IJCSN International Journal of Computer Science and Network, Volume 5, Issue 1, February 2016
ISSN (Online) : 2277-5420 www.IJCSN.org
Impact Factor: 1.02

Novel Approach for Human Identification – Using Skin Color Segmentation

[1] **Kanchan Wani,** [2] **S. V. Patil**

[1,2] J T Mahajan College of Engineering
Faizpur (Maharashtra)

Abstract - In this paper, gives both face detection and recognition techniques and developed algorithms for them. Face detection and recognition is challenging due to the Wide variety of faces and the complexity of noises and image backgrounds. For face detection, we have used Viola and Jones face detector based on the Haar-like features.There are three key contributions. The first contribution is a new a technique for computing a rich set of image features using the integral image. The second is a learning algorithm, based on AdaBoost, which selects a small number of critical visual features and yields extremely efficient classifiers. The third contribution is a method for combining classifiers in a cascade which allows background regions of the image to be quickly discarded while spending more computation on promising object-like regions. Further the algorithms that exist are very much specific to the kind of images they would take as input and detect faces. To detect faces we can put a number of simple rejection blocks in series, until we get the faces. Deeper the rejection block, more specifically it can be trained to eliminate non-faces.

Keywords - *SVM, PCA, LDA, RGB, Skin Color Segmentation.*

1. Introduction

The face plays a major role in our social intercourse in conveying identity and emotion. The human ability to recognize faces is remarkable. We can recognize thousands of faces learned throughout our lifetime and identify familiar faces at a glance even after years of separation. The skill is quite robust, despite large changes in the visual stimulus due to viewing conditions, expression, aging, and distractions such as glasses or changes in hairstyle.

Computational models of faces have been an active area of research since late 1980s, for they can contribute not only to theoretical insights but also to practical applications, such as criminal identification, security systems, image and film processing, and human-computer interaction, etc. However, developing a computational model of face recognition is quite difficult, because faces are complex, multidimensional, and subject to change over time. Generally, there are three phases for face recognition, mainly face representation, face detection, and face identification.

Face representation is the first task, that is, how to model a face. The way to represent a face determines the successive algorithms of detection and identification. For the entry-level recognition (that is, to determine whether or not the given image represents a face), a face category should be characterized by generic properties of all faces; and for the subordinate-level recognition (in other words, which face class the new face belongs to), detailed features of eyes, nose, and mouth have to be assigned to each individual face. There are a variety of approaches for face representation, which can be roughly classified into three categories: template-based, feature-based, and appearance-based. In feature-based approaches, geometric features, such as position and width of eyes, nose, and mouth, eyebrow's thickness and arches, face breadth, or invariant moments, are extracted to represent a face. Feature-based approaches have smaller memory requirement and a higher recognition speed than template-based ones do.

The aim of paper, which believed on to developed a method of face recognition that is fast, robust, reasonably simple and accurate with a relatively simple and easy to understand algorithms and techniques.

2. Literature Survey

The first step in any automatic face recognition systems is the detection of faces in images. Here we only provide a summary on this topic and highlight a few very recent methods. After a face has been detected, the task of feature extraction is to obtain features that are fed into a face classification system.[1] Depending on the type of classification system, features can be local features such as lines or fiducially points, or facial features such as eyes, nose, and mouth. Face detection may also employ features, in which case features are extracted simultaneously with face detection.

Up to the mid-1990s, most work on segmentation was focused on single-face segmentation from a simple or complex background. [2] These approaches included using a whole-face template, a deformable feature-based template, skin color, and a neural network. Significant advances have been made in recent years in achieving automatic face detection under various conditions. Compared to feature-based methods and template-matching methods, appearance or image-based methods. In a detection problem, two statistics are important: true positives (also referred to as detection rate) and false positives (reported detections in non-face regions).An ideal system would have very high true positive and very low false positive rates. In practice, these two requirements are conflicting. Treating face detection as a two-class classification problem helps to reduce false positives dramatically. While maintaining true positives. This is achieved by retraining systems with false positive samples that are generated by previously trained systems.

Engineering started to show interest in face recognition in the 1960s. One of the first re- searches on this subject was Woodrow W. Bledsoe. In 1960, Bledsoe, along other researches, started Panoramic Research, Inc., in Palo Alto, California. The majority of the work done by this company involved AI-related contracts from the U.S. [3] Department of Defense and various intelligence agencies. During 1964 and 1965, Bledsoe, along with Helen Chan and Charles Bisson, worked on using computers to recognize human faces. Because the funding of these researches was provided by an unnamed intelligence agency, little of the work was published. He continued later his researches at Stanford Research Institute. Bledsoe designed and implemented a semi-automatic system. Some face coordinates were selected by a human operator, and then computers used this information for recognition. He described most of the problems that even 50 years later Face Recognition still suffers - variations in illumination, head rotation, facial expression, and aging.For instance, this approach was used in Bell Lab- oratories by A. Jay Goldstein, Leon D. Harmon and Ann B. Lesk. They described a vector, containing 21 subjective features like ear protrusion, eyebrow weight or nose length, as the basis to recognize faces using pattern classification techniques. In 1973, Fischler and Elschanger tried to measure similar features automatically. Their algorithm used local template matching and a global measure of fit to find and measure facial features.

The first one that developed a fully automated face recognition system was Kenade in 1973. [4] He designed and implemented a face recognition program. It ran in a computer system designed for this purpose. The algorithm extracted sixteen facial parameters automatically. In his work, Kenade compares this automated extraction to a human or manual extraction, showing only a small difference. He got a correct identification rate of 45-75 percent. He demonstrated that better results were obtained when irrelevant features were not used.

He first mention to Eigen-faces in image processing, a technique that would become the dominant approach in following years, was made by L.Sirovich and M. Kirby in 1986. Their methods were based on the Principal Component Analysis. Their goal was to represent an image in a lower dimension without losing much information, and then reconstructing it. Their work would be later the foundation of the proposal of many new face recognition algorithms.

The 1990s saw the broad recognition of the mentioned eigen-face approach as the basis for the state of the art and the first industrial applications. In 1992 Mathew Turk and Alex Pentland of the MIT presented a work which used eigen-faces for recognition.. [5] Many approaches have been taken which has lead to different algorithms. Some of the most relevant are PCA, ICA, LDA and their derivatives.The face recognition algorithms are Principal Component Analysis (PCA), Multilinear Principal Component Analysis (MPCA) and Linear Discriminant Analysis (LDA).Every algorithm has its own advantage.

3. Face Detection

Face detection is the first step of face recognition as it automatically detects a face from a complex background to which the face recognition algorithm can be applied. But detection itself involves many complexities such as background, poses, illumination etc.

A face detection algorithm is very specific to the kind of problem and cannot be guaranteed to work unless it is applied and results are obtained. We have followed a multiple algorithm approach for face detection, which is in effect a series of simple rejection blocks. In designing the final algorithm many different schemes have been tried. The first step is skin segmentation, which is good enough to reject most of the data.

Thus this forms the first step of the final algorithm also. Neural networks have also been applied (which is described later) but have not been included in the final algorithm. As the data gets more compact and we need more specific rejection classifiers. Fisher Linear Discriminants and Template matching are found not to per- form as well as eigenface method. So in the final version we used eigenface projection method.

3.1 Skin Color Segmentation

This representing the RGB image into a new 3-D transformed space such that the various skin colors lie close to each other and this space is a small, constrained space. Skin color segmentation is nothing but initial method of rejection. The smaller the space in which the skin values lies, the better is the quality of segmentation, that implies better is the rejection

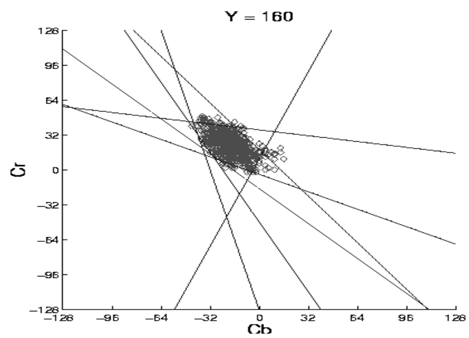

Figure.1: Skin color values in YCbCr space.

YCbCr gives better results than the HSV space. The transformation equations from RGB to YCbCr space are shown below.

$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

As shown in the figure 1, the skin color values form quite compact space, and are bounded by the lines shown. The equations for the lines are also shown in figure1. This skin segmentation does well in marking out the areas where there is actually skin, i.e. faces, hands etc. But it also marks the points on unwanted objects like the wall, the bar, trees, skin colored jackets etc. These false positives do cover a lot of area as compared to the actual skin.

3.2 Neural Network

The neural network is based on histogram approach rather than directly training the neural net- work of a fixed size image. The neural network first converts the RGB image to YES space. The equations for the conversion are shown below. The transformed skin color values have the E, S component close to zero.

$$\begin{bmatrix} Y \\ E \\ S \end{bmatrix} = \begin{bmatrix} 0.253 & 0.684 & 0.063 \\ 0.500 & -0.500 & 0.000 \\ 0.250 & 0.250 & -0.500 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (2)$$

The neural network takes input as an image, much smaller than a group photograph, usually a size which contains a single face; and tell whether the given image has a face or not. We feed the neural network with blocks cut from the given image and then according to the output keep the image for further processing otherwise reject the block. Exact details are described later. The given image (or block of image) is first converted to YES space. And then histograms are constructed for each of the dimensions. These histograms values are fed to the neural network. The number of histograms decides the complexity of the neural network. We have kept his value at 20.

3.3 Viola Jones Algorithm

In this it decipher the Viola-Jones algorithm, the first ever real-time face detection sys- tem. There are three ingredients working in concert to enable a fast and accurate detection the integral image for feature computation, Adaboost for feature selection and an attentional cascade for efficient computational resource allocation. Here we propose a complete algorithmic description, a learning code and a learned face detector that can be applied to any color image. Since the Viola-Jones algorithm typically gives multiple detections, a post-processing step is also proposed to reduce detection redundancy using a robustness argument.

1	1	1
1	1	1
1	1	1

Input image

1	2	3
2	4	6
3	6	9

Integral image

Figure: 2 The integral Image

The basic principle of the Viola-Jones algorithm is to scan a sub-window capable of detecting faces across a given input image. The standard image processing approach would be to rescale the input image to different sizes and then run the fixed size detector through these images. This approach turns out to be rather time consuming due to the calculation of the different size images. Contrary to the standard approach Viola-Jones rescale the detector instead of the input image and run the detector many times through the image each time with a different size.

At first one might suspect both approaches to be equally time consuming, but Viola-Jones have devised a scale invariant detector that requires the same number of calculations whatever the size. This detector is constructed using a so-called integral image and some simple rectangular features reminiscent of Haar wavelets. The next section elaborates on this detector.

3.4 The Scale Invariant Detection

The first step of the Viola-Jones face detection algorithm is to turn the input image into an integral image. This is done by making each pixel equal to the entire sum of all pixels above and to the left of the concerned pixel. This is demonstrated in Figure 3 this allows for the calculation of the sum of all pixels inside any given rectangle using only four values. These values are the pixels in the integral image that coincide with the corners of the rectangle in the input image. This is demonstrated in Figure 3. since both rectangle B and C include rectangle A the sum of A has to be added to the calculation.

It has now been demonstrated how the sum of pixels within rectangles of arbitrary size can be calculated in constant time. The Viola-Jones face detector analyzes a given sub-window using features consisting of two or more rectangles. The different types of features are shown in Figure 4.

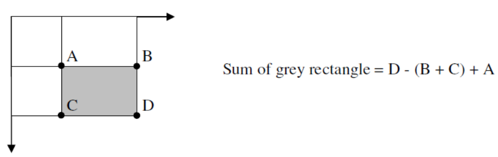

Figure 3: Sum Calculation

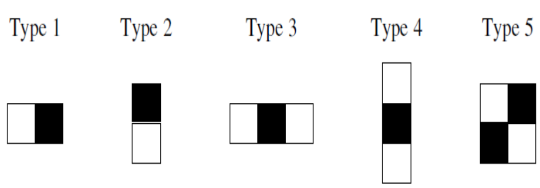

Figure 4 : The Different Types Of Features

Each feature results in a single value which is calculated by subtracting the sum of the white rectangle(s) from the sum of the black rectangle(s).

Viola-Jones have empirically found that a detector with a base resolution of 24*24 pixels gives satisfactory results. When allowing for all possible sizes and positions of the features in Figure 4 a total of approximately 160.000 different features can then be constructed. Thus, the amount of possible features vastly outnumbers the 576 pixels contained in the detector at base resolution. These features may seem overly simple to perform such an advanced task as face detection, but what the features lack in complexity they most certainly have in computational efficiency. One could understand the features as the computers way of perceiving an input image. The hope being that some features will yield large values when on top of a face. Of course operations could also be carried out directly on the raw pixels, but the variation due to different pose and individual characteristics would be expected to hamper this approach. The goal is now to smartly construct a mesh of features capable of detecting faces and this is the topic of the next section.

3.5 The Modified AdaBoost Algorithms

As stated above there can be calculated approximately 160.000 feature values within a detector at base resolution. Among all these features some few are expected to give almost consistently high values when on top of a face..AdaBoost is a machine learning boosting algorithm capable of constructing a strong classifier through a weighted combination of weak classifiers. (A weak classifier classifies correctly in only a little bit more than half the cases.) To match this terminology to the presented theory each feature is considered to be a potential weak classifier. A weak classifier is mathematically described as Where x is a 24*24 pixel sub-window, f is the applied feature, p the polarity and θ the threshold that decides whether x should be classified as a positive (a face) or a negative (a non-face).Since only a small amount of the possible 160.000 feature values are expected to be potential weak classifiers the AdaBoost algorithm is modified to select only the best features. An important part of the modified AdaBoost algorithm is the determination of the best feature, polarity and threshold. There seems to be no smart solution to this problem and Viola- Jones suggest a simple brute force method. This means that the determination of each new weak classifier involves evaluating each feature on all the training examples in order to find the best performing feature. This is expected to be the most time consuming part of the training procedure.

$$h(x,f,p,\theta)=\begin{cases} 1, & \text{if } p(x)>P(\theta); \\ 0, & \text{Otherwise.} \end{cases} \quad (3)$$

The best performing feature is chosen based on the weighted error it produces. This weighted error is a function of the weights belonging to the training examples. As seen in Figure 5 part 4) the weight of a correctly classified example is decreased and the weight of a misclassified example is kept constant. As a result it is more expensive for the second feature (in the final classifier) to misclassify an example also misclassified by the first feature, than an example classified correctly. An alternative interpretation is that the second feature is forced to focus harder on the examples misclassified by the first.

3.6 The Cascaded Classifier

The basic principle of the Viola-Jones face detection algorithm is to scan the detector many times through the same image each time with a new size. Even if an image should contain one or more faces it is obvious that an excessive large amount of the evaluated sub-windows would still be negatives (non-faces). This realization leads to a different formulation of the problem: Instead of finding faces, the algorithm should discard non-faces.

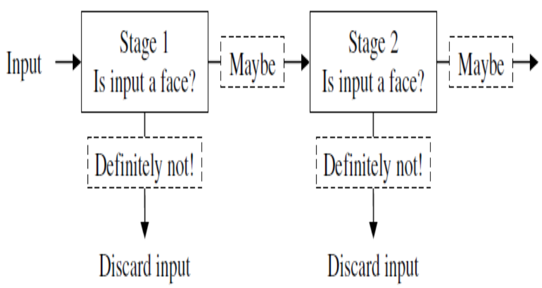

Figure 5: The cascaded classifier.

The cascaded classifier is composed of stages each containing a strong classifier. The job of each stage is to determine whether a given sub-window is definitely not a face or maybe a face. When a sub-window is classified to be a non-face by a given stage it is immediately discarded. Conversely a sub-window classified as a maybe-face is passed on to the next stage in the cascade. It follows that the more stages a given sub-window passes, the higher the chance the sub-window actually contains a face. The concept is illustrated with two stages in Figure5.

In a single stage classifier one would normally accept false negatives in order to reduce the false positive rate. However, for the first stages in the staged classifier false positives are not considered to be a problem since the succeeding stages are expected to sort them out. Therefore Viola-Jones prescribe the acceptance of many false positives in the initial stages. Consequently the amount of false negatives in the final staged classifier is expected to be very small. 3.4 Result of Face Detection.

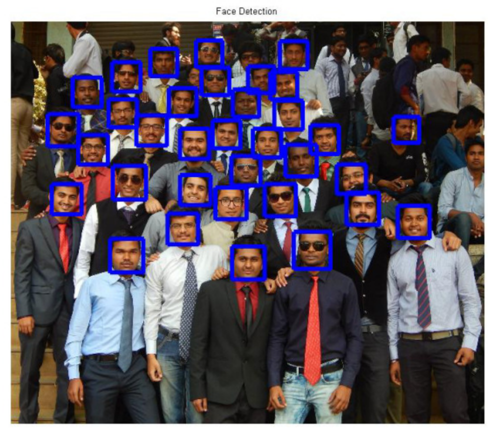

Figure 6: Multiple face detection

3.7 Feature Extraction

Several methods are used to extract image face features vector, which presents small inter-person variation. This feature vector is feed to a multilayer perceptron to carry out the face recognition or identity verification tasks. Proposed system consists in a combination of Gabor and Eigen- faces to obtain the feature vector. Evaluation results show that proposed system provides robust- ness against changes in illumination, wardrobe, facial expressions, scale, and position inside the captured image, as well as inclination, noise contamination and filtering. Proposed scheme also provides some tolerance to changes on the age of the person under analysis. Evaluation results using the proposed scheme with identification and verification configurations are given and compared with other feature extraction methods to show the desirable features of proposed algorithm.

3.8 Eigen Faces

The objective of the recognition by the Eigenfaces method is to extract relevant information from face image, encode this information as efficiently as possible and compare them with each model stored in a database. In mathematical terms, we wish to find the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images.

3.9 Face Recognition

Face recognition is a K class problem. Where K is the number of known individuals; and support vector machines (SVMs) are a binary classification method. By reformulating the face recognition problem and reinterpreting the output of the SVM classifier. We developed a SVM -based face recognition algorithm. The face recognition problem is formulated as a problem in difference space. Which models dissimilarities between two facial images. In difference space we formulate face recognition as a two class problem. The classes are: dissimilarities between faces of the same person. And dissimilarities between faces of different people. By modifying the interpretation of the decision surface generated by SVM.

3.10 Principal Component Analysis

Principal component analysis (PCA) was invented in 1901 by Karl Pearson. PCA involves a mathematical procedure that transforms a number of possibly correlated variables into a number of uncorrelated variables called principal components, related to the original variables by an orthogonal transformation. This transformation is defined in such a way that the first principal component has as high a variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen Love transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD). The major advantage of PCA is that the eigenface approach helps reducing the size of the database required for recognition of a test image. The trained images are not stored as raw images rather they are stored as their weights which are found out projecting each and every trained image to the set of eigenfaces obtained.

3.11 Independent Component Analysis

The face recognition process by ICA initially performs the preprocessing procedure in the training data set images using the PCA and the features from the ICA are used in the classification process. In classification, the Euclidian distance classifier classifies the testing images based on the features vectors. The proposed face recognition method utilized the images with large rotation angles with poses and variation in illumination conditions. They used the database which has the large rotation angles up to 1800 change between the images of person while looking right and or left. The face images having various orientations of the face are looking front, looking left, looking right, looking up, looking up towards left, looking up towards right and looking down. In this study they have considered the samples of individual person which consist of sufficient number of images having expressions, changes in illumination and large rotation angles. The dimensionality reduced data results from PCA are given to the feature vectors extraction process based on ICA. The ICA based face recognition was presented.

Independent component analysis (ICA) is a method for finding underlying factors or components from multivariate (multidimensional) statistical data. There is a need to implement face recognition system using ICA for facial images having face orientations and different illumination conditions. The independent components are computed from the PCA result Eigen vector matrix and make the matrix as square by reduce the size of the matrix. The feature vectors matrix contains the independent components are further utilized in the classification process. The Euclidian distance classifier finds the distance between the input testing image and the recognized training data set images. If the distance between these two images is small we say that the two images are same otherwise the images are different.

3.12 Linear Discriminant Analysis

LDA which is known as Linear Discriminant Analysis is a computational scheme for evaluating the significance of different facial attributes in terms of their discrimination power. The database is divided into a number of classes each class contains a set of images of the same person in different viewing conditions like different frontal views, facial expression, different lighting and background conditions and images with or without glasses etc. It is also assumed that all images consist of only the face regions and are of same size.

By defining all the face images of the same person in one class and faces of other people in different classes we can establish a model for performing cluster separation analysis. We have achieved this objective by defining two terms named between class scatter matrix and within class scatter matrix. The database used here is a FERET database which is a reference database.

3.13 Support Vector Machines

Support vector machines (SVMs) are formulated to solve a classical two class pattern recognition problem. We adapt SVM to face recognition by modifying the interpretation of the output of a SVM classifier and devising a representation of facial images that is concordant with a two class problem. Traditional SVM returns a binary value, the class of the object. To train our SVM algorithm, we formulate the problem in a difference space, which explicitly captures the dissimilarities between two facial images. This is a departure from traditional face space or view-based approaches, which encodes each facial image as a separate view of a face. In difference space, we are interested in the following two classes: the dissimilarities between images of the same individual, and dissimilarities between images of different people. These two classes are the input to a SVM algorithm. A SVM algorithm generates a decision surface separating the two classes. For face recognition, we re-interpret the decision surface to produce a similarity metric between two facial images. This allows us to construct face-recognition algorithms.

4. Conclusion

There are several methods for face detection, but we have done it by two method. This are as Skin Color Segmentation, Voilo-Jones method. In Skin Color Segmentation some limitations such as background should not be complex. Distance between face and camera must be appropriate and there must be a single face in input image. Hence, looked for another method that is Voila-Jones method. It gives good result for Face [1] Detection as compared to Skin Color Segmentation. Advantages of Voila-Jones over the Skin Color Segmentation are it detects the multiple faces, there is no restriction on kind of background. It detects even small face in an image because of these advantages we used this methods for detection. For feature extraction we used eigenface feature extraction methods. This is totally mathematical method in which we first resize detected face in square form then we calculate eigen values and corresponding eigen vectors. [2] These eigen vectors are used for further processing. As this method is mathematical we find it easy to understand. It introduced a new technique for applying SVM to face recognition.It demonstrated the algorithm on both verification and identification applications.It compared the performance of proposed algorithm to a PCA-based algorithm. For verification, the equal error rate of our algorithm was almost half that of the PCA algorithm, 7 percent versus 16.25 percent.For indentation, the error of SVM was half that of PCA, 73.08 percent versus 90.58 percent. This indicates that SVM is making more efficient use of the information in face space than the baseline PCA algorithm. Error rate and false acceptance rate, false rejection ratio is as follows,

1) Error Rate

First, The Error Rate (ER) which is defined as number of false detection in the image divide by the total number of detections (face and non-face.

$$\textbf{ErrorRate(ER)}=\frac{\textbf{NUMBER OF FALSE DETECTION}}{\textbf{NUMBER OF TOTAL DETECTION}}\textbf{(4)}$$

Here, number of false detection means those objects that are identified as face but are not face. The total number of detections is the summation of face detected and non-face object detected.

The algorithm achieved ER of 16.57%.for total 85 images

2) False Acceptance Rate (FAR)

The False Acceptance rate (FAR) is the probability that the system incorrectly authorizes a non-authorized person, due to incorrectly matching the biometric input with a template.

The FAR is normally expressed as a percentage, following the FAR definition this is the percentage of invalid inputs which are incorrectly accepted.

False Acceptance Rate (FAR)

$$=\frac{\text{Number of false acceptance}}{\text{Number of Identification attempt}}\% \quad (5)$$

The overall Face acceptance rate of 85 images is 4.7%

3) False Rejection Rate (FRR)

The FRR or False Rejection Rate is the probability that the system incorrectly rejects access to an authorized person, due to failing to match the biometric input with a template. The FRR is normally expressed as a percentage, following the FRR definition this is the percentage of valid inputs which are incorrectly rejected.

False Rejection Rate

$$\text{FRR}=\frac{\text{Number of False Rejection}}{\text{Number of Identification Attempt}}\%(6)$$

The overall face rejection rate of 85 images is 1.1%

4) Face Detection Success Rate (FDSR)

It is defined as the number of faces detected correctly over the total number of faces.

The Fourth parameter is Face detection success rate (FDSR) Face detection success rate

$$\textbf{FDSR} = \frac{\textbf{Number of Faces detected}}{\textbf{Total number of faces}}\,\% \ \textbf{(7)}$$

The total number of face detected is 77 out of 85 images. The Face detection success rate is 90.58%.

References

[1] H. Moon and P. J. Phillips. Analysis of PCA based face recognition algorithms. In K W.Bowyer and P. J. Phillips, editors, Empirical Evaluation Techniques in Computer Vision. IEEE Computer Society Press, Los Alamitos, CA. 1998.

[2] R. Chellappa, C. Wilson, and S. Sirohey, Human and Machine Recognition of Faces: A Survey, Proc. IEEE, vol. 83, no. 5, pp. 705- 740, 1995.

[3] Turk M. and Pentland A., Eigenfaces for Recognition, Media Labs, M.I.T.

[4] Raphael Feraud, Olivier Bernier, Jean Emmanuael Viallet, and Michel Collobert. A Fast and Accurate Face Detector for Indexation of Face Images. In International Conference on Face and Gesture Recognition. IEEE, March 2000

[5] K. Sobottka and I. Pitas, Face localization and feature extraction based on shape and color infor-mation, Proc. IEEE Intl Conf. Image Processing, pp. 483-486, 1996.

About Author:

Ms. Kanchan Wani had completed her BE in E&TC and pursuing M.E from J. T. Mahajan college of engineering Faizpur, Maharashtra.

Mr. S. V. Patil M.E (Control & Instrumentation) working as a Sr. Lecturer in Dept. of E&TC. J. T. Mahajan College of Engineering, Faizpur. Maharashtra.