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Iris Recognition Using Singular Value Decomposition Along With Seven State Hidden Markov Model: A Review

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Abstract: **In this review paper, we. Propose a Hidden Markov Model (HMM)-based iris recognition system and. The person is identified using 7- state HMM as classifier and Singular Values Decomposition (SVD) coefficients as features for iris recognition. Using quantized SVD as feature describing blocks of the image, each iris is considered as a numerical sequence that can be easily modeled by HMM.**

Keywords: **Iris Recognition, Hidden Markov Model, Singular Value Decomposition.**

1. INTRODUCTION

Iris recognition is one of the best topic in the image processing and pattern recognition due to the new interest in, security ,smart environments, and access control it is useful in finding out exact identity of any person by performing iris recognition technique which is intregral part of biometric .iris recognition techniques have two categories, one is based on the iris representation which uses appearance-based, which requires large set of training samples, by using statistical analysis techniques it is easy to analyze the Characteristics of a iris out of all existing iris images and the other type is based on feature based, which uses geometric iris features (iris, pupil ,ratina scelra etc.), and geometric relationships between them. The features which are extracted from iris are processed and compared with similar iris s available in the existing database, if it matches then that person is recognized otherwise unrecognized. If any person's iris image is not recognized then that image is stored in database for next recognition procedure [1].

Iris recognition using HMM and SVD coefficient shows an approach using one dimensional Discrete HMM as classifier and Singular Values Decomposition (SVD) coefficients as features for iris recognition. Here seven states used in HMM to take into account maximum iris regions [2]. In HMM, the state is not directly visible, but output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens.

Singular value decomposition is a method for transforming correlated variables into a set of uncorrelated ones that better expose the various relationships among the original data items. It is a method for identifying and ordering the dimensions along which data points exhibit the most variation. This shows that once identified where the most variation is, it's possible to find the best approximation of the original data points using fewer dimensions. These are the basic ideas behind SVD: taking a high dimensional, highly variable set of data points and reducing it to a lower dimensional space that exposes the substructure of the original data more clearly and orders it from most variation to the least.

Hence, it shows that SVD is a good method for data reduction .Therefore the sequence of tokens generated by an HMM gives some information about the sequence of states. This approach gives good accuracy with increasing speed .To obtain result of iris recognition a collection of set of iris images is required. These iris images become the database of know irises. So need to determine whether or not an unknown iris matches any of these known iris . All iris images must be of the same size (in pixels), must be gray scale, with values ranging from 0 to 255. The most useful iris sets have multiple images per person. This sharply increases accuracy

A successful iris recognition system depends heavily on the feature extraction method. One major improvement of our system is the use of SVD coefficients as features instead of gray values of the pixels in the sampling windows, blocks. After learning process, each class (iris) is associated to a HMM. For a K-class classification problem, it finds K distinct HMM models. Each test image experiences the block extraction, feature extraction and quantization process as well. Indeed each test image like training images is represented by its own observation vector [3]-[5].

2. CURRENT STATE OF THE ART

Major investigation on iris recognition has been started in the last decade. Iris recognition is becoming an active area of research in biometrics due to its high reliability for personal identification. A variety of techniques have been developed for iris localization.

According to John Daugman [9], scientist in Cambridge University, developed very efficient method for iris recognition in 1992. In Daugman's system, Integro-differential operator was used for detecting the iris boundaries and 2D Gabor filter was used for feature extraction. Canny filter were applied for the iris localization.Haar Wavelet transform used for feature extraction. Neural network is used to classify the extracted vectors.we use Learning vector quantization (LVQ) model due to low complicity & high learning capacity[10].

T. Rakesh, M G Khogare [11] Hough transformation, integro differential operator, gradient based edge detection are used to localize the portions of iris and the pupil from the eye image. In the feature extraction process Gabor wavelet transform and wavelet transform which are widely used for extracting features. Haar wavelet transform was used for optimizing the dimension of feature vectors in order to reduce processing time and space.

R.Meenakshi Sundaram , Bibhas Chandra Dhara[12] Iris localization using Circular Hough transform (CHT). Then normalized image is decomposed by 2-D Haar wavelet and textural features are extracted. The matching purposes probabilistic neural network (PNN) is used. we have used Gray Level Co occurrence Matrix (GLCM) based features to describe an iris pattern. GLCM based features are widely used for texture analysis .And for the matching purpose probability neural network (PNN) is used Anjana Peter, Revathi N, Ms. Merlin Mercy[13] iris localization using Circular Hough Transform (CHT). normalized image is decomposed by 2-D Haar wavelet and textural features are extracted. for matching pur poses Artificial Neural Network (ANN) with back propagation is used. Daugman's rubber sheet model is used to normalize the iris model .Gray Level Co-occurrence Matrix (GLCM) based features to describe an iris pattern. GLCM based features are widely used for texture analysis.

3. PROPOSED SYSTEM

In the previous section we have discussed the current state of the art. The proposed method will be based on 7-state HMM as classifier and Singular Values Decomposition (SVD) coefficients as features for iris recognition.

3.1 IRIS RECOGNITION USING HMM WITH SVD COEFFICIENT:

Following diagram (Fig. 1) shows flow of processing flow in Iris recognition:

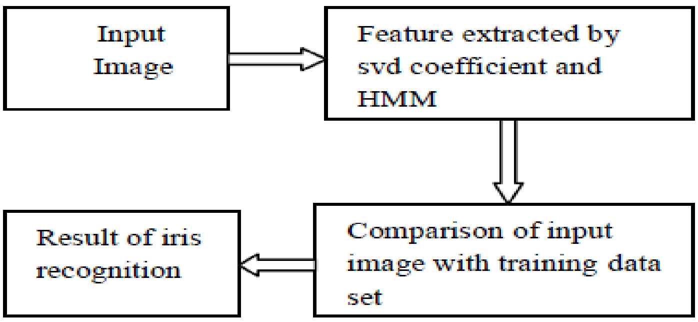

Fig.1 Iris recognition system

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iris recognition using Singular value Decomposition and HMM consist of steps in which it captures the information content in an image of a iris which are further useful for iris recognition efficiently .In processing flow of iris recognition using SVD and HMM approach, it includes extraction of iris features by SVD coefficient, Seven state HMM divides iris image in seven states then by using classifier, there is comparison of input image with training data set. If input image matches with training dataset image then iris is said to be recognized otherwise iris is unrecognized. Below diagram shows training process of a training image which includes filtering, block extraction, feature extraction and quantization.

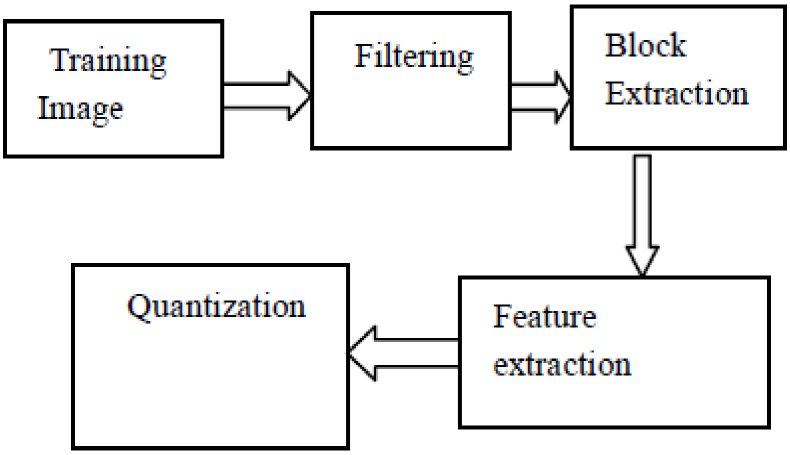

Fig. 2 : The training process of a training image

Fig. 2 shows training process of a training image which consists of steps like filtering, block extraction, feature extraction and quantization. All these steps are useful in iris recognition using hidden Marko model.

3.2 HIDDEN MARKOV MODEL :

Hidden Marko Models are useful in modelling one dimensional data in iris finding, object recognition and iris recognition. HMM is associated with non-observable hidden states and an observable sequence generated by the hidden states individually. The elements of a HMM are as N= S is the number of states in the model, where S=$\{S_1, S_2 \ldots..S_N\}$ is the set of all possible states. $M = V$ is the number of the different observation symbols, where $V = \{V_1, V_2 \ldots \ldots V_N\}$ is the set of all possible observation symbols .HMM models are performed in the observation vectors space [6].

HMMs generally work on sequences of symbols called observation vectors, while an image usually is represented by a simple 2D matrix. The observation vector is a vector of observation symbols of length *T*. *T* is defined by user based on the in hand problem.

$A = \{a_{ij}\}$ is the state transition probability matrix, where:

$a_{ij} =$ p $[q_{t+1} = s_j | q_t = s_j]$,1 ≤ i ,j < = N

0< = a_{ij}< = 1

$\sum_{J=1}^{N} aij = 1, 1 \le i \le N$ (1)

$B = \{b\, j\, (k)\}$ is the observation symbol probability matrix,

where

b_j(k) = p $[O_t = V_k | q_t = s_j]$,1< =N,1≤ K≤ M

=$\{\pi_1, \pi_2, \pi_3, \ldots \ldots \ldots .., \pi_N\}$

is the initial state distribution, where:

$$\pi_i = P[q_1 = s_i], 1 \le i \le N$$

λ = (A ,B ,π)

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$\pi = \{\pi_1, \pi_2, \pi_3 \dots \dots \dots \dots, \pi_N\}$ is the initial state distribution,

where,

$\pi_{i=}$ p $[q_1 = s_i]$

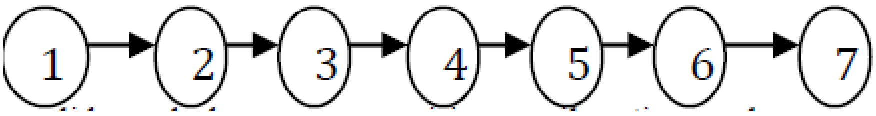
$\pi_{i=}$ p $[q_1 = s_i]$, $1 \leq i \leq N$

So HMM is defined as follows

$\lambda = (A, B, \pi)$ (4)

HMMs generally work on sequences of symbols called observation vectors, while an image usually is represented by a simple 2D matrix [3] .Here iris image is divided into seven regions which each is assigned to a state in a left to right one dimensional HMM. In hidden Markov model probability of each subsequent state depends only on what was the previous state. HMM is a Markov chain with finite number of unobservable states .These states has a probability distribution associated with the set of observation vectors.HMM consist of evaluation decoding and learning. It can be characterize by three steps that are, State transition probability matrix, Initial state probability distribution, Probability density function associated with observations for each of state[1]-[14].

In the case of using a one dimensional HMM in iris recognition problems, the recognition process is based on iris view where the iris regions like eyelid, eyelashes, iris, pupil, sclera and retina come in a natural order from top to bottom



Eyelid eyelashes cornea iris pupil retina sclera

Fig .4: A one dimensional HMM model with seven state for a iris image

3.3 SINGULAR VALU DECOMPOSITION:

The Singular Value Decomposition (SVD) has been an important tool in signal processing and statistical data analysis [7]. Singular values of given data matrix contain information about the noise level, the energy, the rank of the matrix, etc.. SVD provides a new way for extracting algebraic features from an image. SVD provides a new way for extracting algebraic features from an image. A singular value decomposition of a m × n matrix X is any function of the form

$X = U \sum V^T$

Where (*m* × *m*) and *V* (*n* × *n*) are orthogonal matrix,. The columns of the orthogonal matrices *U* and *V* are called the left and right singular vectors respectively. An important property of *U* and *V* is that they are mutually orthogonal. Singular values represent algebraic properties of an image

4. FILTERING

In this system a specific filter is used which directly affects the speed and recognition rate of the algorithm Here Order-statistic filter is used for filtering process. Most of the face recognition systems commonly use processing to improve their performance.. Order-statistic filters are nonlinear spatial filters. A two dimensional order statistic filter, which replaces the cantered element of a 3× 3 window with the minimum element in the window, is used in the proposed system. It can simply be represented by the following equation.

$f(x, y) = \min(s, t) \in S_{xy}\{g(s, t)\}$ (6)

In this equation, *g*(*s*, *t*) is the grey level of pixel (*s*, *t*) and $S_{XY}$is the mentioned window.

Since HMMs require a one-dimensional observation sequence and iris images are two dimensional, the images should be interpreted as a one dimensional sequence. The observation sequence is generated by dividing each iris image of width *W* and height *H* into overlapping blocks of height *L* and width *W*. The technique is shown in Figure. These successive blocks are the mentioned interpretation. The number of blocks extracted from each iris image is given by:

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$$T = \frac{H-L}{L-P} + 1 \qquad (7)$$

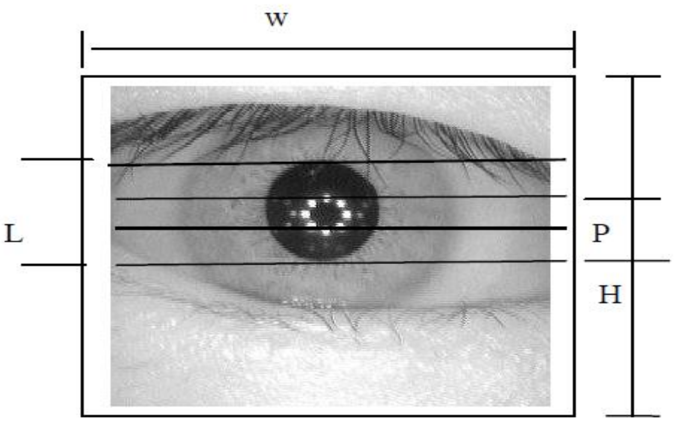

FIG.5 The sequence of overlapping blocks

A high percent of overlap between consecutive blocks significantly increases the performance of the system which increases the computational complexity. This experiment showed that as long as P is large ($P \leq L-1$) and $L \approx H/10$, the recognition rate is not very sensitive to the variations of L.

In order to reduce the computational complexity and memory consumption, it is necessary to resize iris databases into 56× 46 which results in data losing of images, so to achieve high recognition rate feature extraction method is necessary. A successful face recognition system depends heavily on the feature extraction method. One major improvement of our system is the use of SVD coefficients as features instead of gray values of the pixels in the sampling windows. Using pixels value as features describing blocks, increases the processing time and leads to high computational complexity. This process computes SVD coefficients of each block and uses them as our features.

The problem of feature selection is as there is given a set of *d* features; select a subset of size *m* that leads to the smallest classification error and smallest computational cost. This procedure selects features from singular values which are the diagonal elements. It has been shown that the energy and information of a signal is mainly conveyed by a few big singular values and their related vectors. Figure shows the singular values of a 56× 46 *iris* image. The first two singular values are very bigger than the other ones based on the SVD theory, have more significance

The SVD coefficients have innately continuous values. These coefficients build the observation vectors. If they are considered in the same continuous type, it is necessary to determine infinite number of possible observation vectors that can't be modelled by discrete HMM. So quantization is important. In quantization process, used in the proposed system, consider a vector $X = (X_1, X_2 \ldots\ldots.. X_n)$ with continuous components. Suppose *xi* is to be quantized into *Di* distinct levels. So the difference between two successive quantized values will be as equation x.

$$\Delta_i = \frac{x_{imax} - x_{imin}}{D_i} \qquad (8)$$

x_{imax}andx_{imin} are the maximum and minimum values that *xi* gets in all possible observation vectors respectively.

$$x_{iquantized} = [\frac{x_i - x_{imin}}{\Delta_i}] \qquad (9)$$

At last each quantized vector is associated with a label that here is an integer number. Considering all blocks of an image, the image is mapped to a sequence of integer numbers that is considered as an observation vector. After representing each iris image by observation vectors, they are modelled by a 7-state HMM

After learning process, each face class is associated to a HMM. For a K-class classification problem, it finds K distinct HMM models. Each test image experiences the block extraction, feature extraction and quantization process as well. Here each test image like training images is represented by its own observation vector. Here for an incoming face image, simply calculate the probability of the observation vector (current test image) given each HMM iris model. A iris image *m* is recognized as iris *d* if:

$$P\left[O^{(m)}\middle|\lambda_d\right] = max_n P(O^{(m)}|\lambda_n) \qquad (10)$$

The proposed recognition system tested on the Casia database. The database contains 10 different iris images per person of 40 people with the resolution of 56× 46 pixels

5. APPLICATIONS

Iris recognition has tremendous potential for security in any field .The iris is extremely unique and cannot be artificially impersonated by a photograph (Daugman , 2003).This enables security to be able to restrict access to specific individuals. An iris is an internal organ making it immune to environmental effects. Since an iris does not change over the course of a lifetime, once an iris is encoded it does not need to be updated .The only drawback to iris recognition as a security instalment is its price, which will only decrease as it becomes more widely used.

A recent application of iris recognition has been in the transportation industry, most notably airline travel. The security advantages given by iris recognition software have a strong potential to fix problems in transportation (Breault, 2005). Its most widely publicized use is in airport security. IBM and the Schiphol Group engaged in a joint venture to create a product that uses iris

Recognition to allow passengers to bypass airport security This product is already being used in Amsterdam. A similar product has been installed in London's Heathrow, New York's JFK, and Washington's Dulles airports (Airport, 2002, ¶ 2 & 3). These machines expedite the process of passengers going through airport security, allowing the airports to run more efficiently. Iris recognition is also used for immigration clearance, airline crew security clearance, airport employee access to restricted areas, and as means of screening arriving passengers for a list of expelled persons from a nation (Daugman, 2005). This technology is in place in the United States, Great Britain, Germany, Canada, Japan, Italy, and the United Arab Emirates

6. CONCLUSION

In this paper about has been a discussed recognition system .iris feature extraction is a major step for the efficient and effective representation of iris features. The goal of the iris feature extraction is to find an efficient and effective representation of the iris images which would provide robustness during recognition process. This paper propose an HMM based iris recognition system

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