

# Face Recognizing Robot

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## Abstract

In the biological evolution process, logical thinking has been the last to evolve, and lies at the surface of our consciousness, its means and methodologies available for introspection. On the other hand, the intelligence required to interpret sensory signals and activate motor commands is so well known biologically that it is buried in the subconscious and is entirely inaccessible at the conscious level. The variation in human intelligence is usually measured by the ability to process logical information, whereas the other forms of intelligence needed in daily life are not normally associated with the word intelligence.

In the recent years man wants to develop a machine having its own intelligence. He wants to make machine, to which he can treat as a real servant. In this paper a simulated robotic system is described, which can be used as a criminal-detecting robot. In this project, an attempt will be made to design a Robot and it's software, which will have an optimal solution of conditions (for which the Robot is to be designed i.e. security). It will not only reduce the cost (the cost spend in security of VIP's is very high) but also will increase the security strength and stop the criminal activities. It will take snaps of the people and match from its database to check for criminals. Thus, such operations with minimum errors will cause the better security.

Computer vision concerned with the sensing of vision data and its interpretation by a computer. Detecting faces in images with complex backgrounds is a difficult task. The approach presented in this paper, which obtains state of the art results, is based on a new neural network model. To detect a face in an image means to find its position in the image plane (x, y) and its size or scale (z). An image of a face can be considered as a set of features such as eyes, mouth, and nose with constrained positions and size within an oval: an explicit model can be used. The

next step after face detection is face recognition. In general two methods of face recognition are in practice. Feature based face recognition methods and Neural Network based methods. Both have their possibilities and features. In feature-based approach, project relies on finding the facial measures and construction of facial feature vectors. The query facial vector is compared with the vector database by finding the least cost function. Techniques such as edge detection, tolerant subtraction etc. are also employed. Where as in Neural Network approach, automatic detection of eyes and mouth is followed by a spatial normalization of the images. The classification of the normalize images is carried out by a hybrid Neural Network which combines unsupervised and supervised methods for finding structures and reducing classification errors respectively.

## **1. Introduction**

In the biological evolution process, logical thinking has been the last to evolve, and lies at the surface of our consciousness, its means and methodologies available for introspection. On the other hand, the intelligence required to interpret sensory signals and activate motor commands is so well known biologically that it is buried in the subconscious and is entirely inaccessible at the conscious level. The differences between human beings are also more pronounced in the logical reasoning area, than, say, in the ability to walk around a room avoiding obstacles, or to recognize human faces. Hence the variation in human intelligence is usually measured by the ability to process logical information, whereas the other forms of intelligence needed in daily life are not normally associated with the word intelligence.

Scientists and Engineers want to make a substitution or a helper of human being in the era of Information Technology. This helper works on the instruction of Man. Thus, it can also be called a servant, a servant who is faithful and perform the exact orders. It will think only in favor of his master. It will help in general works and in special tasks as well, like security, management etc. It will provide the high degree of security and perfect ness in performing orders. The Robot will become a perfect servant of human. Nowadays, Scientists have made efforts to make such Robots. But still, artificial intelligence is the main problem. A man can

think and adjust himself in any condition, can take the optimal and possible decision. The Robot can perform only those tasks and take decisions, which are specified in its programming code.

In this project, an attempt will be made to design a Robot and its software, which will have an optimal solution of conditions (for which the Robot is to be designed i.e. security). It will not only reduce the cost (the cost spend in security of VIP's is very high) but also will increase the security strength and stop the criminal activities.

The objective of the proposed project is to design and make a Robot and its Artificial Intelligence environment (software), which will perform all the basic and high end security checking. It will take snaps of the people presented towards it and match the snaps from its database to check for criminals. It will also check the thumb impression and perform metal detection and scanning. Thus, such operations with minimum errors will cause the better security. This Robot will also have arms to lift the objects and it will also have path planning to move avoiding obstacles.

The Robotics projects are basically implemented in educational and research institutions. Some institutions work only on Robot movement and arm manipulation. The use of digital camera and image processors, thumb impression detector, metal detector and other related things are not under consideration. Many research centers and institutes work on mechanical Robots.

The facilities are available but the exposure in artificial intelligence, Robotics and image processing is not much so that one can implement the thinking and ideas in real time projects. Some software are available for thumb impression detection and digital camera film creation but they are not implemented everywhere and have some difficulties in operation while in security checks.

In Japan, USA, UK, Korea, the real time Robotics projects is in very fast process. The scientist and engineers are working in such projects and they have achieved to make some Robots, which have the artificial intelligence, equivalent to lizard. NEC a Japanese company has made a Robot named PAPER0, which can recognize the faces of about 3000 human faces.

The main purpose of this project is to build such type of Robot, which has maximum numbers of algorithms to handle optimal security. It can self manage the condition and may be able to take conditional steps. This would be widely used by police, military and other security agencies. This Robot could do the work of at least ten security men and react very fast. It would

also be helpful for securing the household things. The Robot, on just changing some instructions in the program, can also handle the security of shops, houses, banks etc.

## **2. Fundamental Issues in Face Recognition**

The requirement for reliable personal identification in computerized access control has resulted in an increased interest in biometrics. Biometrics being investigated includes fingerprints, speech, signature dynamics, and face recognition. Sales of identity verification products exceed \$100 million. Face recognition has the benefit of being a passive, non-intrusive system for verifying personal identity. The techniques used in the best face recognition systems may depend on the application of the system. We can identify at least two broad categories of face recognition systems:

1. We want to find a person within a large database of faces (e.g. in a police database). These systems typically return a list of the most likely people in the database. Often only one image is available per person. It is usually not necessary for recognition to be done in real-time.
2. We want to identify particular people in real-time (e.g. in a security monitoring system, location tracking system, etc.), or we want to allow access to a group of people and deny access to all others (e.g. access to a building, computer, etc.). Multiple images per person are often available for training and real-time recognition is required.

We are interested in recognition with varying facial detail, expression, pose, etc. We do not consider invariance to high degrees of rotation or scaling - we assume that a minimal preprocessing stage is available if required. We are interested in rapid classification and hence we do not assume that time is available for extensive preprocessing and normalization. Good algorithms for locating faces in images can be found in. Robust face recognition requires the ability to recognize identity despite many variations in appearance that the face can have in a scene. The face is a 3D object that is illuminated from a variety of light sources and surrounded by arbitrary background data (including other faces). Therefore, the appearance a face has when projected onto a 2D image can vary tremendously. If we wish to develop a system capable of performing non-contrived recognition, we need to find and recognize faces despite these variations. In fact, 3D pose, illumination and foreground-background segmentation have been

pertinent issues in the field of computer vision as a whole. Additionally, our detection and recognition scheme must also be capable of tolerating variations in the faces themselves. The human face is not a unique rigid object. There are billions of different faces and each of them can assume a variety of deformations. Inter-personal variations can be due to race, identity, or genetics while intra-personal variations can be due to deformations, expression, aging, facial hair, cosmetics and facial paraphernalia. Furthermore, the output of the detection and recognition system has to be accurate. A recognition system has to associate an identity or name for each face it comes across by matching it to a large database of individuals. Simultaneously, the system must be robust to typical image-acquisition problems such as noise, video-camera distortion and image resolution. Thus, we are dealing with a multi-dimensional detection and recognition problem. One final constraint is the need to maintain the usability of the system on contemporary computational devices (100 MIPS). In other words, the processing involved should be efficient with respect to run-time and storage space. Research in intensity image face recognition generally falls into two categories: holistic (global) methods and feature-based methods. Feature-based methods rely on the identification of certain fiducial points on the face such as the eyes, the nose, the mouth, etc. The location of those points can be determined and used to compute geometrical relationships between the points as well to analyze the surrounding region locally. Thus, independent processing of the eyes, the nose, and other fiducial points is performed and then combined to produce recognition of the face. Since detection of feature points precedes the analysis, such a system is robust to position variations in the image. Holistic methods treat the image data simultaneously without attempting to localize individual points. The face is recognized as one entity without explicitly isolating different regions in the face. Holistic techniques utilize statistical analysis, neural networks and transformations. They also usually require large samples of training data. The advantage of holistic methods is that they utilize the face as a whole and do not destroy any information by exclusively processing only certain fiducial points. Thus, they generally provide more accurate recognition results. However, such techniques are sensitive to variations in position, scale and so on, which restrict their use to standard, frontal mug-shot images.

### **3. Limitations of Face Recognition Technology**

Although face recognition technology presents some very promising potential uses, there are several concerns that must be appropriately addressed if face recognition technology is to gain widespread acceptance in the future. Specifically, it is necessary to address concerns such as privacy, false acceptance, false rejection, and technology standards.

#### **3.1 Privacy**

The issue with face recognition technology and privacy bears revisiting. Users are typically wary of giving companies access to digital representations of their personal physical traits. Although face recognition templates are not nearly as invasive as fingerprint authentication methods, there is nevertheless concern expressed by users of this technology. The privacy issue can be greatly reduced by implementing the hybrid biometric and smart card security methods.

#### **3.2 False Acceptance**

False acceptance occurs when an unauthorized individual is authenticated as authorized by the biometric system. False acceptance rates vary depending on the particular biometric software being used, and the templates stored on the system. The FAR is increased in one-to-many searching systems because of the potential for several users to have similar Eigen faces stored in the central repository. This risk is greatly reduced in one-to-one matching systems because the possibility of similar eigenfaces confusing the authentication process is eliminated. Despite the type of searching/matching employed, in general, face recognition biometrics achieves a FAR of less than 1%.

#### **3.3 False Rejection**

False rejection occurs when an authorized individual is inappropriately denied access by the biometric system. Like FAR, false rejection rates also vary depending on software being used and the desired level of matching accuracy. In addition, environmental factors such as lighting,

age, facial hair, and glasses can result in a higher FRR. Face recognition biometrics is typically prone to false rejection more often than false acceptance by design. However, like FAR, FRR for face recognition biometrics is still less than 1% in most configurations.

### **3.4 Technology Standards**

Like any new technology, standards are a very important consideration when choosing an authentication method, due to concerns related to integration with future systems and product support long-term. Unfortunately, there are very few standards for biometric authentication systems presently. While the image-capturing medium is fairly standardized, the proprietary algorithms that generate the numerical eigenface representations are far from standard. Several initiatives are currently underway by various agencies to attempt to develop a standard for generating eigenfaces. These standards are essential to ensuring biometrics place in the future of authentication systems. Without standards, biometric systems will not be able to work with each other to provide the strong-layered security structure that they were designed to accomplish.

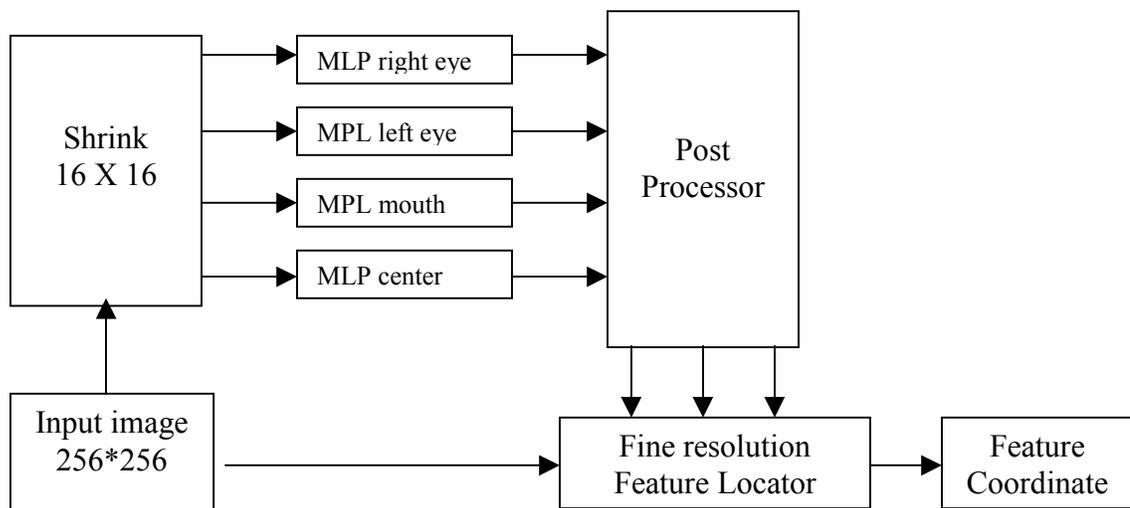
### **4.1 Face Finding in Image**

This project is being undertaken to produce a system, based on the use of neural network feature detectors, to robustly locate and track features in digital image sequences. The solution to the feature location problem is the Hierarchical Perceptron Feature Locator (HPFL) system. This consists of a coarse resolution stage followed by a high-resolution stage. The first stage generates search regions for eyes and mouth and the second stage searches inside these regions to accurately locate the individual feature points. Both stages employ Multi-Layer Perceptrons (MLPs) for feature detection and their outputs are post-processed in order to protect against errors.

A low resolution binary image containing searches regions for one feature is called a feature map. It would be impossible to rely on the outputs of the MLPs without having a mechanism for detecting and protecting against errors; otherwise it is prone to the location of spurious features, and sometimes fail to locate features that are present. Therefore it was decided

to post-process the outputs of the MLPs using symbolic reasoning, thereby turning HPFL into a hybrid intelligent system. Eyes and mouths form an isosceles triangle in 3D object space and this geometric constraint leads to a set of rules with which to generate cleaned up search regions. A second technique to improve performance is to use inter-frame knowledge. Constraints can be put on the extent of allowable motion between frames, and this is used to remove transient spurious errors in the feature maps.

The high-resolution stage was also much improved by having a structured representation of eyes and mouth. Each of these compound features is represented by a constellation of simple localized features called micro-features. The neural networks are trained to act as Bayesian classifiers and this means that probabilistic reasoning is to find the most likely configurations of micro-features and this requires calculation of likelihood levels.



**Scheme of the Hierarchical Perceptron Feature Locator**

## 4.2 Generation of Feature Maps

The feature detectors required in the low resolution stage of the HPFL are required to perform a subtly different function to a straightforward classifier, or those required in the high resolution stage. The purpose of the low-resolution feature detectors is to locate candidate feature points.

MLPs with a 5X5 input window, two or three hidden 2<sup>nd</sup> degree neurons and a single output neuron have been used as detectors to perform candidate feature point classification for

the HPFL. Each detector is scanned across the 16X16 pixel image, and its threshold output is used to create a 16 X 16 binary image known as a feature map.

### **4.3 MLP Training**

The low resolutions MLPs are trained using a customized version of the back-propagation algorithm. The back-propagation method is a simple yet highly effective method for training neural networks containing neurons with non-linear neurons and it has done much to popularize connectionism.

There are two broad aspects to the learning: the selection of training parameters and the type of algorithm used in a training session. A 'single training session' is defined here as a sequence of epochs resulting in a particular set of weight values. Prior to the first epoch an MLP is randomly initialized and during each epoch all training data will have been presented to the MLP and weights adjusted. At the end of a single training session a trained MLP is produced. The quality of the MLP is affected by chosen parameters. Therefore it is necessary to explore parameter space by running a series of individual training sessions and selecting the best MLP. This is referred to here as batch training. Batch training raises interesting issues, such as computational complexity and ways of automating the search process.

### **4.4 Algorithm for a single training session**

#### **(1) Classification of pattern vectors**

As the MLP is scanned across the source image there is one occasion when the scanning window is closest to the desired feature. When this occurs the expected output of the MLP is a high value (1,0) and the pattern vector on its input will be referred to as a feature vector. In all other positions the MLP output is expected to be low (0,0). The pattern vectors that form the input to the MLP on these occasions will be referred to as background vectors.

## **(2) Presentation ratio**

The MLPs were trained on 30 images selected from a set of 60 head and shoulder images. For each low resolution image there are 144 MLP input window positions, corresponding to 143 background vectors and 1 feature vector. This is calculated from the expression for the total number of scan able positions,  $W$ , in an image.

$$W=(Width_{image}-Width_{window}+1)(Height_{image}-Height_{window}+1)$$

If each vector is presented only once during a training epoch then the contribution to weight updating made by the feature vector is swamped by the effects of the background vectors, failure to detect the feature vector means that only 1 in 144 pattern vectors are misclassified, a misleading success rate of 99.3%. This problem is avoided by presenting the two classes of pattern vector in 1:1 ratio; each time a background vector is presented to the MLP it is followed by the feature vector from the same image.

## **(3) Selective training**

Because of the need to ensure that all feature vectors are detected, whilst minimizing the number of background vectors that result in false positives, a selective training procedure was used. In this procedure a pattern vector is used only if the MLPs current response to it is considered unacceptable. In this selective training procedure the feature vectors are presented to the net at the end of a training epoch. If any feature is misclassified, then training enters selective mode, otherwise it enters non-selective mode. In selective mode only feature vectors are presented. Training remains in selective mode until all features are correctly classified. In either mode backpropagation is only applied for those that are misclassified. Misclassification is deemed to have occurred if the net gives an output  $< 0.5$  for an expected output of 1.0, or if the output  $> 0.5$  for an expected value of 0.0

#### (4) Stopping Criteria

It is important to know when performance was optimized during training. The database of head and shoulder images, made available for the second phase, is partitioned into two parts: training data ( $Tr$ ) and the test data ( $Te$ ). Two performance measures are used to assess the ability of an MLP to identify a feature in a database,  $T$ : average size of search regions,  $A^T$ , and the feature, retention rate,  $Ret^T$ . Average size of search regions,  $A^T$ , is the percentage of pixels in an image which belongs to the search regions. Feature recognition rates,  $Rej^T$ , may be similarly defined. More explicitly, the two types of performance measures are defined as follows: -

$$\begin{aligned} A^T &= 100 \cdot \frac{\text{Average search region size}}{\text{Image area}} \\ &= 100 \cdot \frac{\sum_{m=1}^{M^T} \alpha_y \beta_z \text{ Belongs to search region}}{M^T \cdot \text{Width}_{\text{image}} \cdot \text{Height}_{\text{image}}} \\ Ret^T &= 100 \cdot \text{Fraction of feature points retained} \\ &= 100 \cdot \frac{\sum_{m=1}^{M^T} \text{Feature points inside Search Region}}{M^T} \\ Rej^T &= 100 - Ret^T\% \end{aligned}$$

Where the predicates *Belong To Search Region* and *Feature Point Inside Search Region* return either 0 or 1 according to their truth-value. *Belongs To Search Region* ( $x,y,m$ ) is true if the pixel ( $x,y$ ) in the relevant feature map for the  $m^{\text{th}}$  image falls inside the relevant search region.  $M^T$  denotes the number of images in the  $T^{\text{th}}$  database.

#### 4.5 Feature Location in the High Resolution Image

After pixel expansion, the feature maps are passed to the supervisor of the resolution stage of HPFL. Each pixel in a feature map corresponds to a 16 X 16 block in the high-resolution image. It has been found that high-resolution MLP micro-feature detectors generate spurious responses thereby degrading positional accuracy. To overcome this problem each feature in the image is considered to be composed of ‘micro-features’. For each micro-feature detector is trained and the

combined outputs of the micro-feature detectors are post-processed in such a way as to increase the overall detection reliability.

## 5.1 An Efficient Face Recognition Algorithm

We are interested in classifying  $K$  faces,  $F_k$  ( $k=1\dots K$ ), given  $V_k \subseteq \dots \subseteq \mathbb{R}^3 \oplus D$  image views of each unique face  $F_k$ , obtained by regular sampling in the viewing sphere. The aim is to recognize one of the  $K$  faces from test image views.

A face image is modeled as a regular lattice of  $w \times h$  pixels, with each pixel  $P$  having a depth equal to the  $\mathfrak{I}_p$  image planes. We first classify the pixels in  $\mathfrak{I}$  into two classes  $C_{p,1}$  and  $C_{p,2}$ . Class  $C_{p,1}$  consists of all those pixels that represent a face in  $\mathfrak{I}$  such that  $C_{p,1} \cap C_{p,2} = \emptyset$ . We are interested in those pixels in  $C_{p,2}$  with neighbors in  $C_{p,1}$  and call the set of those face boundary pixels  $\beta$ .

Consider  $l$  pixel values extracted along a straight line or “chord” between two points in an image comprising of  $l \times \mathfrak{I}_p$  bits of data. The number of line pixels is small enough for efficient classification but, of course, may not capture the information necessary for correct classification. However, with some reduced probability (larger than random), the line predicts the correct face class. The algorithm we propose is based on the observation that the classification of many such lines from a face image  $\mathfrak{I}$  leads to an overall probability of correct classification (PCC) which approaches 1. This observation serves as the main motivation for the algorithm.

For any two points  $B_1 \in \beta$  and  $B_2 \in \beta$  in an image view  $V_k$  such that the Euclidean distance  $B_1$  and  $B_2$  is greater than a minimum  $D_{\min}$ , let  $L(B_1, B_2) \equiv (L^{(1)}, L^{(2)}, \dots, L^{(l)})$  be a vector of length  $l$ , where  $l$  is the number of equi-spaced connected intensity values  $L^{(q)} = P(L)_q$  (where  $q = 1, 2, \dots, l$ ) along the image rectilinear segment from  $B_1$  to  $B_2$ . We note that in our algorithm, the points  $B_1$  and  $B_2$  need not necessarily belong to the set of face boundary pixels  $\beta$ . Indeed rectilinear line segments may span any two pixels that are outside the face boundary, i.e.,  $B_1, B_2 \subseteq C_{p,2}$ . The relative performance of the algorithm will depend on the coverage of the face by the set of the line segments and maximum performance will generally be achieved when  $B_1, B_2 \in \beta$ .

The line segment length  $l$  is a constant parameter determined a priori; larger values of  $l$  result in better classification rates at the expense of increased processing times. All lines are scaled to the value  $l$  by pixel interpolation. We call  $L(B_1, B_2)$  a lattice line, denoted by  $\mathbf{L}$ . The exact interpolation of  $L$  need not lie on a corner of the boundary pixels  $B_1$  and  $B_2$ .

For each face class in the training set of  $V_k$  image views, we randomly generate  $N_k = V_k \times N_v$  lattice lines ( $N_v$  lines per image view per face class),  $\mathbf{L}_{i,k} \equiv (L_{i,k}^{(1)}, L_{i,k}^{(2)}, \dots, L_{i,k}^{(l)})$  for  $i=1, 2, \dots, N_k$  such lattice lines for  $K$  face classes. The set of lattice lines for all  $K$  face classes is given by:

$$\Psi = \bigcup_{k=1}^K \bigcup_{i=1}^{N_k} \mathbf{L}_{i,k}$$

We define the distance  $D(\mathbf{L}_{r,s}, \mathbf{L}_{m,n})$  between two lattice lines  $\mathbf{L}_{r,s}$  and  $\mathbf{L}_{m,n}$  as

$$D(\mathbf{L}_{r,s}, \mathbf{L}_{m,n}) = \sum ((L_{r,s}^{(q)} - (L_{m,n}^{(q)} + \Delta))^2),$$

for  $r, m = 1, 2, \dots, N_k$  and  $s, n = 1, 2, \dots, K$ , where  $\Delta = \mu(\mathbf{L}_{r,s}) - \mu(\mathbf{L}_{m,n})$  and  $\mu(\mathbf{L}_{r,s}) = \sum_i L_{r,s} / l$ . The value of  $\Delta$  has the effect of shifting the two lines towards the same average value, making the distance measure invariant to illumination intensity.

Consider now a set of test lines sampled from one or more face views in the viewing sphere (for the same face subject). Given an unseen test lattice line  $\mathbf{L}_j$  where, generally  $\mathbf{L}_j \notin \Psi$ , we define  $\mathbf{L}_{j,*}$  such that  $D(\mathbf{L}_j, \mathbf{L}_{j,*})$  is a minimum, where  $\mathbf{L}_{j,*} \in \Psi$ . The nearest neighbor classifier (NNC) maps  $\mathbf{L}_j$  to the class  $F_k$  to which  $\mathbf{L}_j$  belongs. We choose the nearest – neighbor classifier since it has a good performance over a range of problem domains.

We assume that there are  $N$  test lines  $\mathbf{L}_j$  for a given test face, where  $j=1, 2, \dots, N$ . and, for each line, we have obtained an  $\mathbf{L}_{j,*}$  and a  $D_j$ . Let  $D_{max} = k_1 \times \max_{1 \leq j \leq N} \{D_j\}$  for some value of  $k_1$  between  $0 < k_1 < 1$  and  $D_{min} = \min_{1 \leq j \leq N} \{D_j\}$ . We define the cumulative  $l_1$ -norm error statistic for line  $\mathbf{L}_j$ ,  $err_j = (\sum_{q=1}^l (|\mathbf{L}_{j,*}^{(q+1)} - \mathbf{L}_{j,*}^{(q)}|)) / (l-1)$  for  $q = 1, 2, \dots, l-1$  and the maximum cumulative error statistic,  $err_{max} = \max_{1 \leq i \leq N} \{err_i\}$ .

We define the measure of confidence that NNC ( $\mathbf{L}_j$ ) is correct,  $conf_j$ :

$$conf_j = 0 \quad \text{if } D_j > D_{\max}$$

$$= \{W_1 (D_{\max} - D_j) / (D_{\max} - D_{\min})\}^{p_1} * \{ (err_j / err_{\max}) W_2 \}^{p_2} \quad \text{otherwise}$$

where  $p_1$ ,  $p_2$ ,  $w_1$ , and  $w_2 \in \mathbb{R}_{\oplus}$ . The variables  $p_1$  and  $p_2$  control the shape of the confidence function, whereas  $w_1$  and  $w_2$  are the weight magnitudes of the distance and cumulative error statistic components, respectively.

We now state the face recognition algorithm.

### 5.1.1 The Line-Based Face Recognition Algorithm

To classify a face  $F_t$  for which we know its boundary pixel set  $\beta$ , we randomly select  $N$  lattice lines  $\mathbf{L}_j$ ,  $j = 1, 2, \dots, N$ . For each face class  $F_k = 1, 2, \dots, K$ , define  $TC_k = \sum_{j=1}^N conf_j$ , such that  $NNC(\mathbf{L}_j) = F_k$ . We assign  $F_t$  to class  $F_g$  such that  $TC_g$  is maximum. That is,

$$\text{If } TC_g = \max \{TC_k\}$$

$$\text{Then } F_g \leftarrow F_t \text{ for } F_g = 1, 2, \dots, K.$$

Because  $F_t$  is assigned to class  $F_g$  based on the combination of many assignments of individual lines, we may assess the likelihood that our decision is correct by the agreement within the line assignments. Specifically, we define the *confidence measure factor* as the ratio

$$CMF = [TC_g - TC_j^{(2)}] / TC_j^{(2)},$$

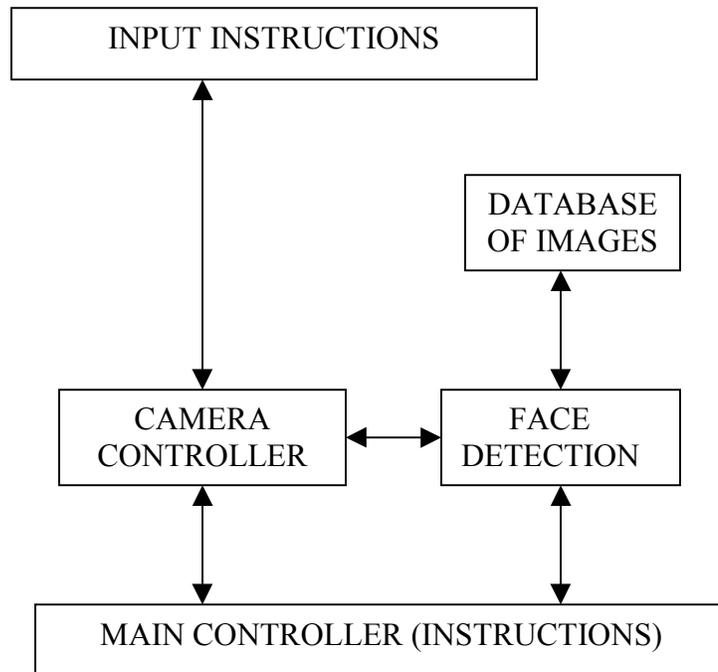
Where  $TC_j^{(2)}$  is the second largest compounded confidence measure that a class obtained. As our decision is based on the maximum score, the associated confidence  $CMF$  is proportional to the difference with the second largest score. The denominator normalizes  $CMF$  for different numbers of testing lines.

It is a considerable advantage if a classifier were to supply a confidence measure factor with its decision as the user is then given information about which assignments are more likely to be wrong so that extra caution can be exercised in those cases. Our implementation makes use of

the confidence measure factor by means of several decision stages. First, the number of testing is to be kept small, an initial decision is arrived at quickly, and the confidence measure factor is evaluated. Second, if the confidence measure factor is smaller than twice the minimum confidence measure factor threshold  $CMF_{min}$ , then the number of testing lines is doubled and a second decision is made at the cost of extra time. Finally, if the second confidence measure factor is smaller than  $CMF_{min}$ , the number of testing lines is doubled again one last time. Thus, by specifying a larger value for  $CMF_{min}$ , the number of test lines will be increased and, hopefully, improve the rate of correct classification. However, by increasing the number of test lines, there will be a commensurate increase in the time required for classification. Therefore, depending on the application task at hand, the user can choose whether to seek a high classification rate at the expense of larger classification times or to achieve a lower classification rate with an accompanying reduction in classification times.

6.

**BLOCK DIAGRAM OF THE PROJECT**



## 7. Acknowledgement

We are thankful to Dr. K.S. Venkatesh, IIT Kanpur, Dr. K.K. Shukla, IT-BHU, Prof. Y.V.Venkatesh, IISc. Bangalore, Dr. R.B. Lokesh, IISc. Bangalore, Prof. A. Rosenfeld, University of Maryland, and Dr. T.N.Singh, IT-BHU for their kind support and guidance.

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