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An Approach for Iris Recognition Based On Singular Value Decomposition and Hidden Markov Model

Sneh Vishwakarma

M.E STUDENT, Electrical department Jabalpur engineering college (JEC), Jabalpur, India

Abstract: **This paper presents a new approach using Hidden Markov Model as classifier and Singular Values Decomposition (SVD) coefficients as features for iris recognition. As iris is a complex multi-dimensional structure and needs good computing techniques for recognition and it is an integral part of biometrics. Features extracted from a iris are processed and compared with similar irises which exist in database. The recognition of human irises is carried out by comparing characteristics of the iris to those of known individuals. Here seven state Hidden Markov Model (HMM)-based iris recognition system is proposed .A small number of quantized Singular Value Decomposition (SVD) coefficients as features describing blocks of iris images. SVD is a method for transforming correlated variables into a set of uncorrelated ones that better expose the various relationships among the original data item. This makes the system very fast. The proposed approach has been examined on CASIA database. The results show that the proposed method is the fastest one, having good accuracy**

Keywords: **Iris recognition, singular value decomposition, hidden markov model.**

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 integral 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, retina sclera 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

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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. HIDDEN MARKOV MODEL

A generic HMM model is illustrated in Fig.1, where *Xi* represents the hidden state sequence. The Markov process is determined by the current state with initial state distribution _ and the transition probability matrix *A*. We observe only the *Oi* (the observation sequence), which is related to the (hidden) states of the Markov process by the emission probability matrix *B*. The HMM model can be generally defined by these three probability matrices (λ, A, B). The goal is to make an efficient use of the observable information so as to gain insight into various aspects of the Markov process.

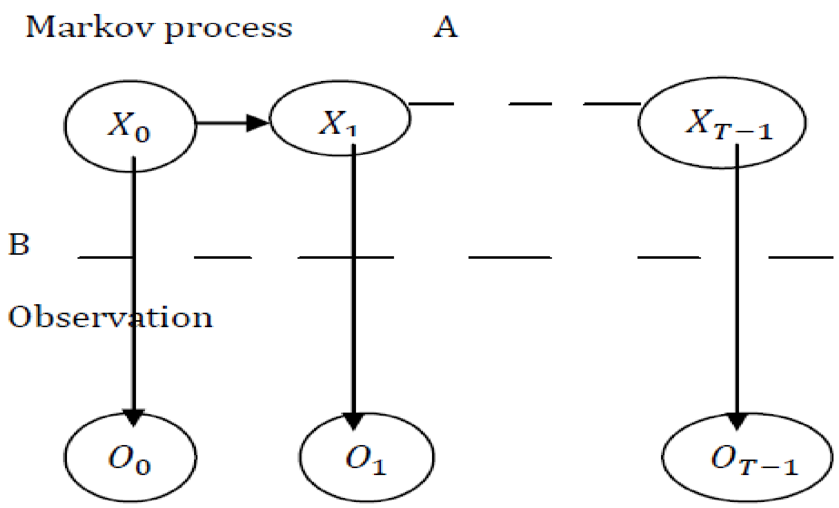

Fig.1 Hidden Markov model (HMM)

3. DATA SETS AND IMAGE PRE-PROCESSING

The SVD-hmm approach (described in section 4)is evaluated on casia iris database .the Casia database contains 400 images in jpg format of 40 individuals ,which we first converted into pgm format .there are 10 images per subject with different iris First, the dataset is divided into two parts – one for training and one for testing. For casia datasets we use 5 images from each folder for training the system and the rest 5 images for testing. Next, SVD is applied to extract features from the images and HMM to build a recognition model. HMM is trained with half of the iris images and tested with a new iris image not used for training. The model returns probabilities of how likely the unseen iris image looks like each one of the images used for training and the iris with the highest probability is assigned as the recognized iris . In order to reduce the computational complexity and memory consumption and improve the speed of the algorithm we propose an effective image preprocessing. First, each iris image is transformed into a gray-scale image (only for colored

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images).Then, it is resized to around 50% of its size, for both. pixels, and after resizing the images go down to 56x46, 112x92, or 64x64 pixels (Fig.2)

Further to that, in order to compensate the flash effect and reduce the salt noise, a nonlinear minimum order-static filter is used (function ordfilt2 in matlab). The filter has a smoothing role and reduces the image information; see [H. Miar-Naimi et al., 2008] for more details.

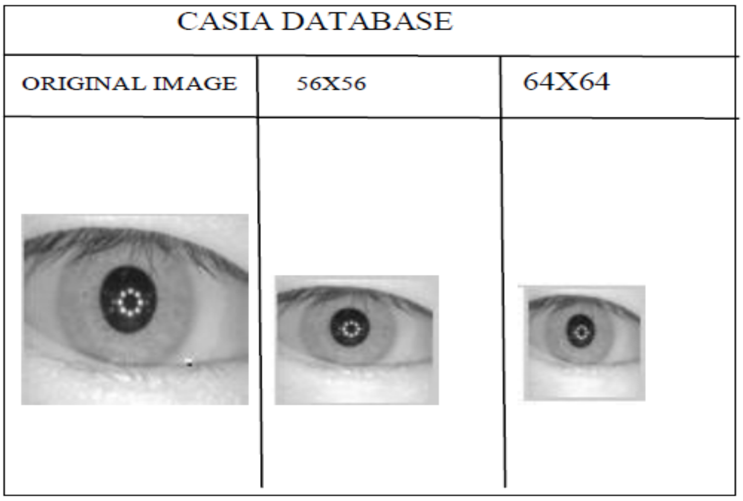

Fig 2. An example of resized image

4. SVD-HMM IRIS RECOGNITION ALGORITHM

The SVD-HMM algorithm for iris recognition consists of the following steps.

4.1 Block extraction:

In order to create the HMM model the two dimensional images has to be transformed into one dimensional observation sequence. For that each iris image is divided into overlapping blocks with the same width *W* as the original image, and height *L*, different from the height *H* of the whole image. *P* = L-1 is the size of overlapping. The number of blocks *T*, extracted from each iris image, is

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

Computed by the following formula, see Table 1

Table.1 The computation of overlapped block

size	
56x46	$T = \frac{H-L}{L-P} + 1,$ $T = \frac{56-1}{5-4} + 1 = 52$
64X64	$T = \frac{64-5}{5-4} + 1 = 60$
112X92	$T = \frac{112-5}{5-4} + 1 = 98$

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4.2 Singular Values Decomposition (SVD):

SVD is applied to each extracted block:

$$X_{mxn} = U_{mxm} * \sum_{mxn} * (V_{nxn}) \quad (2)$$

Where *U* and *V* are orthogonal matrices and $\sum$ is a diagonal matrix of singular values. The coefficients *U(1, 1),* $\sum(1,1)$ and $\sum(2,2)$ are empirically chosen as the most relevant image features, [H. Mia r- Naimi et al., 2008]. Each block is thus represented by an observation vector with *n* elements:

$$C = Coeff_1, Coeff_2, \dots \dots Coeff_n \quad (3)$$

4.3 Quantization:

Each element of (3) is quantized into *Di* distinct levels. The difference between two quantized values is:

$$\lambda i = \frac{coefficientmax - cofficientmin}{Di} \quad (4)$$

Where $coeff_{imax}$ and $coeff_{imin}$ are the maximum and the minimum of the coefficients in all observation vectors. Every element from vector *C* is replaced with its quantized value:

$$qt_i = \frac{coeffi - coffimin}{\gamma i} \quad (5)$$

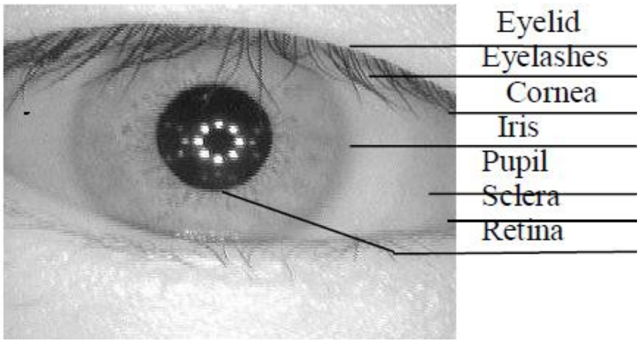
The distinct values (*Di*) used in the present algorithm to quantize the coefficients U(1 1) S(1 1) S(2 2) are 18, 10 and 7. These values are chosen following the experimental results in [H. Miar-Naimi and all, 2008]. The next step is to represent each block by only one discrete value called label,

$$Label = qt_1 * 10 * 7 + qt_2 * 7 + qt_3 + 1, \quad (6)$$

Where qt1, qt2 and qt3 are the quantized values. Note that if the coefficients (3) are all zero the label will be 1 and if they are 18, 10 and 7, the label will have the maximum value of 1260. As a result each iris image is represented by an observation sequence with 52, 98 or 60 observed states, corresponding to the number of blocks. These observation vectors are input into the seven-state HMM model

4.4 HMM model:

Recognition process is based on iris view. From top to bottom the iris image can be divided into seven distinct regions: eyelid eyelashes cornea iris pupil sclera and retina These are the seven hidden states in the Markov model.



A fig.4 iris region from top to bottom assuming a block which moves from top to bottom of the iris image and in any time that block shows one of the seven regions. The block is moving consequently and it cannot miss a state. For example, if we have a block in the state "iris", the next state can never be "sclera", it will always be the state "pupil". Hence the probability of moving from one state to the next one is 50% and staying in the same state is 50%. The initial state of the system is always "eyelid" with a probability of 1. And the final state of the system is always "retina". Thus the initial state distribution (π, matrix).

Eyelid Eyelashes Cornea Iris Pupil Sclera Retina

$$\pi = [1 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]$$

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The transition matrix A is:

	Eyelid	Eyelashes	Cornea	Iris	Pupil	Sclera	Retina
Eyelid	0.5	0.5	0	0	0	0	0
Eyelashes	0	0.5	0.5	0	0	0	0
Cornea	0	0	0.5	0.5	0	0	0
Iris	0	0	0	0.5	0.5	0	0
Pupil	0	0	0	0	0.5	0.5	0
Sclera	0	0	0	0	0	0.5	0.5
Retina	0	0	0	0	0	0	1

A and *B* matrices define the generic iris model that is trained with the training sub-dataset

$$B=\begin{array}{c} \begin{array}{cccc} 1 & 2 & \cdots & 1260 \end{array} \\ \begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 & 1 & \cdots & 1 \\ 1 & 1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & 1 \end{bmatrix} \end{array} /1260$$

5. RESULT

This directory contains a set of iris taken by CASIA iris database .There are 10 different images of 40 different persons.. The size of each image is 56× 46 8-bit grey levels. The images are organized .A fast and efficient system was presented. Images of each iris were converted to a sequence of blocks. Each block is featured by a few number of its SVD parameters. Each class has been associated to hidden Markov model as its classifier. The evaluations and comparisons were performed on the iris image data bases It process approximately having a recognition rate of 74% the system is very fast. This was achieved by resizing the images to smaller size and using a small number of features describing blocks.

Parameter	

params_blk_height = 5;
params.blk_overlap = 4;
params.coeff1_quant = 18;
params.coeff2_quant = 10;
params.coeff3_quant = 7;
number_of_states = 7;
params.iris_height = 56;
params.iris_width = 46;
Index of training images= [1 5 6 8 10];
Index of testing images = [2 3 4 7 9];
SVD features: U(1, 1), S(1, 1),S (2,2)
	recognition rate is 74%

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6. CONCLUSION

Iris recognition applications such as information security, Access management, biometrics, personal security and entertainment. A fast and efficient system is presented. Images of each iris are converted to a sequence of blocks. Each block featured by a few number of its SVD parameters. Every class is associated to hidden Markov model as its classifier. The evaluations and comparisons are performed on iris image data base CASIA IRIS database images and some other individuals. The system recognition rate is approximately74 %,. It is achieved by resizing the images to smaller size and using a small number of features describing blocks.. It is obvious that if the minimum distance between the test image and other images is zero, the test image entirely matches the image from the training base.

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