ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

R.F.S. SECURITY SYSTEM FOR PARLIAMENT AND HIGH PROFILE PLACES

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ABSTRACT

It has been observed that increasing instances of identity theft and terrorism incidences in past few years, biometrics based security system has been an area of quality research. Modern day biometrics is a cutting edge technology which enables the automated system to distinguish between a genuine person and an imposter. Automated face recognition and speaker recognition are the areas of biometrics which are widely used because of the uniqueness of one human to other human. In this paper we have come up with a idea of having a 3 level security which will enhance the security of high profile places. Security includes face recognition using eigenface algorithm, speaker recognition using Mel Frequency Cepstrum Coefficient (MFCC) and RFID card technique.

KEYWORDS: Image Processing, Speech Processing, RFID, Security.

INTRODUCTION

In today's world national security has become a major concern.The whole world is facing a new kind of threat – "terrorism". As we all know there was a attack on the parliament of India a few years back. The whole security of parliament was in questioned.

In this project we have come up with a idea of having a 3 level security which will improve the security of high profile places such as defense institutes, research institutes, parliaments etc.

Here we propose to have 3 level securities. Any user who wants to enter the premises has to have the password for all the three levels, then only the entry granted. Thus making sure that the entry is authentic.

BACKGROUND

As part of the security arrangements in Parliament Complex, Door Frame Metal Detectors have been installed at various gates. Visitors accompanying the Members of Parliament and Ex-Members of Parliament are required to pass through the Door Frame Metal Detector and they may also be subjected to physical search. The baggage etc. being carried by them, may also be scanned by the Security.

Members are also advised not to bring their guests/visitors inside Parliament House without valid passes. Visitors having valid passes may be taken inside Parliament House through gates where Door Frame Metal Detectors have been installed.

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For facilitating entry of cars owned by Members into the Parliament House Complex, special car labels are issued to Members by the Notice Office on filling up the requisite form.

RFID CARD TECHNIQUE

RFID readers have two data line i.e. DATA0 and DATA1. Both the line are active low and are connected at the external interrupt pins (INT0, INT1) of the microcontroller logic 1 is transmitted on DATA1 line and logic 0 is transmitted on DATA0 line.

Interfaced RFID reader continuously transmits the electromagnetic field across it. The range is max of 10cm. when the RFID tag/card come within this range, the RFID card gets powered up and provide their 26 bit ID data to the RFID reader.

The frame format of the WIEGAND protocol is as follows:

Table.1

Bit Number	Purpose
Bit 1	Even parity over bit 2 to 13
Bits 2 to 9	Facility code (0 to 255); bit 2 is MSB
Bits 10 to 25	ID Number (0 to 65,535); bit 10 is MSB
Bit 26	Odd parity over bits 14 to 25

WIEGAND PROTOCOL

WIEGAND protocol is an Interrupt based protocol in which the data is given to the µC in the form of interrupts. Which means that the data is not transferred directly to the µC .The µC has to interpret the data from the interrupts that it gets from data 1 and data 0 line of RF reader, which are connected to the INT1 and INT 0 of the µC respectively.

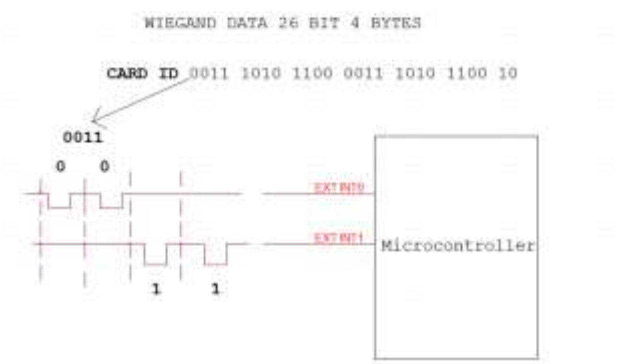

Fig.1 the data is coming in the form of interrupts to the µC.

The data format of the WIEGAND protocol is as follows

For a digital '0' → a low edge pulse on INT 0 pin of µC
For a digital '1' → a low edge pulse on INT 1 pin of µC
So, when the data comes in this manner the µC converts the interrupts into corresponding 1's and 0's and stores the card ID in the HEX format and stores it in the internal memory.
RFID reader works on WEIGAND protocol and transmits the wireless signal at 125 kHz.

FACE RECOGNITION TECHNIQUE

Until Kirby and Sirovich applied the KarhunenLoeve Transform to faces, face recognition systems utilized either feature-based technique, template matching or neural networks to perform the recognition. PCA technique which is

ISSN: 2277-9655
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provided by Kirby and Sirovich not only resulted in a technique that efficiently represents pictures of faces, but also laid the foundation for the development of the "eigenface" technique of Turk and Pentland. Such patterns, which can be observed in all signals, could be - in the domain of facial recognition - the presence of some objects (eyes, nose, mouth) in any face as well as relative distances between these objects. These characteristic features are called eigenfaces in the facial recognition domain .out of original image data these characteristics can be extracted with the help of a mathematical tool called Principal Component Analysis (PCA). The face space is described by a set of eigenfaces. By projecting a face onto the space expanded by eigenfaces is efficiently represented. Principal component analysis is applied to find the aspects of face which are important for identification. Eigenvectors (eigenfaces) are calculated from the initial face image set. New faces are projected onto the space expanded by eigenfaces and represented by weighted sum of the eigenfaces. To identify faces we make uses of these weights.

Eigenvectors and Eigen values

We make use of Eigenvectors and Eigenvalues for face recognisition with PCA. So we prepare an initial set of face images [X1, X2, ..., Xn]. The average face of the whole face distribution is

X = (X1 + X2 + ... + Xn)/n

Then the average face is subtracted from each face,

Xi' = Xi - X, i = 1, 2, ... , n

[Y1, Y2, ..., Yn] eigenvectors are calculated from the new image set [X1', X2', ... Xn'].

[Y1, Y2, ..., Yn] eigenvectors are calculated from the new image set [X1', X2', ... Xn']. These eigenvectors are orthonormal to each other. These eigenfaces look like sort of face they do not correspond directly to any face features like eyes, nose and mouth. They are a set of important features which describe the variation in the face image set.

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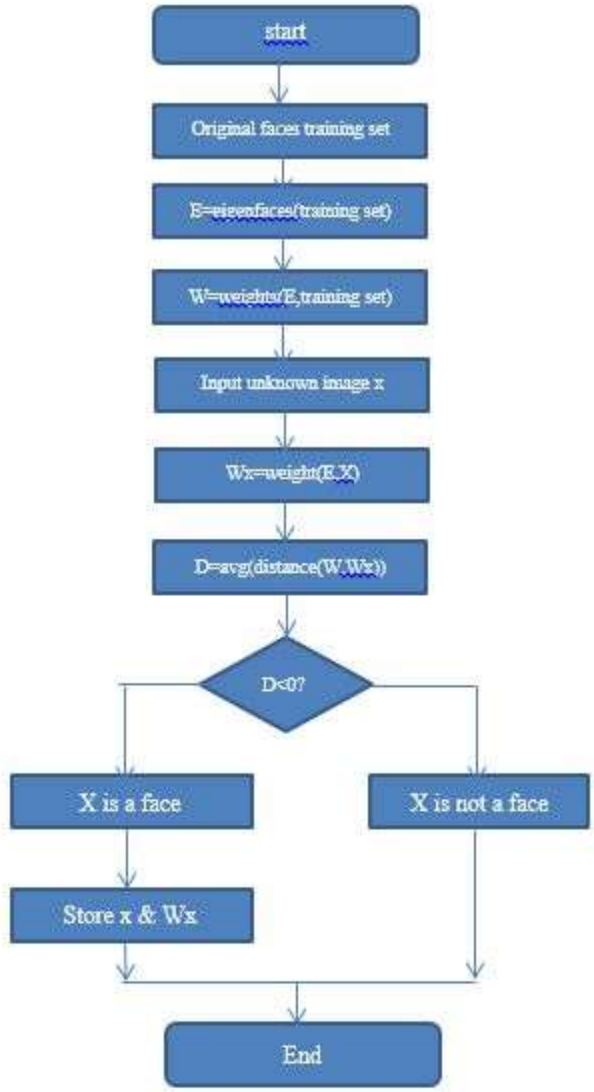

Each eigenvector has an eigenvalue associated with it. Eigenvectors on face variation with bigger eigenvalues provide more information than those with smaller eigenvalues. After the eigenfaces are extracted from the covariance matrix of a set of faces, each face is projected onto the eigenface space and represented by a linear combination of the eigenfaces, or has a new descriptor corresponding to a point inside the high dimensional space with the eigenfaces as axes. If we use all the eigenfaces to represent the faces, those in the initial image set can be completely reconstructed. But these eigenfaces are used to represent or code any faces which we try to learn or recognize.

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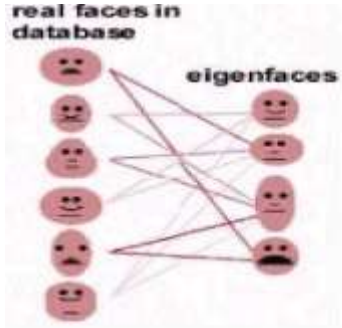


Fig.3

An important feature of PCA is that by combining the eigenfaces one can reconstruct any original image from the training set. Remember that eigenfaces are nothing less than characteristic features of the faces. Therefore original face image can be reconstructed from eigenfaces if one adds up all the eigenfaces (features) in the right proportion. Starting with a pre-processed image
I(x, y), which is a two dimensional N by N array of intensity values. This may be considered a vector of dimension N2.
A database of M images can therefore map to a collection of points in this high dimensional "face space" as Γ1, Γ_2, Γ_3…..ΓM.. With the average face of the image set defined as

$$\Psi = 1/M \sum_{n=0}^{m} \Gamma n \qquad \ldots(1)$$

Each face can be mean normalized and be represented as deviations from the average face by Φ1=Γi-Ψ. The covariance matrix, defined as the expected value of ΦΦT can be calculated by the equation

$$C = 1/M \sum_{n=1}^{M} \phi_n \phi_n^T \qquad \ldots(2)$$

Set of very large vectors is subject to PCA, which seeks a set of M ortho-normal vectors, u_n, which best describes the distribution of the data. The k^{th} vector, u_k is chosen such that

$$\lambda_k = 1/M \sum_{n=1}^{M} (u_k \phi_n^T)^2 \quad \ldots(3)$$

Is a maximum, subject to

$$u_i^T u_j = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \qquad \ldots(4)$$

Given the covariance matrix C, we can now proceed with determining the eigenvectors u and eigenvalues Λ of C in order to obtain the optimal set of principal components, a set of eigenfaces that characterize the variations between face images.

$$\lambda_1 = u_i^T C u_i$$

$$\lambda_i = \frac{1}{M} u_i^T \sum_{n=1}^{M} \phi_n \phi_n^T u_i$$

$$\lambda_i = \frac{1}{M} \sum_{n=1}^{M} u_i^T \phi_n \phi_n^T u_i$$

$$\lambda_i = \frac{1}{M} \sum_{n=1}^{M} (u_i \phi_n^T)^T (u_i \phi_n^T)$$

$$\lambda_1 = \frac{1}{M} \sum_{n=1}^{M} (u_i \phi_n^T)^2$$

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M}(u_i\Gamma_n^T - mean(u_i\Gamma_n^T))^2$$

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M} var(u_i\Gamma_n^T) \quad \ldots(5)$$

Consider an eigenvector ui of C satisfying the equation

$$C=AA^T \qquad \ldots(6)$$

Turk and Pentland thus suggest that by selecting the eigenvectors with the largest corresponding eigenvalues as the basis vector, the set of dominant vectors that express the greatest variance are being selected. Recall however, that an N-by-N face image treated as a vector of dimension N2 is under consideration. Therefore, if we use the approximated equation derived in Eq. 5, the resultant covariance matrix C will be of dimensions N2 by N2. A typical image of size 256 by 256 would consequently yield a vector of dimension 65,536, which makes the task of determining N2 eigenvectors and eigenvalues intractable and computationally unfeasible. Recalling that A= [Φ1, Φ2….. Φ_M], the matrix multiplication of ATA results in an M-by-M matrix. Since M is the number of faces in the database, the eigenvectors analysis is reduced from the order of the number of pixels in the images (N2) to the order of the number of images in the training set (M). In practice, the training set is relatively small (M<< N2), making the computations mathematically manageable. The simplified method calculates only M eigenvectors while previously it was proven that there are mathematically N2 possible eigenvectors. Only the eigenvectors with the largest corresponding eigenvalues from the N2 set are selected as the principal components. Thus, the eigenvectors calculated by the alternative algorithm will only be valid, if the resulting eigenvectors correspond to the dominant eigenvectors selected from the N2 set.

Consider the eigenvectors, vi, of A^TA such that

$A^TAv_i=\mu_iV_i$

Pre-multiplying both sides by A and using Eq. (5), we obtain

$AA^T\ Av_i=\mu iAVi$

Following this analysis, we construct the M by M matrix L- A^TA, where

$$L_{mn} = \phi_m^T\phi_n$$

and find the M eigenvectors, vi of L. these vectors determine linear combinations of the M training set face images to form the eigenfaces u_i

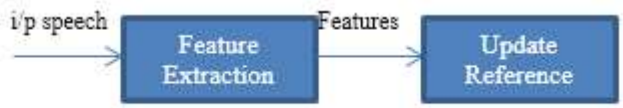
$$u_l = \sum_{l=1}^{M} V_{lk}\phi_K$$

with this analysis the calculations are greatly reduced, If the no of data points in face space is less than the dimension of space itself, which in our case is true since M<< N^2, it follows logically that there will only be M – 1, rather than N^2, meaningful eigenvectors and so calculation becomes quite manageable. Where M is no of images in the training set and N^2 is number of pixels in the image. Thus rather than calculating the N^2 eigenvectors of AA^T, we can instead compute the eigenvectors of A^TA, and multiply the results with A in order to obtain the eigenvectors of the covariance matrix, C = AA^T Recalling that A= [Φ1, Φ2….. Φ_M], the matrix multiplication of A^TA results in an M-by-M matrix. Since M is the number of faces in the database, the eigenvectors analysis is reduced from the order of the number of pixels in the images (N^2) to the order of the number of images in the training set (M). In practice, the training set is relatively small (M<<N^2), making the computations mathematically manageable. The simplified method calculates only M eigenvectors while previously it was proven that there are mathematically N^2 possible eigenvectors. As demonstrated In Eq. (5) only the eigenvectors with the largest corresponding eigenvalues from the N^2 set are selected as the principal components. Thus, the eigenvectors calculated by the alternative algorithm will only be valid, if the resulting eigenvectors correspond to the dominant eigenvectors selected from the N^2 set.

SPEAKER RECOGNITION

The human speech contains numerous discriminative features that can be used to identify speakers. Speech contains significant energy from zero frequency up to around 5 kHz. The objective of automatic speaker recognition is to extract, characterize and recognize the information about speaker identity. The property of speech signal changes markedly as a function of time. To study the spectral properties of speech signal the concept of time varying Fourier representation is used. However, the temporal properties of speech signal such, as energy, zero crossing, correlation etc are assumed constant over a short period. That is its characteristics are short-time stationary .Therefore, using hamming window, Speech signal is divided into a number of blocks of short duration so that normal Fourier transform can be used.

Like any other pattern recognition systems, speaker recognition systems also involve two phases namely, training and testing. Training is the process of familiarizing the system with the voice characteristics of the speakers registering. Testing is the actual recognition task. The block diagram of training phase is shown in Fig.4. Feature vectors representing the voice characteristics of the speaker are extracted from the training utterances and are used for building the reference models. During testing, similar feature vectors are extracted from the test utterance, and the degree of their match with the reference is obtained using some matching technique. The level of match is used to arrive at the decision. The block diagram of the testing phase is given in Fig.4



The Block Diagram Of Training Phase.

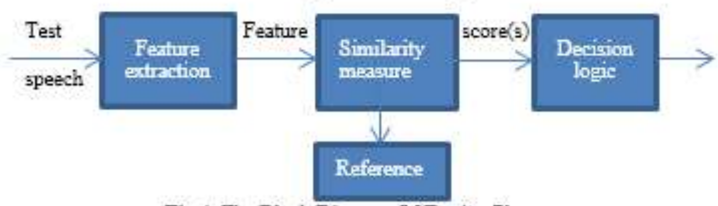


Fig.4. The Block Diagram Of Testing Phase.

MEL FREQUENCY CEPSTRAL COEFFICIENTS

The Mel frequency Cepstrum Coefficient (MFCC) feature has been used for designing a text dependent speaker identification system. The extracted speech features (MFCC's) of a speaker are quantized to a number of centroids using vector quantization algorithm. These centroids constitute the codebook of that speaker. MFCC's are calculated in training phase and again in testing phase. Speakers uttered same words once in a training session and once in a testing session later. The Euclidean distance between the MFCC's of each speaker in training phase to the centroids of individual speaker in testing phase is measured and the speaker is identified according to the minimum Euclidean distance. The code is developed in the MATLAB environment and performs the identification satisfactorily.

MFCC is based on the human peripheral auditory system. The human perception of the frequency contents of sounds for speech signals does not follow a linear scale. Thus for each tone with an actual frequency *t* measured in Hz, a subjective pitch is measured on a scale called the 'Mel Scale' .The mel frequency scale is a linear frequency spacing below 1000 Hz and logarithmic spacing above 1kHz.As a reference point, the pitch of a 1 kHz tone, 40 dB above the perceptual hearing threshold, is defined as 1000 Mels.

The extraction and selection of the best parametric representation of acoustic signals is an important task in the design of any speech recognition system; it significantly affects the recognition performance. A compact representation would be provided by a set of Mel-frequency cepstrum coefficients (MFCC), which are the results of a cosine transform of the real logarithm of the short-term energy spectrum expressed on a Mel-frequency scale. The MFCCs are proved more efficient. The calculation of the MFCC includes the following steps.

Mel-frequency wrapping

Human perception of frequency contents of sounds for speech signal does not follow a linear scale. Thus for each tone with an actual frequency, f, measured in Hz, a subjective pitch is measured on a scale called the 'mel' scale. The mel-frequency scale is a linear frequency spacing below 1000 Hz and a logarithmic spacing above 1000Hz .As a reference

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Scientific Journal Impact Factor: 3.449
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point ,the pitch of a 1 KHz tone ,40dB above the perceptual hearing threshold, is defined as 1000 mels. Therefore we can use the following approximate formula to compute the mels for a given frequency *f* in Hz.

$$\mathrm{Mel}(f) = 2595*\log10(1 + f/700)$$

Ours approach to simulate the subjective spectrum is to use a filter bank, one filter for each desired mel-frequency component. That filter bank has a triangular band pass frequency response and the spacing as well as the bandwidth is determined by a constant mel-frequency interval. The mel scale filter bank is a series of l triangular band pass filters that have been designed to simulate the band pass filtering believed to occur in the auditory system. This corresponds to series of band pass filters with constant bandwidth and spacing on a mel frequency scale.

Cepstrum

In this final step, we convert the log mel spectrum back to time. The result is called the Mel Frequency Cepstrum Coefficients (MFCC).The cepstral representation of the speech spectrum provides a good representation of the local spectral properties of the signal for the given frame analysis. Because the mel spectrum coefficients (and so their logarithm) are real numbers, we can convert them to the time domain using the discrete cosine transform (DCT). In this final step log mel spectrum is converted back to time. The result is called the Mel Frequency Cepstrum Coefficients (MFCC).The discrete cosine transform is done for transforming the mel coefficients back to time domain.

$$C_n = \sum_{k=1}^{k} (\log S_k) \cos\left\{n\left(k - \frac{1}{2}\right) * \frac{\pi}{k}\right\},$$

N=1,2,…k

Whereas Sk,K=1,2,…,K are the outputs of last step. Complete process for the calculation of MFCC is shown in

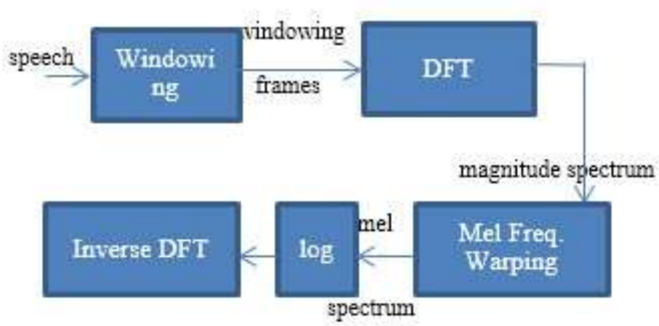

Fig 5.complete pipeline for MFCC

ACKNOWLEDGMENT

We express our deepest sense of gratitude towards our Honorable Head of department Prof G. C. Patil for giving permission to use the college resources and his constant encouragement for this work.

We are grateful to Mrs. S. A. Bhisikar for his technical support, valuable guidance, encouragement and consistent help without which it would have been difficult for us to complete this project work. We are thankful to our entire staff of Electronics and Telecommunication Department for their timely help and guidance at various stages of the progress of the project work.

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