IRIS RECOGNITION OPTIMIZED BY ICA USING PARALLEL CAT SWARM OPTIMIZATION

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ABSTRACT

Feature selection is an optimization technique used in Iris recognition technology. For producing the most accurate recognition of iris from the database, feature selection removes the unrelated, noisy and unwanted data. Parallel Cat Swarm Optimization Algorithm is one of the latest optimization algorithms in the nature league based algorithm. Its enhancement results are better than the PSO and CSO optimization algorithms. The proposal of applying the Parallel Cat Swarm algorithm is mainly used for feature selection in the process of Iris recognition. For human identification iris can be used as it is an integral part of the human body. Biometric iris recognition system compares the two iris images and produces a matching score to determine their degree of equality or inequality. Eyelid and eyelash are considered to be the unwanted parts of the eye apart from iris. By using Structure Tensor Analysis we can mask the unwanted parts of iris by taking the iris as region of interest. By using Independent Component Analysis, we can extract the texture feature in the iris from the eye. The best features are then selected using Parallel Cat Swarm algorithm from the extracted texture features. For identification purpose we need to compare the best feature with a number of features of various individuals in the database.

Keywords: iris recognition, independent component analysis (ICA), Parallel Cat Swarm Optimization, computational intelligence, CSO, PSO.

1. INTRODUCTION

Iris is the visible colored ring around the pupil. Through the process of iris recognition, it can be measured and utilized for biometric verification or identification. Iris is an internal part of the eye [8]. Although it is externally visible, it is well protected. Even the iris patterns of the right and left eye of a person are unrelated. The pattern of iris is extremely complex, unique and stable throughout one's life. The chance of having two IRIS being identical is almost impossible. This unique quality is very well suited for biometric identification [3].

As iris is taken under near-infrared (near-IR) illumination we can obtain a high-quality photograph of iris scan. Iris patterns can be clearly seen under near-IR light than the visible light which can be also used to illuminate the eye. Narrow-angle cameras are generally used for iris recognition systems and user's eyes are positioned accordingly in the camera's field of view. Then, the location of iris and extracted feature information are analyzed from the resulting photograph using algorithms. Figure-1 shows the iris image with its various parts marked on it [4].

a) Acquire sample

Iris image is captured at a distance of 10-20cm by a high-resolution camera. The camera acquires the digital iris image by computing the distance of the person and neglecting the reflections from glasses.

b) Feature extraction

Iris location is first determined by the feature extraction algorithm. To obtain this localization, we need to exclude pupil and eyelashes from the photo and locate the iris, pupil and both eyelid boundaries. So, iris mapping is created which is independent of size of the image, dilation of pupil and distance of the target [6].

c) Comparing templates

The matching process is done by performing logical OR operation between two iris codes, thus calculating the average hamming distance between two iris codes compared [14]. For measuring the correlations between two iris images various methods have been implemented but still they are under development.

d) Declaring match

In all biometric systems, a matching score is produced by the matching pattern process and then moved to the decision process. In decision process, according to application adjustment we can compare the specific score to a decision threshold. Computation of threshold can be easily obtained in the case of iris recognition. This can be done in identification mode by allowing 0 false matches which does not depend on the iris images in the CASIA V3 database and also minimal false non-matches are ensured [7].

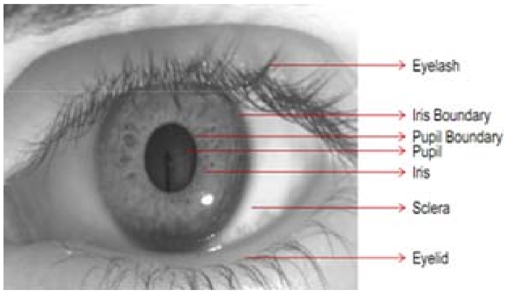

Figure-1. Iris image.

2. INDEPENDENT COMPONENT ANALYSIS

An introduction to independent component analysis (ICA) is presented in this paper. ICA is based on the assumption of statistical independence, whereas uncorrelatedness and normality are basis for principal component analysis (PCA). PCA is performed, whenever gaussianity is assumed. The two new orderly audio combinations would be the resulting components (Figure-2). Therefore, to isolate each speaker's voice such techniques tend to fail [1].

On the other side, the result will be different even for the same problem when we apply Independent Component Analysis (ICA), if non Gaussianity is assumed. From the linear combination of their voices, ICA will be able to differentiate the voice from each speaker. Multiple source signals (e.g. EEG) which are involved in many biological recording can also be applied for this reasoning. However, there are two major differences between ICA and PCA in the interpretation of extracted components. First, each component is not associated with order of magnitude in ICA. In other words, there are no more desirable or lowest components. Second, the sign of the sources are invariant to the extracted components. For example, in digital image processing, a black letter on a white background is the same as a white letter on a black background.

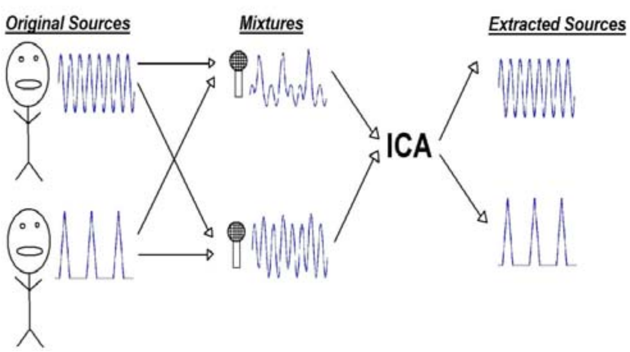

Figure-2. Example of ICA.

ICA can be summarized under five assumptions as follows.

(1) Under assumption it is made that unrelated source signals arises if two speakers have two different physical processes. Specifically, it is assumed that source signals are statistically individualistic.

(2) When many different physical sources are contributed from a weighted signal (e.g. a microphone output) then it usually contains a combination of irrelevant source signals. [Note that many simultaneously recorded signal mixtures are required in most of ICA methods (e.g. microphone outputs)].

(3) Statistical individualistic is usually maintained in unrelated signals, and it can be seen that 'maximum entropy' are obtained in function g of individualistic signals. Therefore, from a set of combined signals we can recover a set of signals with maximum entropy then such signals are individualistic.

(4) In general, by adjusting a isolated matrix W we can recover individualistic signals from a set of combined signals. This can be done until W is maximized and thereby entropy of a fixed function g of signals can be recovered. By using W we can recover the independency of signals indirectly. In order to maximize the entropy of a function g of signals recovered by W, we need to adjust W. As maximum entropy signals are individualistic, it ensures that the estimated source signals which are recovered by W are also individualistic.

(5) By maximizing the statistical independence of the estimated components, ICA finds the independent components. We may choose one of many ways to define independence, and this choice governs the form of the ICA algorithms. The two broadest definitions of independence for ICA are

- Minimization of mutual information.
- Maximization of non-gaussianity.

The iris has a particularly interesting structure and provides abundant texture information. So, it is desirable to explore representation methods which can describe global and local information in an iris [2]. We present an Independent Component Analysis approach, which can obtain both global and local information for an iris.

The ICA is an unsupervised learning algorithm using high order statistics [12]. Typical algorithms for ICA use centering, whitening (usually with the Eigen value decomposition), and dimensionality reduction as pre-processing steps in order to simplify and reduce the complexity of the problem for the actual iterative algorithm. Whitening and dimension reduction can be achieved with principal component analysis or singular value decomposition. Whitening ensures that all dimensions are treated equally *a* priori before the algorithm is run.

It is desirable to estimate the linear transform from the data itself so that the transform could be perfectly adapted to the kind of data that is being processed. Let us denote the random observed vector $X = [X_1, X_2, \ldots X_m]^T$ whose *m* elements are mixtures of *m* independent elements of a random vector $\mathbf{S}=[S_1, S_2, \ldots S_m]^T$ given by

$$X = AS \qquad (1)$$

Where "A" represents an $m \times m$ mixing matrix, the sample value of X_j is denoted by x_j and j=1, 2, ..., m. The aim of

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ICA is to find the inverse of "A" i.e. unmixing matrix "W" that will give "Y" which is almost equal to S.

$$Y=WX \approx S \tag{2}$$

a) Iris representation with ICA

An iris image after image preprocessing can be viewed as a vector. If an iris's width and height are w and h pixels respectively, the number of components of this vector will be w*h. Each pixel is coded by one vector component. The construction of this vector from an image is performed by a simple concatenation - the rows of the image are placed each beside one another. This iris vector belongs to a space. This space is the iris space, the space of all images whose dimension is w by h pixels. The full image space is not an optical space for iris description. ICA's task aims to build an iris space which better describes the irises [5].

Let $X' = [X'_1,X'_2,\ldots X'_m]^T$ a training iris image set with n random variables which are assumed to be linear combination of k*m* unknown ICs, denoted by $S' = [S'_1,S'_2,\ldots S'_m]^T$. For all *i, i=1,2…n,* the image X'_i, and the independent component S'_i are converted into vectors X_i and S_i by row concatenation and denoted as $X = [X_1,X_2,\ldots X_m]^T$ and $S = [S_1,S_2,\ldots S_m]^T$ respectively. As described in the above sub-section, the relation between S and X can be modeled as X = AS. From this relationship, each iris image X'_i is represented by a linear combination of $S_1,S_2,\ldots S_m$ with weighting by fixed-point algorithm. Thus, mixing matrix represents the subspace of all training images. Figure-3 shows the input image and Figure-4 shows the extracted features of iris using ICA.

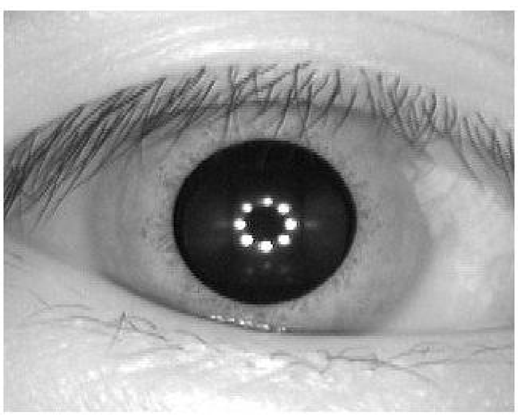

Figure-3. Input image.

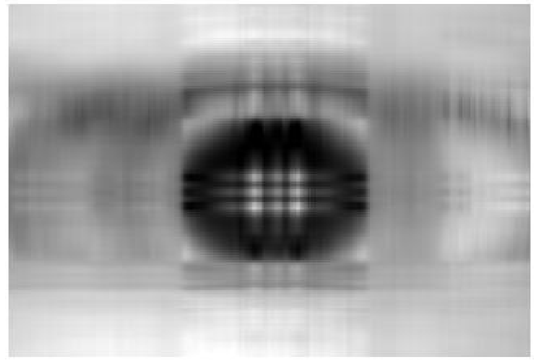

Figure-4. Extracted features using ICA.

3. PARALLEL CAT SWARM OPTIMIZATION

Feature selection is an important step in iris recognition system. This reduces the number of features to be checked thus effectively reducing the computation time [9].

By partitioning the amount of populated groups into several sub-groups, we can construct the parallel structure. These sub-groups occasionally share the information they have and works independently. However for each sub-group the populated group size has resulted in reduction but benefit of cooperation was to be their achievement. When individuals stay in the seeking mode they work independently and this can be guaranteed by analyzing the structure of CSO. Alternatively in the tracing mode they share the global best solution, similar information according to their knowledge to the present. The structure of this framework is still followed in PCSO. The procedure in tracing mode is modified in order to parallelize these individuals in CSO [10].

Separating the individuals into several sub-groups was to be the first step in PCSO. Hence, in tracing mode the individuals do not move forward directly to the global best solution, but they move forward to the local best solution of its own group in general. At present the sub-populated groups jump the local best solutions and randomly the worst individual in the selected sub-populated group can be replaced by a selected sub-populated group and this can be done only if the programmed iteration has achieved. Basically, the PCSO and CSO have similar main framework. *N* individuals are created and separated into *G* groups at the beginning of the algorithm. The Parallel tracing mode process and the information exchanging process are the two modes of operation and it is described below. Under assumption *G* is set one, and then in the original CSO, PCSO is returned [13].

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a) Parallel tracing mode process

The parallel tracing mode process can be described as follows:

i. For every dimension *vk,d(t)* for the catk the velocities are updated at the current iteration according to equation (3).

ii. We need to check whether the velocities are in the range of maximum velocity and in case if the new velocity exceed the limit of maximum range then it is set equal to the limit.

iii. According to equation (4) the position of cat *k* is updated.

$$v_{k,d}(t)=v_{k,d}(t-1)+r1.c1.[x_{lbest,d}(t-1)-x_{k,d}(t-1)] \quad (3)$$

$d=1,2,....M$

where M is the position of the cat, who has the best fitness value, at the previous iteration in the group that cat k belongs to

$$x_{k,d}(t) = x_{k,d}(t-1)+ v_{k,d}(t) \quad (4)$$

The steps of PCSO are given as flowchart in Figure-5.

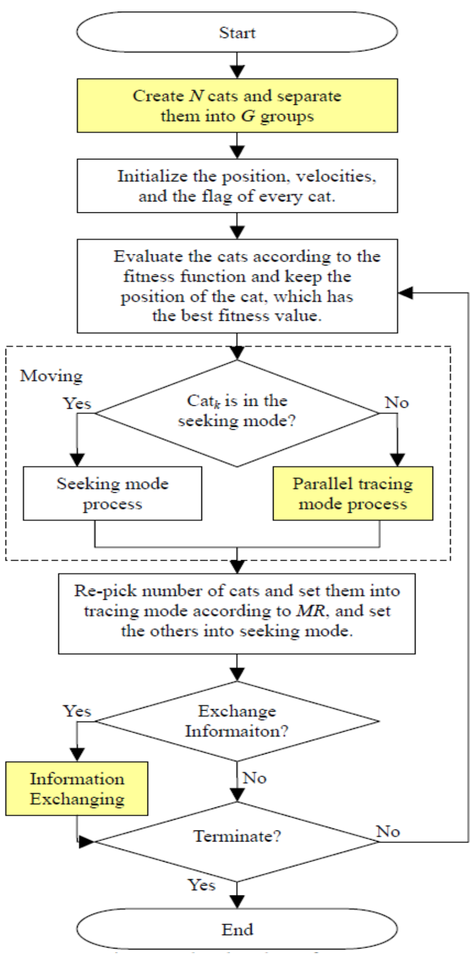

Figure-5. Flowchart of PCSO.

b) Information exchanging

The cooperation is somehow achieved in this mode by forcing the sub-populated groups to exchange their information. The exchange of information between sub-populated group is controlled by a parameter called *ECH* which is specifically defined in this mode. The information exchanging is applied once per *ECH* iterations [11].

The information exchanging consists of three steps.

- Firstly, a group of the sub-populated groups are picked up sequentially and according to their fitness value the individuals in this group are sorted.
- Secondly, from an unrepeatable group we randomly select a local best solution.
- Thirdly, the selected local best solution replaces the individuals who are having the worst fitness value in the group.

Figure-6 gives the output image of iris after applying parallel catswarm algorithm. Then histogram of input test image and that of image from database are calculated and compared. Figure-7 shows two iris images with same histogram and Figure-7 shows two iris images with different histograms.

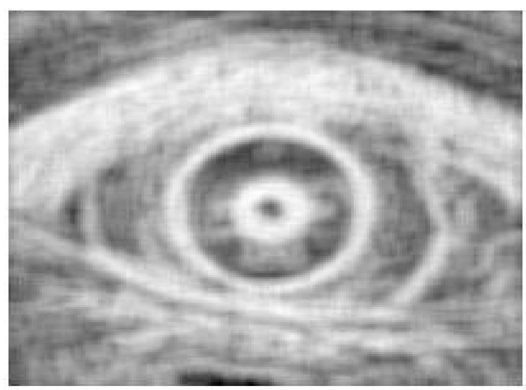

Figure-6. Parallel cat swarm output.

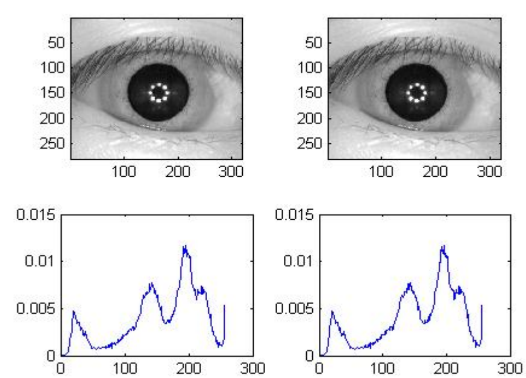

Figure-7. Person identified.

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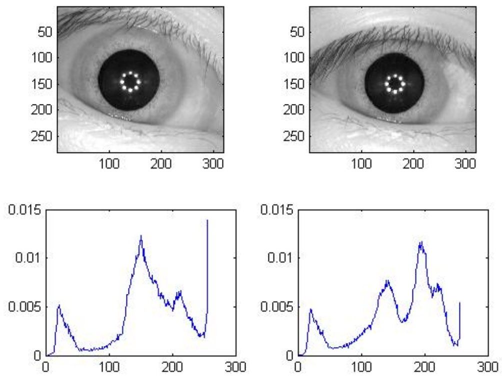

Figure-8. Person not identified.

4. EXPERIMENTAL RESULTS

In this experiment, we use CASIA-IrisV3 that includes three subsets namely CASIA-Iris-Twins, CASIA-Iris-Interval, and CASIA-Iris-Lamp. CASIA-IrisV3 has about 22,034 iris images from nearly 700 individuals. All these images are gray-level JPEG images of 8 bit size collected with near infrared illumination and the resolution of each image is of 320*280 [15]. We conducted experiments with CASIA Iris Interval which contain 2,639 images from 249 subjects. We use Independent Component Analysis for feature extraction. At last, in the identification stage we use histogram matching method to match a test image & a training image. Depending upon the best selected feature, histogram compares the features and determines whether the person is identified or not.

5. CONCLUSIONS

In this project human identification is performed by iris recognition using Parallel Cat Swarm Algorithm. By using ICA each iris image is filtered for texture feature extraction. The best features are then selected using Parallel Cat Swarm algorithm from the extracted texture features. Then, the best features are compared with a number of features of various individuals in the database to identify a person.

The future works include building a bigger database involving more images and to check its effectiveness with other methods of human recognition.

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