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Development of Feature Extraction Technique

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ABSTRACT

A problem of personal verification and identification is an actively growing area of research in pattern recognition, computer vision, and digital image processing. A Face acknowledgment system is largely significant move toward in our life. Face acknowledgment method must be proficient to robotically identify images of face. This system mainly used to recognize a person and make available a protection during various features of our life. It is extremely complicated job for investigator to obtain mainly excellent face acknowledgment velocity in a variety of circumstances and benchmarks. Face recognition is grassland of computer visualization to uses faces to recognize or authenticate a human being. Principal Component Analysis (PCA) is accomplished and used for feature extraction and measurement lessening. The feature extraction is used to reduce the dimension of the face space by transforming it into feature representation. Features may be symbolic, numerical or both. The symbolic feature is color and numerical feature is weight. The combined feature extraction of PCA, LDA and Wavelet are used in proposed feature extraction algorithm for human face recognition system. The structure is tested and achieves high recognition rates. Information regarding individuals was stored in a database.

Keywords : Face Detection, Face Recognition, Feature Extraction, Biometrics, Neural Network, PCA, LDA Wavelet.

I. INTRODUCTION

A problem of personal verification and identification is an actively growing area of research in pattern recognition, computer vision, and digital image processing. Human face recognition problem has become one of the most relevant research areas in pattern recognition. In recent years, it has attracted lot of attention of the researchers because of its wide range of potential applications [1] in the real world. Because of the nature of the problem, not only computer science researchers are interested in it, but neuroscientists and psychologists also. It is the general opinion that advances in computer vision research will provide useful insights to neuroscientists and psychologists into how human brain works, and vice versa [2]. Most of the commercial applications of the face recognition are identity authentication, criminal identification, security system, image and film processing, video conferencing and credit-card verification. Face recognition is considered to be an important part of the biometrics technique, and meaningful in scientific research [3]. It has the potential of being a non-intrusive form of biometric identification.

Face recognition is technologies which recognize the human by his/her face image. A wide variety of face recognition methods have been presented in this field. They can be categorized into two core approaches namely, feature-based [4-6] known as content-based and appearance based [7-9] approaches. Feature-based or Content- based recognition is based on the geometrical relationships between facial features like eyes, mouth, nose, and chin. However, although these approaches rely greatly on the accuracy of facial feature extraction methods, it has been argued that existing feature-based techniques are not reliable enough for practical applications [10]. Appearance-based approaches, also called the holistic method, utilize global facial features based on high-dimensional intensity vector representation. In this approach, the face is treated as a two dimensional pattern of intensity variation.

Over the past two decades, the considerable research attention has been directed towards developing reliable automatic face recognition systems. A number of independent tests have also been administered to compare the performance of two dimensional face recognition algorithms. These include a series of Facial Recognition Technology (FERET) tests [11-12], and the Face Recognition Vendors Tests [13]. The Face Recognition Vendors Test was conducted in the year 2002 (FRVT 2002) to establish performance metrics for fully automatic 2D face recognition algorithms [14]. In such evaluations, a few 2D face recognition algorithms have consistently demonstrated superior performance. These include algorithms based on Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Local Feature Analysis (LFA), and Elastic Bunch Graph Matching (EBGM).

Face recognition commonly includes feature extraction, feature reduction and recognition or classification. Many surveys are carried out on feature extraction of human face [1,15-17]. They specify various existing techniques of feature extraction for human face recognition process. Feature extraction is to find the most representative description of the faces, making them can be most easily distinguished from others. The usage of a mixture of techniques makes it difficult to classify these systems based purely on what types of techniques they use for feature representation or classification [1]. Recognition or classification is to choose the best available measure method such as Euclidean distance, which is used to classify the feature of face images present in the database and test image.

During the past several years, the evaluations of state-of-the-art recognition techniques conducted and have confirmed that age variations, illumination variations and pose variations are three major problems plaguing current face recognition systems [18]. The performance of most face-recognition systems would significantly decrease if there were several pose, lighting conditions and variations in the illumination of the input image [19]. Many algorithms have been proposed to solve this problem. These approaches can generally be classified into pre-processing, invariant feature extraction, face modelling and distance measure approaches.

1.1 ROPOSED FEATURE EXTRACTION TECHNIQUE

The feature extraction is used to reduce the dimension of the face space by transforming it into feature representation. Features may be symbolic, numerical or both. The symbolic feature is color and numerical feature is weight. Features may also result from applying a feature extraction algorithm, classification and calculating distance measures of testing and training dataset. The combined feature extraction of PCA, LDA and Wavelet are used in proposed feature extraction algorithm for human face recognition system.

1.1.1 Algorithm of Proposed Technique

Step -1: Load face images from face database

Step -2: Database partition into training data and testing data of 60% imagesand 40% images respectively.

Step -3: Converting each image matrix into column vector

Step -4: Create an image-space-matrix of size (128 x 128) pixel x testingimages

// ex. 16384 x 160 = 2621440 pixels – Testing dataset

// ex. 16384 x 240 = 3932160 pixels – Training datasetStep -5: Apply DWT

Step -6: Wavelet decomposition up-to 3 levels using 'db1' typeStep -7: Determine wavelet coefficients

Step -8: Apply Gabor wavelet filter to determine the features

Step -9: Convert the training data and testing data in PCA space, LDA spaceStep -10: Determine the features using PCA and LDA separately.

Step -11: Combine the Wavelet feature, PCA feature and LDA featureStep -12: Apply classifiers – k-NN

Perform the classification with Distance metric and Euclidean DistanceStep -13: Analyze the performance by comparing Threshold (**ϵ**) and EUC

Compare Threshold (**ϵ**) value and Euclidian Distance (EUC)If EUC $\leq$ **ϵ**

Display "Recognized Image"
Else
Display "Image is not recognized"
Else Step -14: Stop

1.1.1 Design of Proposed Framework for Human Face Recognition

The design and implementation of any technique needs the study of variety of face recognition methods in this field. It can be categorized into feature-based and appearance-based approaches. Feature-based approaches extract features based on the properties and geometrical relationships of individual facial characteristics, including the eyes, nose, mouth, and chin. These approaches are greatly used on the accuracy of facial feature extraction methods. Appearance-based approaches called the holistic method and used in global facial features based on high-dimensional intensity vector representation. Many researchers focused on these methods and the effectiveness of these approaches has been proven in the literature.

The recognition result of specific person can be obtained by applying feature extraction algorithm. The related problems of feature selection and feature extraction must be addressed at the outset of any face recognition system design. The key is to choose and to extract features that are computationally feasible and reduce the problem data into a manageable amount of information without discarding valuable information.
An automated system for human face recognition is extremely desirable. The successful feature extraction for recognition of human face should have the following properties.

- Geometrical facial characteristics like the eyes, nose, mouth and chin.
- Appearance based characteristics
- Feature selection
- Filtering feature and decomposition
- Finding statistical measures
- Pattern matching and recognition

The above desirable properties are considered in feature extraction process. This research work presents the development and implementation of new framework (figure 4.1) of feature extraction technique for human face recognition system [48].

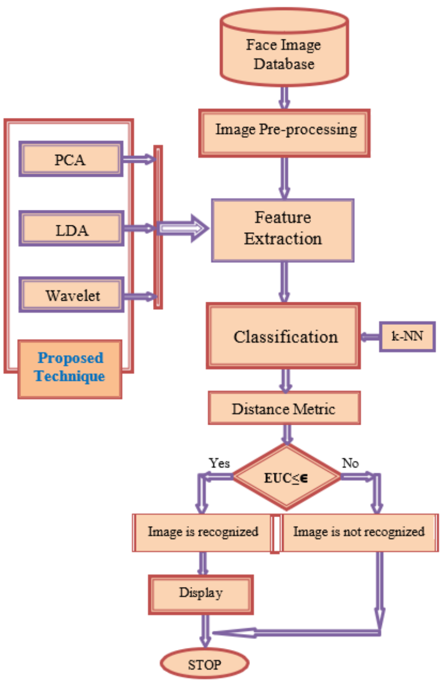


Fig. 1.1: Proposed Framework of Feature Extraction Technique for Human Face Recognition

1.1.2 Used Feature Extraction Techniques

1.1.3.1 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) [20,21,22,23,27,28] is a dimensionality reduction technique that is used for image recognition and compression. This reduction in dimensions removes information that is not useful and precisely decomposes the face structure into orthogonal (uncorrelated) components known as Eigen faces. In PCA, Eigenfaces recognition derives its name from the German prefix 'eigen', meaning 'own' or 'individual'. The basic idea of using the eigenfaces was first proposed by Kirby and Sirovich [21] using Karhunen-Loeve (KL) transform to represent human faces. This approach was very successful in representing faces using the above mentioned analysis. It is also known as Karhunen-Loeve transformation (KLT) or eigenspace projection [20-21]. In this method, faces are represented by a linear combination of weighted eigenvector, known as eigenfaces. Turk and Pentland [20] developed a face recognition system using PCA. However, PCA-based methods suffer from two limitations, namely, poor discriminatory power and large computational load. PCA is a method of transforming a number of correlated variables into a smaller number of uncorrelated variables. It decomposes a signal (or image) into a set of additive orthogonal basis vectors or eigenvectors. PCA can be applied to the task of face recognition by converting the pixels of an image into a number of eigenface feature vectors, which can then be compared to measure the similarity of two face images.

PCA is used in all forms of analysis, from neuroscience to computer graphics. Because it is a simple, non-parametric method of extracting relevant information from confusing data sets. PCA provides a roadmap for how to reduce a complex data set to a lower dimension to reveal the sometimes hidden, simplified dynamics that often underlie it. In PCA, faces are represented as a linear combination of weighted eigenvectors called as

Eigenfaces [20,24,25]. These eigenvectors are obtained from covariance matrix of a training image set called as basis function. The number of Eigen faces that obtained would be equal to the number of images in the training set. Eigenfaces takes advantage of the similarity between the pixels among images in a dataset by means of their covariance matrix. When a face image is projected to several face templates called eigenfaces then the difference between the images will be calculated which can be considered as a set of features that are considered as the variation between face images. When a set of eigenfaces is calculated, then a face image can be approximately reconstructed using a weighted combination of the eigenfaces.

The PCA algorithm is as follows:

1. Acquire an initial set of face images (the training set and testing set) and form its feature vector representation.
2. Calculate the covariance matrix as per equation number 4.
3. Form the Eigen-faces according to the highest Eigen value of the covariance matrix.
4. Classify the given face image, according to the Euclidean distance and threshold values.

PCA algorithm consists of mathematical calculation of shape vector, mean vector of all face images, covariance matrix and Eigen vectors. The mean vector consists of the means of each variable and the variance-covariance matrix consists of the variances of the variables along the main diagonal and the covariance's between each pair of variables in the other matrix positions.

The steps for recognizing faces based on PCA: Lets us consider a training database consists of N images which are of same size. The images are normalized by converting each image matrix to equivalent image vector Zi. The training set matrix Z is the set of images vectors with Training set.

$$Z = [Z_1\, Z_2\, \ldots\, Z_N] \qquad [1]$$

$$Me(\mu) = \frac{1}{N}\sum_{k=1}^{q} Z_k \qquad [2]$$

The deviation vector for each image Ωi(omega) (subtract mean from each image in the training set) is given by:

$$\Omega i = Zi - \mu \text{ ; where } i = 1,2,3, \ldots N \qquad [3]$$

Consider a difference matrix B= [Ω1 Ω2 … ... ΩN] which having only the distinguishing features for face images and removes the common features. To find eigenfaces we have to calculate the Covariance matrix C of the training image vectors by [26]:

$$C=B.BT \qquad (4)$$

Due to large dimension of covariance matrix C, we consider matrix N of size (Nt X Nt) which gives the same effect with reduces dimension.

The eigenvectors of C (Matrix U) can be obtained by using the eigenvectors of N (Matrix V) as given by:

$$Ui=BVi \qquad (5)$$

To find the weight of each eigenvector αi to represent the image in the Eigen face space, as given by [20]:

$$\alpha_i = U_i^{\,T} (Z - \mu), \quad i=1,2,3, \ldots\ldots, N \qquad (6)$$

where ai is eigenvector.

$$\text{Weight matrix } A = [\mu 1, \mu 2, \ldots\, \mu N]\, T \qquad (7)$$

Mathematically, recognition is finding the minimum Euclidean Distance (EUC), between a test image and a training image. When the new face image (test dataset) to be recognized its eigenvalue and weights are calculated. Then these weights are compared with the weights of the known face images in the training dataset. It is done by calculating the Euclidian distance between the new face image and the faces in training set. If the Euclidian distance is minimum, then the face is known and if it is maximum, then the face is unknown. The Euclidean distance between two weight vectors thus provides a measure of similarity between the corresponding images.

The main advantages of PCA are its ability to recognize face images quickly and its easy implementation. Therefore, a higher correct recognition rate, a better efficiency and less running time can be achieved. In PCA, the size and location of each face image must remain the same. Different illumination, head pose and facial expressions lead to reduced recognition rate. In statistical approach PCA, it is difficult to express structural information unless an appropriate choice of features is possible. Training is computationally intensive and it is hard to decide suitable thresholds. The methods deal with unknown faces and non-faces are not good enough to differentiate them from known faces.

1.1.3.2 Linear Discriminant Analysis (LDA)

Fisherfaces approach is based on Fisher's famous Linear Discriminant Analysis. Linear Discriminant Analysis (LDA) [29,30,31,32,33,34] is a powerful face recognition technique that overcomes the limitation of Principal Component Analysis technique by applying the linear discriminant criterion. LDA is a dimensionality reduction technique which is used only for classification problem not for regression. The main aim is to find the linear combinations of the data that maximize the between-class variability while minimizing the within-class variability. This means it tries to find a new reduced subspace that provides the best separation between the different classes in the input data. The basic idea is similar to applying the PCA for face recognition. Each face image is considered in higher dimensional space. After applying LDA to the data to get new vectors called as Fisherfaces. The face image is then projected from two dimensional spaces to C dimensional space, where C is the number of classes of the images. The LDA method tries to find the subspace that discriminates different face classes.

The goal of LDA [22,34] is to maximize the ratio of the determinant of the between-class scatter (extra personal variability) matrix measure of the projected samples to the determinant of the within-class scatter (intrapersonal variability) matrix measure of the projected samples. Linear discriminant methods group images of the same classes and separates images of the different classes. To identify an input test image, the projected test image is compared to each projected training image, and the test image is identified as the closest training image. The between-class scatter matrix and the within-class scatter matrix are denoted as SB and SW respectively.

The measure of the within-class scatters is defined as:

$$S_w = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i) * (x_k - \mu_i)^T \tag{8}$$

The measure of the between-class scatters is defined as:

$$S_B = \sum_{i=1}^{c} N_i * (x_i - \mu) * (x_i - \mu) \tag{9}$$

where Ni is the number of training images in class i, c is the number of distinct classes, μi is the mean vector of samples belonging to class i and Xi represents the set of training images (samples) belonging to class i with xk being the kth image of that class. SW represents the scatter of features around the mean of each face class and SB represents the scatter of features around the overall mean for all face classes.

The LDA algorithm is applied to all face images as below:

1. Acquire the training set and test set of face images and form its feature vector representation.

2. Calculate the within class and between-class covariance matrices SW and SB matrices as per equations (8) and (9).
3. Classify the given face image, according to the Euclidean distance and threshold values.

Linear Discriminant Analysis method provides better ability to recognize a face and provides better discrimination between faces. Fisher LDA works well for different illumination and different facial expressions. A good recognition system should have the ability to adapt over time. Reasoning about images in face space provides a means to learn and subsequently recognize new faces in an unsupervised manner. A difficulty in using the LDA method for face recognition is the high- dimensional nature of the image vector. Actually, the variations between the images of the same face due to illumination and viewing direction are almost larger than image variations due to change in face identity.

1.1.3.3 Discrete Wavelet Transform (DWT)

Gabor wavelet [35] captures the properties of orientation selectivity, spatial localization and optimally localized in the space and frequency domains. It has been extensively and successfully used in face recognition [36]. The 2D Gabor wavelet representation pioneered by Daugman in computer vision in 1980's [37]. The characteristics of Gabor wavelets are quite similar to those of human visual system for frequency and orientation representations.

Discrete Wavelet Transform (DWT) [38] is used in image and signal analysis. It decomposes an image into a set of basic functions called wavelets and the decomposition is defined as the resolution of an image. Wavelets are functions that satisfy certain mathematical requirements and are used in presenting data or other functions, similar to sine and cosine in the Fourier transform. However, it represents data at different scales or resolutions, which distinguishes it from the Fourier transform.

Wavelet transform is an increasingly popular tool in computer vision and image processing. In the recent years, DWT has been investigated to be a very useful tool for image compression, detection, recognition, and image retrieval [39]. It supports the multi resolution (different scales) analysis of data and allows progressive transmission and zooming of the image without the need of extra storage. Wavelet transform has nice features of space-frequency localization and multi-resolutions. The wavelet transform of a 1-D signal f(x) is defined as:

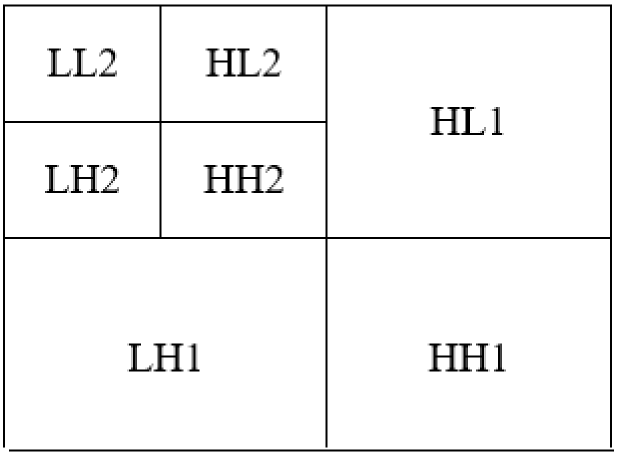
$$\left.\begin{aligned} (W_a f)(b) &= \int f(x)\, T_{a,b}(x)\,dx \\ \text{with } \quad {}_{a,b}(x) &= \frac{1}{\sqrt{a}}\, T\left(\frac{x-b}{a}\right) \end{aligned}\right\} \qquad [10]$$

where a is the power of binary scaling and b is a constant of the filter.

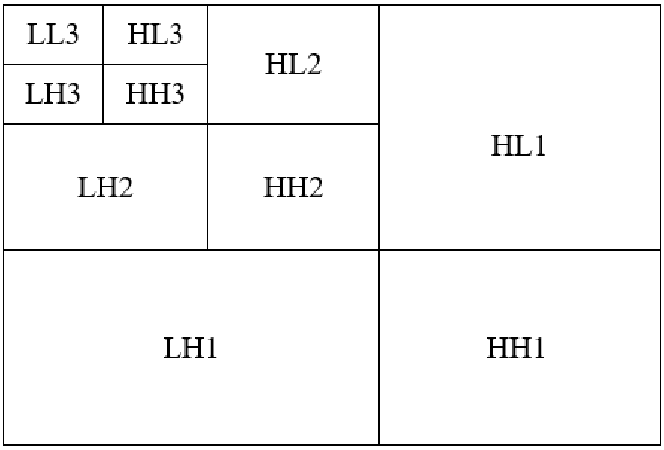
The mother wavelet Ψ(Psi) has to satisfy the admissibility criterion to ensure that it is a localized zero-mean function. Equation (10) can be discretized by restraining α and b to a discrete lattice. Typically, some more constraints are imposed on Ψ to ensure that the transform is non-redundant, complete and constitutes a multi- resolution representation of the original signal. 2-D DWT is generally carried out using a separable approach, by first calculating the 1-D DWT on the rows, and then the 1-D DWT on the columns : DWTn[DWTm[x[m,n]]. Two-dimensional DWT is implemented as a set of filter banks, comprising of a cascaded scheme of high-pass and low-pass filters. 2D-DWT decomposes an image into 4 "sub-bands" that are localized in frequency and orientation, by LL, HL, LH, HH [40].

LL1	HL1
LH1	HH1

(a)



(b)



(c)

Fig.1.2: Discrete Wavelet Transform: a) 1-D DWT b) 2 level 2-D DWT c) 3 level 2-D DWT

Discrete Wavelet Transform (DWT) [41-43] is obtained by filtering the signal through a series of digital filters at different scales. The scaling operation is done by changing the resolution of the signal by the process of sub sampling. In DWT, the input sequence is decomposed into low-pass and high-pass sub-bands, each consisting of half the number of samples in the original sequence. Each of these sub bands can be thought of as a smaller version of the image representing different image properties. In DWT, an image signal can be analyzed by passing it through an analysis filter bank followed by decimation operation. The analysis filter bank consists of a low-pass and high-pass filter at each decomposition stage. When the signal passes through these filters, it splits into two bands.

The band LL is a closer approximation to the original image. The bands LH and HL record the changes of the image along horizontal and vertical directions, respectively. The HH band shows the high frequency component of the image. Second level decomposition can then be conducted on the LL sub band. The various wavelet transforms like Daubechies wavelets, Coiflets, Biorthogonal wavelets, and Symlets are different in mathematical properties such as symmetry, number of vanishing moments and orthogonality.
For finding out DWT coefficients, the various families of wavelet and their abbreviations can be used as a mother wavelet.

Table 1.1: Family of Wavelet

Sr. No.	Family	Abbreviation
1	Haar Wavelet	haar
2	Daubechies	Db
3	Symlets	Sym
4	Coiflets	Coif
5	Biorthogonal	Bior
6	Reverse Biorthigonal	Rbio
7	Mexican hat wavelet	Mexh
8	Discrete approximation of Mayer wavelet	dmey

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1 Haar Wavelet haar
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6 Reverse Biorthigonal Rbio
7 Mexican hat wavelet Mexh
8 Discrete approximation of Mayer wavelet dmey

Earlier studies concluded that information in low spatial frequency bands play a dominant role in face recognition. Nastar et al. [44] has investigated the relationship between variations in facial appearance and their deformation spectrums. They found that facial expressions and small occlusions affect the intensity manifold locally. Under frequency-based representation, only high-frequency spectrum is affected, called high-frequency phenomenon. Moreover, changes in pose or scale of a face affect the intensity manifold globally, in which only their low-frequency spectrum is affected, called low-frequency phenomenon. Further decomposition to the LL sub-band (two-level decomposition), leads to lower dimensionalities and a multi resolution image.

An advantage of DWT over other transforms is it allows good localization both in time and spatial frequency domain. Because of their inherent multi-resolution nature, wavelet coding schemes are especially suitable for applications where scalability and tolerable degradation are important.

1.2 CLASSIFICATION TECHNIQUE

Image classification is perhaps the most important part of digital image analysis. The main intent of the classification process is to categorize all pixels in a digital image into one of several classes. The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object. Classification techniques such as supervised or unsupervised learning are then be selected on the basis of the training data sets. Various classification techniques are compared with the training data, so that an appropriate decision rule is selected for subsequent classification. The classified results are checked and verified for the recognition accuracy and reliability.

1.2.1 k-NN classifier

The k-Nearest Neighbour method is a well-known non-parametric classifier, where a posteriori probability is estimated from the frequency of nearest neighbours of the unknown pattern. k-Nearest Neighbor [45-47] classification method is used in this work. k-NN was proposed by Cover and Hart, is a non-parametric method for classifying objects based on closest training samples in the feature space. In k-nearest neighbor, an object is classified by majority votes of its neighbors, with the object being assigned to the class most common amongst its k nearest neighbors. If k=1, then the object is simply assigned to the class of its nearest neighbor. k-NN is also known as “Memory based classification”. When using a k-nearest neighbor algorithm on an input with ‘n’ attributes the input is classified by taking a majority vote of the k, where k is some user specified constant, “closest” training records across all ‘n’ attributes. Here “closest” means the distance an attribute is away from the same attribute of the training set, evaluated using some specified similarity metric. k-NN is widely used in the field of face recognition, pattern recognition, object recognition, text recognition, ranking models and event recognition applications.

Each sample x in a data set having ‘n’ attributes which combine to form an n- dimensional vector as, x = (x1, x2, . . . , xn). These ‘n’ attributes are considered to be the independent variables. Each sample also has another attribute, denoted by y the dependent variable, whose value depends on the other ‘n’ attributes of x. Assume that y is a categorical variable, and there is a scalar function f which assigns a class, y = f(x) to every such vectors. Then, set a class of T, such that vectors are given together with their corresponding classes as: x(i), y(i) for i = 1,2, . . . , T.

Algorithm:

1. For each test point, x to be classified, find the k nearest samples in the training data.

2. Set a class of T, such that x(i),…, x(T) , where i=1, …, T.
3. Classify the point x according to the majority vote of their class labels

1.3 Distance Metric

Normally, the classification of database images and the given query image is performed by using some distance metric that estimates the similarity between them through some defined function. Several similarity metrics have been proposed in literature, some of which have been applied in this research work and the same are briefly described here.

1.3.1 Euclidean distance (EUC)

It is also known as L2 – norm or nearest neighbor classifier. The basis of many measures of similarity and dissimilarity is Euclidean Distance. The distance between vectors x and y is defined as follows:

$$d(\mathrm{x},y) = \left(\sum_{\mathrm{i}}^{n}(\mathrm{x}_{\mathrm{i}} - y_{\mathrm{i}})^2\right. \qquad [11]$$

In other words, Euclidean distance is the square root of the sum of squared differences between corresponding elements of the two vectors.

Euclidean Distance = sqrt[(x1-y1)2+ (x2-y2)2 + (x3-y3)2]

Euclidean distance is most often used to compare profiles of respondents across variables. Our data consist of face information on a sample of individuals, arranged as a variable matrix. Each row of the matrix is a vector of m numbers, where m is the number of variables. The variables are the columns. A variable records the results of a measurement. We can evaluate the similarity (or, in this case, the distance) between any pair of rows. In order to compute similarities or dissimilarities among rows, we do not need to try to adjust for differences in scale. Hence, Euclidean Distance is usually the right measure for comparing face images.

1.3.2 D4 or City Block distance (CTB)

It is also known as L1 – norm, absolute value distance or Manhattan distance. It represents the shortest distance along each axis between two points. It measures the distance between two sets of feature vectors separately as

$$d(\mathrm{x},y) = |\mathrm{x} - y| = \sum_{\mathrm{k}=1}^{L}|\mathrm{x}_{\mathrm{k}} - y_{\mathrm{k}}| \qquad [12]$$

where x and y are the feature vectors of database and the query image, respectively and L is the number of features in these vectors.

1.3.3 D8 or Chessboard distance (CSB)

The distance between two points is the sum of the (absolute) differences of their coordinates. The chessboard distance d(x,y) between the vectors x and y in an n- dimensional real vector space is given as follows.

$$d(\mathrm{x},y) = s[\max(|\mathrm{x}_{\mathrm{i}} - y_{\mathrm{i}}|)] \qquad [13]$$

Above similarity metrics are used in order to carry out the experimentation of the proposed framework of feature extraction for human face recognition. Next chapter covers the experimentation, performance evaluation and results.

II. CONCLUSION

It is concluded that if there is a lot of sunlight and wind energy available, then these two sources are very useful for generating electrical energy. The micro-grid system by interconnecting the renewable energy sources of photovoltaic (PV) and wind power generation (WPG) along with a battery energy storage system (BESS) implemented in MATLAB/SIMULINK

Software. In solar power generation utilized P&O MPPT topology to extract maximum power from the solar panel and similarly utilized active and reactive power control topology for wind power generation to get the stable output. The BESS implemented to maintain un-interrupted power supply for microgrid and load. The PV and WPG system tested under different environmental changes and critical load conditions. The Proposed system gives best alternative solution for fossil fuel power generation systems.

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