Metrics used to evaluate the performance of the system are Precision, Recall and F-Score. Precision and Recall rates have been computed based on the number of Correctly Detected Characters (CDC) in an image, in order to evaluate the efficiency and robustness of the algorithm. The metrics are as follows

Definition 1*:* False Positives (FP) / False alarms are those faces in the database which are actually not face of the person in the input image , but have been detected by the algorithm as the face in the input .

Definition 2*:* False Negatives (FN)/ Misses are those faces in the database which are actually the faces of input image, but have not been detected by the algorithm.

Definition 3*:* Precision rate (P) is defined as the ratio of correctly detected faces to the sum of correctly detected faces plus false positives as represented in equation below.

$$P=CDF(\text{true positives})x100\%/(CDF+FP)$$

Definition 4: Recall rate (R) is defined as the ratio of the correctly detected faces to sum of correctly detected faces plus false negatives as represented in equation below.

$$R=CDF(\text{true positives})x100\%/(CDF+FN)$$

Definition 5: F-score is the harmonic mean of precision and recall as shown in equation as below.

$$F\text{-}Score=2PR/(P+R)$$

Table 3:Results of LVP with K-nearest neighbor Classifier (KNNC)

True Labels	1	2	Totals
1	19	1	20
2	1	29	30
Totals	20	30	50

Here calculation of the true positives, false positives, false negatives, precision, recall is done based on the above formulas. 100 images are taken and 98 true positives are found and 2 false negatives are found.

Table 4:

True positives	False positives	False negatives	Precision	Recall	F-score
98	2	2	98%	98%	98%

4.5 SUMMARY

In this project, we developed a novel pattern descriptor, called local vector pattern (LVP), for use in face recognition. We mainly aimed at enhancing the proposed method with respect to the aforementioned problems (high redundancy and feature length increasing). To resolve these two problems, we developed a novel vector representation by calculating the various directions with diverse distances to represent the 1D direction and structure information of the face texture. Based on the vector representation, the LVP encodes various pairwise directions of vector as a facial descriptor to strengthen the structure of micropatterns.

CHAPTER 5

CONCLUSION

The algorithm uses local vector patterns to characterize faces that effectively distinguish faces of persons with different expressions. The LBP, LDerp, LVP images were used to find the feature vectors. These feature vectors are given as a input to the KNNC. The developed algorithm is evaluated under different circumstances: changing the number of faces, database with different expressions. It was observed that the best results were obtained with the LVP.

Thus in this project it has been proved that the LVP is better based on the F-Score value, and any image with different expressions can be recognized. Here we have taken 100 mages with different expressions and 98 have been identified precisely, which is far better than the previous LBP and LDerP.

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