Iris Recognition for Personal Interconnection Using Lamstar NeuralNetwork

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Abstract: *One of the most promising biometric recognition methods is iris recognition. This is because the iris texture has many features such as freckles, wreaths, stripes, furrows, crypts, etc. These traits are unique and distinguishable to different people. Such unique features in the anatomical structure of the iris make it possible to distinguish between individuals. Therefore, in recent years, many people have tried to improve performance. This article first explains various general steps for the iris recognition system. Then a special type of neural network is used for the recognition part. Experimental results show that high accuracy can be achieved, especially if the first few steps are performed well.*

Keywords: *Iris recognition, biometric identification, pattern recognition, automatic segmentation.*

1. Introduction:

Biometric in general:

Biometrics is the identification of human identity based on special physiological characteristics. Therefore, scientists have tried to find a solution to the development of technologies that can analyze these characteristics and ultimately distinguish between different people. Some popular biometric features are features in fingerprint, language, DNA, face and different parts of it, and hand movement. Among these methods, face recognition and speaker recognition have been considered more than others in the past two decades. The idea of automated iris recognition was first proposed by Flom and Safir. They showed that the iris is an accurate and reliable code for biometric identification. First, the iris is an easily visible internal part of the body. Visible patterns are also unique to each individual. So it's really difficult to find two people with identical iris patterns.

Also, the iris pattern is different even for the left and right eyes. Furthermore, these patterns are almost immutable and will not change throughout life. Therefore, the patterns of the iris are almost constant throughout a person's life. This minimizes the likelihood of two people having the same traits when using traits that are very unique. Taking this uniqueness into account and proposing an algorithm to correctly extract the iris would result in a stable and accurate system to solve the human identification problem. Although some new research has revealed that there are some methods to hack these types of systems.

Background:

Alphonse Bertillon and Frank Burch, both ophthalmologists, suggested that iris patterns could be a reliable method for identification systems [2, 13], while John Daugman [3] was the first to invent an identification verification system based on iris patterns. Another valuable work by R. Wildes et al. Their method differed in both the algorithm used to extract the iris code and the pattern matching technique. Because the Daugman system has a proven record of high performance and a truly low failure rate, his systems are patented by Iriscan Inc. and are also used commercially by Iridian Technologies, British Telecom, the UK National Physical Lab, etc. So in our research the Daugman model is used to extract the iris pattern. In addition to using common steps used in other works, such as image acquisition and preprocessing, iris localization and normalization, our research uses powerful neural networks such as LAMSTAR [9] for the recognition part. Due to the availability of the Daugman model [6, 7] and the associated source code, a brief overview is given in each section to describe the theoretical approach and its results. The paper mainly focused on the neural network used and its implementation, as well as first experimental results and suggestions for performance improvement.

Image acquisition:

o get a reasonable result, this step should be done carefully. If you get a high-quality image with minimal noise, you reduce the necessary noise reduction process and promote the result of other steps. Especially when pictures are taken at close range, removing the reflection effect reduces errors originating from different steps. To focus on our method, which is actually a special type of classifier, the image provided by CASIA (Institute of Automation, Chinese Academy of Sciences) is used as the data set. These images were taken for the purpose of researching and implementing iris recognition software. Due to the use of infrared light to illuminate the eye, the effect of specular reflections was reduced in this dataset. Therefore, some initial steps to reduce errors caused by reflection are not required here. It is clear that real-time applications require a reflection removal process.

2. IRIS LOCALIZATION:

Method:

The part of the eye that contains information is only the iris region. As shown, the iris is located between the sclera and the pupil. Therefore, it is necessary to extract the iris from the eye image. Actually, a segmentation algorithm should be used to find the inner and outer boundaries. There are numerous studies on image segmentation such as [5] or those based on more sophisticated algorithms, but the most popular segmentation method is edge detection. The Cany edge detector has proven successful for this purpose. The Canny detector mainly consists of three main steps: finding the gradient, non-maximal suppression and hysteresis thresholding [8,11]. As suggested by Wildes, viewing the threshold in a vertical direction would diminish the effect of the eyelids.

Knowing that using this method will remove some pixels at the circle boundary, an additional step, which is actually a Hough transform, would result in successfully locating the boundary even if those pixels are not present . The computing effort is also lower, since the boundary pixels for the calculation are smaller. The procedure is summarized in the following steps. For a pixel gradian_image(x,y) in the gradient image and given the orientation Theta(x,y), the edge intersects two of its 8 connected neighbors. The point in (x,y) is a maximum if it is not less than the values of the two points of intersection. Applying the next step, namely hysteresis thresholding, would eliminate the faint edges below a low threshold, but not if they are connected to an edge above a high threshold by a chain of pixels all above the low threshold. On the other hand, the pixels should be separated above a threshold T1. Then these points are only marked as edge points if all the pixels surrounding them are larger than a further threshold value T2. The values for the threshold were determined provisionally by trial and error and are 0.2 and 0.19 according to [8].

Normalization:

Extracted iris has different size and value. In order to feed this pattern to a classifier, all patterns should be normalized. A method called Daugman's Rubber Sheet Model [6,7] was used to normalize the iris regions. With this method, the center of the pupil is used as a reference point and radial vectors pass through the iris region. The procedure is shown in Figure 1. Multiple data points are selected along each radial line. This is called radial resolution. Also, the number of radial lines that go around the iris is called the angular resolution. Since the pupil can sometimes not be concentric with the iris, a technique called remapping must be used to rescale points based on the angle around the circle. This is given by

$$r' = \sqrt{\alpha}\beta \pm \sqrt{\alpha\beta^2 - \alpha - r_I^2}$$

with

$$\alpha = o_x^2 + o_y^2$$

$$\beta = \cos\left(\pi - \arctan\left(\frac{o_y}{o_x}\right) - \theta\right)$$

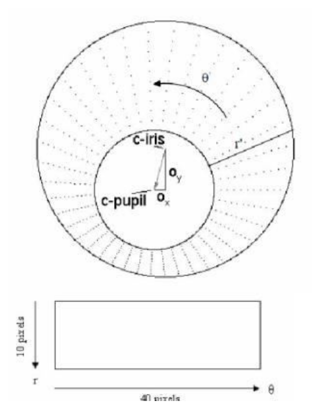

Figure 1

Figure 2. Result of iris localization

Here the displacement of the centre of the pupil relative to the centre of the iris is given byo_x ,$o_y$while r' is the distance between the edge of the iris and edge of the pupil at an angle, θ around the region. Alsor_I is the radius of the irissuch asFig (1). The remapping equation first gives the radius of the iris region as a function of the angle θ. A constant number of points are chosen alongeach radial line, then a constant number of radial data points are taken at a particular angle. The normalized pattern was made by transferring the radial and angular position in the normalized patternto the Cartesian coordinates of data points. From the 'Doughnut' iris region, normalizationgenerate a 2D array with horizontal dimensions of angular resolution and vertical dimensions of radial resolution. The result for iris localization isshown in Fig (2). In this section all the procedure is the same as [10] model including removing rotational inconsistencies that is done at the matching stage based on Daugman's rubber sheet model.

Results of localization and normalization:

The result of normalizationstep based on mentioned methodshowed to be liable like some results shown in Figure 3.But, the normalization was not able to reconstruct the same pattern perfectly from images with changingof pupil dilation. This means that deformation of the iris results in small changes of its surface patterns. For example consider situation that the pupil is smaller in one image respect to another. Thenormalization process rescales the iris region to reach to constant dimension. Here, the rectangular representation is made by 10,000 data points in each iris. Until now the rotational inconsistencies have not been considered by the normalization. So the two normalized patterns are misaligned in theangular direction. The result of whole process is shown in fig (3). For all images in the folder the template is calculated that is actually a matrix. Size of matrix is 20×480. Then those matrix are saved to be used in future as a training set. This process is shown in figure (4).

Figure 3. Resulting matrix after normalization

3. Classifier

In order to provide accurate recognition of individuals, neural network can be used. For this research a special neural networks has been used. So after makingour template and some initial steps mentioned before we have a matrix with the dimension of 20× 480. So for 16 number of class our classifier should be trained.In the next section implementation using LAMSTAR Neural network has been discussed. We decided to test it because it has been shown that is really powerful in other problems such as character recognition problem.

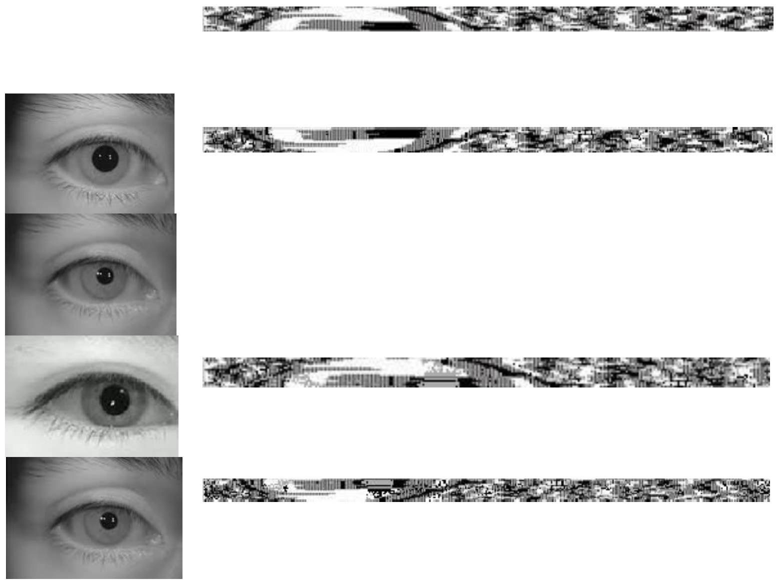

Figure 4. Training set

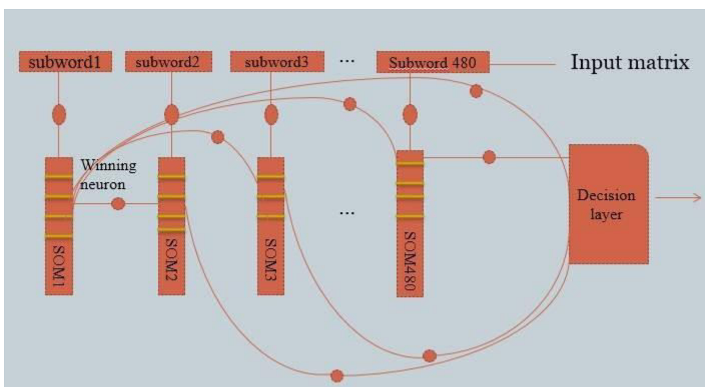

Figure 5. LAMSTAR structure

4. LAMSTAR neural network:

4.1) Introduction to LAMSTAR:

The problem consists in the realization of a LAMSTAR Artificial Neural Network for IRIS recognition. The LAMSTAR neural network, is a complex network, made by a modified version of Kohonen SOM modules. It doesn't need of the training. In fact, the input patterns are divided into many subwords, for example we considered columns of template as our subwords, so we have 480 subwords. These subwords are used for setting the weights of the SOM modules of the LAMSTAR. When a new input word is presented to the system, the LAMSTAR inspects all weights in SOM. If any pattern matches to an input subword, it is declared as winning neuron for that particularly subword.The SOM-module is based on "Winner take All" neurons, so thewinning neuron has an output of 1, while all other neurons in that SOM module have zero output.Here, the SOM is built statically.

This means that for every subword, we instantiate every time a new matrix that represents the SOM, and if computing the products between the stored weights and the input subword, we obtain a winner "1", we don't establish a new neuron. Otherwise, if computing that products, no one of the neurons that are present in the SOM module converge to "1", in other words, if we haven't a winner neuron, we instantiate a new neuron in the SOM module.

Every time that we instantiate a neuron, we normalize the new weights following the function such as [12, 15]:

$$x'_i = \frac{x_i}{\sqrt{\sum_j x_j^2}}$$

To converge the output of the winning neuron to "1" we follow the function below:

$$w_{(n+1)} = w_{(n)} + \alpha[\mathrm{X} - w_{(n)}]$$

Where α = 0.8 and it is the learning constant, w is the weight at the input of the neuron, and x the subword.A particular case could happen: when the second training pattern is input to the system, this is given to the first neuron, and if its output is close to "1", another neuron isn't built. We create neurons only when a distinct subwordappears.The output layer is provided by the punishment and reward principle such as [14, 16]. If an output of the particular neuron is what is desired, the weight of the output layer is rewarded by an increment, while punishing it if the output is not what is desired.

We'll explain better this layer in the design section, reporting also the code for the sake of clarity.

4.2) Design:

The structure of the neural network is shown in figure (5). In this network we have 16 different representations for eyes that are both the left and right eyes of 8 people. The input pattern consists of templates extracted from images using the final pre-processing steps. The size of these templates after normalization is 20,480. Here we've treated each column as a word, so each word is a vector of size 20. In addition, 5 different images are used for the training for each person. Therefore, we selected images from the data set containing more than 5 images for each case could be used as a reminder for the test. So after we have created sub-words, we normalize each sub-word with respect to itself as we said in the introductory section. After normalizing the inputted sub-words, we need to train the system starting from the SOM layer. We call a function each time we change the subword. As we can read, we initialize som_out (that's the current SOM module) and then create it if we don't have a winning neuron (flag=0), otherwise we take the current neuron as a winning neuron. Once that After the weights of the SOM modules are set (w_som), we proceed to output training. This is complex because we have to look to the sum of all the weights between the winning neurons of the SOM modules and the output layer (they are firstly set to zero). If the sum of all the weightsis negative, we understand that result as "0". If is positive, we understand as "1". So the punishment and the reward is based on adding a small increment. Obviously for a negative sum, the punishment consist into adding a small positive increment, while the reward on adding a small negative increment. And vice versa for the positivesum. In this way, the system converges faster to the desired output if there's a reward, and it takes long if there's a punishment. Briefly, the algorithm follows this few steps:

1) Get the train patterns
2) Realize the subwords for every pattern
3) Normalize every subword
4) Set the weights of SOM module, creating every time a new neuronif it isn't a winning neuron for the new subword.
5) Set the output of the winning neuron to 1.
6) Set the weights of the Decision Layer to zero
7) Adjust the weights of last layer taking into account the desired output, with punishment and reward principle.

4.3) Normalized version of LAMSTAR:

Based on the reward/punishment, the connection weights are rewarded if a neuron is to be fired upon wish triggering. If this happens for some time, the link weight value can be high enough to cause unwanted neuron firing. To avoid this situation, we use the normalized LAMSTAR neural network, in which we divide the link weights by the frequency with which the corresponding neuron was rewarded for eliciting desires. Considering the above advantages, we can add more positive points to LAMSTAR if we use the normalized version. A neuron's link weight does not gradually increase as it gains a lot of time. Convergence time is reduced because normalization improves desired resolution and increases efficiency.RESULT

The LAMSTAR and the modified LAMSTAR are applied to the CASIA interval database. Both are really fast. The time required for the training was 66.1584 seconds immediately and for the test 2.5939 seconds, while the accuracy was 99.39% for the regular LAMSTAR and 99.57% for the modified LAMSTAR. After following the program for each individual frame, I found that the preprocessing needed to be changed. In fact, the performance of a classifier is directly related to the performance of the algorithm used to find the template. For example, rotational inconsistency should be considered. Therefore, steps including segmentation and normalization need to be improved to accurately preserve the iris and create a template that serves as input to our neural network. It seems that having accurate templates would increase performance.

Algorithm	Recognition rate
Duagman	%98.58
LAMSTAR	%99.39
Modified LAMSTAR	%99.57

Table1. Comparison between performance of our proposed method and Duagman

5. Conclusion and future work:

In this thesis a new neural network method for iris identification is presented. A template is created using image processing techniques. The classification is mainly done by the neural network LAMSTAR. The structure of this network makes it a good candidate for classification. The software code for image processing and network was written in MATLAB R2014a considering the image processing toolbox and the fact that it is very user-friendly in image processing applications [11]. After the reprocessing step, all template matrices are saved and loaded as input to the classifier in the next step. The overall result suggests that normalized LAMSTAR increases efficiency and convergence time. The next step in increasing efficiency is to account for rotation inconsistency. Also, having a matrix with 480 columns doesn't seem to make sense, so reducing its size might help, especially to reduce the memory needed to run a database with more images. Compared to other methods, the performance of normalized LAMSTAR seems to be better The convergence time is much faster than methods based on other networks such as back propagation. Stability and insensitivity to initialization are other positive aspects of using LAMSTAR. The ability to deal with incomplete and fuzzy input data sets makes the LAMSTAR neural network an effective candidate for problems like iris classification.

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