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IRIS IDENTIFICATION SYSTEM BASED ON RLM TEXTURE FEATURES

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ABSTRACT: *Among biometric identification technologies, iris recognition has attracted lots of attention because of uniqueness and long term stability. In this paper, a new iris recognition system based on texture has been proposed and used for identification of person. Texture features such as Run Length Matrix features (RLM) will be used for feature extraction. Inner and outer boundary will detect. Then iris region will divide into blocks and the importance degree of each block will assign as weights according to sigmoid function. Sixteen RLM features will be computed (eight features in each 0 and 90 directions). To evaluate the performance of proposed method, it applied to identify iris image from MMU ver.1 data set. Experimental results on 88 classes show that the new method give good recognition rates (99.3%) with smallest features vector as compared with other methods***.**

KEYWORDS: Biometric, Iris Recognition, RLM, Texture Feature, Local Enhancement.

INTRODUCTION

Biometrics aims to accurately identify each individual physical, chemical or behavioral attributes of the person such as fingerprints, face, iris, retina, gait, palm-prints and hand geometry. The iris is considered one of the best biometric to be used because it always unique and different in features (Manikandan et al. 2010). The iris is a part of human eye; it's covered with cornea (which covers both the iris and the pupil) and its shape like a circle, an inner circle to the iris is pupil area, it normally appears darker than the iris. It is believed that the iris texture is determined randomly during fetal development of the eye. Meanwhile, iris is believed to be different between one person to another, and between the left and right eye of the same person (Anil K. et al. 2007).

Several researchers in the field of human recognition have been conducted and investigated the iris recognition methods. The most well-known one is that proposed by Daugman (Daugman J. 1993) who become the inventor of the most successful commercial iris recognition system now. Boles (Boles et al.1995) decomposed one-dimensional intensity signals computed on circles in the iris and use zero-crossing of the decomposed signals for the feature extraction. Lima et al.(L. Ma et al. 2002) adopted texture analysis approach, in this approach a multi-channel Gabor filtering to capture both global and local details in an iris image. Recently, several researchers interest with iris recognition field. Sheeba and et al (S.J. Sheebaet et al. 2013) proposed method in 2013 to build security system using iris, in their method the Local Binary Pattern (LBP) is used to extract texture features and Learning Vector Quantization

(LVQ) method is used for classification. Lenina et al. (L.Birgale et al. 2012] suggested the use ridgelets transforms to extract textural data. The proposed method was tested only on 33 subjects from CASIA V.3 interval class. This method skips normalization step. The method achieved accuracy 99.82%, 0.1309%FAR, 0.0434%FRR. Kshamaraj et al (K. Gulmire et al. 2012) proposed iris recognition method in 2012 using Independent Component Analysis for feature extraction. The iris region was detected using Daugman's method. For matching stage Euclidian distance was used between the test image and training image. The method was testes on 10 persons from CASIA V.1. The accuracy rate was 89.5%.

This paper presents an efficient method for iris identification using run length matrix RLM. This method could improve system recognition accuracy since it depends on dividing iris region into blocks and assign weight (i.e. importance degree) for each block.

Proposed Method

The proposed method consists generally of the following steps:

- Iris segmentation
- Feature extraction
- Iris matching.

The following sections describe each step.

Iris Segmentation

The iris segmentation algorithm is applied in spatial domain using our proposed method (Suhad A. and Loay E. 2013). In this method inner and outer iris boundaries will detected. We start by determining the inner boundary (i.e. pupil region) using combination of image processes such as (image stretching, image morphology, seed filling and thresholding). While, a scheme based on image contrast stretching and smoothing operations have been used to allocate the iris outer boundary. Figure (1) shows samples of detected iris regions using our developed method. The attained localization accuracy rate for this approach was 0.98%. Then the localized iris area is mapped to be flattened, rectangular area instead of being circular; and to do this mapping task a transformation from polar coordinates (r,θ) to Cartesian coordinates (x,y) is applied upon each point within the iris region.

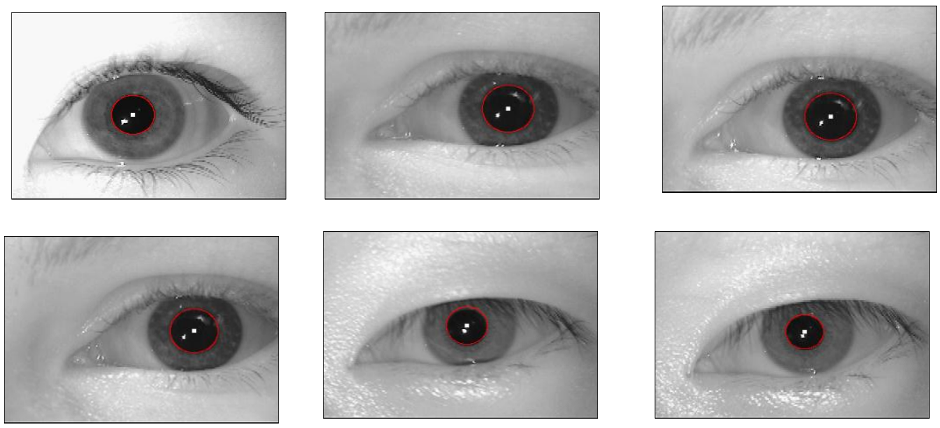

Figure 1. Samples of accurate pupil localization from MMU1 database

Because the iris images may be captured at different illumination conditions (e.g., the variation in light source position may cause different brightness distribution) which in turn may cause problem at recognition stage. To countermeasure such problem a combination of stretching and cubic spline process is used. Figure (2) shows the enhancement process.

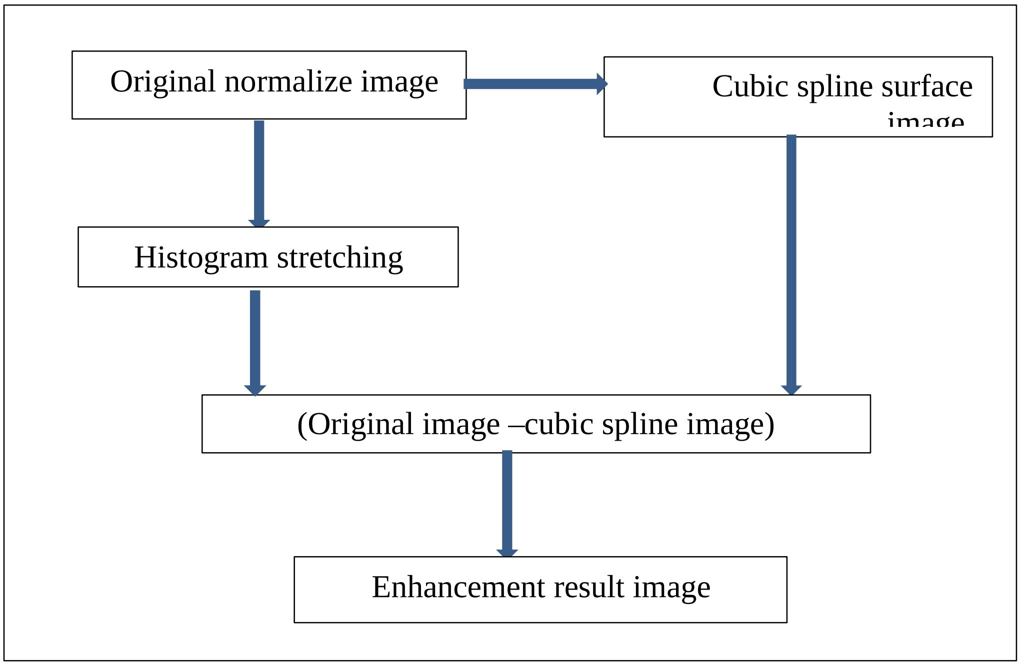

Figure 2. Enhancement Process Diagram

Features Extraction:
In this phase the signature of iris will be extracted using texture features such as Run Length Matrix features (RLM). At first, the normalized image will be divided into overlap blocks with size (20*20), and overlap ratio value equal to 0.1 in both vertical and horizontal directions. Then for each block do the following steps:

Block Weighting: to determine the importance of each block, at first the blocks should be divided into two sets: *noisy blocks and iris blocks sets* by using the following condition

If number of noisy pixels < (0.95 *block size) then
Block belong to iris blocks set
Else
Block belong to noisy blocks set

Noisy blocks will be neglected by assigning the value zero to its weight while each block belongs to iris blocks set will assign weight according to the following formula:

$$blockweight = 1 - \frac{1-e^{-\mu \times \propto}}{1+e^{-\mu \times \propto}}, \ldots\ldots \quad (1)$$

Where $\propto$ parameter its value computed from the following formula

$$\propto = \frac{Number\ of\ noisy\ pixels}{block\ size}, \ldots\ldots \ (2)$$

The μ parameter value is computed by testing. The value of block weight should be in the range [0, 1]. From experiment it was found that the blocks lie nearest pupil region take highest weight values, while block weight decrease at blocks nearest eyelids and eyelash regions.

Quantization of block values with quantization step *Qstep* to reduce computation complexity. The following algorithm describes the quantization process.

Algorithm (1) Quantization Process

Goals: minimization of gray levels to speed computation RLM features
Inputs: block ( ) // is the block of iris image
Blockheight// is the height of the block
Blockwidth// is the width of the block
Qstep // no. of required gray levels
Output: blockq( ) // is block with quantize values

Step 1: computation of quantization blocks For x=0→ Blockheight-1 For y=0→ Blockwidth-1 $blockq(x,y) = \frac{block(x,y)}{255} * (Qstep - 1)$ **Step 2: return blockq ( )**

Computation of run length matrix P as follows: The gray level run length method is a way for extracting higher order statistical texture features. A gray level *run* is a set of consecutive pixels having the same gray level value. The *length* is the number of pixels in the run, and the run value is the number of times such a run occurs in an image. The gray level run length matrix *P* is a two dimensional matrix, where each element *P(i, j)* represent the number of runs with pixels of gray level intensity equal to *i* and length of run equal to *j* along a specific orientation. The size of the matrix *P* is *n* by *k*, where *n* is the maximum gray level in the image and *k* is equal to the possible maximum run length in the corresponding image. An orientation is define using a displacement vector *d(x, y)*, where *x* and *y* are the displacements for the x-axis and y-axis, respectively. The typical orientations are 0, 45, 90 and 135, and calculating the run length encoding will produce four run length matrixes (S.F.Bahget et al. 2012).

Features Computation: After the run length matrices are calculated along the direction 0 and 90, several feature descriptors are calculated to capture the texture properties. The set of RLM features is given below, where all features have denominator equal to the total number of run lengths in the matrix (Albregtsen, F et al.1995).

- Short Run Emphasis

$$SRE = \frac{\sum_{i=1}^{G}\sum_{j=1}^{R}(\frac{P(i,j)}{j^2})}{\sum_{i=1}^{G}\sum_{j=1}^{R}P(i,j)} ,\ldots\ldots (3)$$

This feature measure emphasizes small run length due to the division byj^2.
Long Run Emphasis

$$LRE = \frac{\sum_{i=1}^{G}\sum_{j=1}^{R} j^2\, P(i,j)}{\sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)} \text{ , ... (4)}$$

This gives emphasis to long run lengths. LRE is larger for smoother images.

- Long Run Low Gray Level Emphasis

$$LRLGE = \frac{\sum_{i=1}^{G}\sum_{j=1}^{R}\left(\frac{j^2 P(i,j)}{i^2}\right)}{\sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)} \text{,………. (5)}$$

Measure the joint distribution of long runs and low gray level values. The LRLGE is expected large for the image with many long runs and low gray level values.

- Short Run High Gray Level Emphasis

$$SRHGE = \frac{\sum_{i=1}^{G}\sum_{j=1}^{R}\left(\frac{i^2 P(i,j)}{j^2}\right)}{\sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)} \text{,…….. (6)}$$

Measure the joint distribution of short runs and high gray level values. The SRHGE is expected large for the image with many short runs and high gray level values.

- Short Run Low Gray Level Emphasis

$$SRLGE = \frac{\sum_{i=1}^{G}\sum_{j=1}^{R}\left(\frac{P(i,j)}{i^2 j^2}\right)}{\sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)}\text{, …….. (7)}$$

Measure the joint distribution of short runs and low gray level values. The SRLGE is expected large for the image with many short runs and lower gray level values.
Long Run High Gray Level Emphasis

$$LRHGE = \frac{\sum_{i=1}^{G}\sum_{j=1}^{R}\ i^2 j^2 P(i,j)}{\sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)} \text{,………. (8)}$$

Measure the joint distribution of long runs and high gray level values. The LRHGE is expected large for the image with many long runs and high gray level values.

- High Gray Level Run Emphasis

$$HGRE = \frac{\sum_{i=1}^{G}\sum_{j=1}^{R} i^2 P(i,j)}{\sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)} \text{,……….. (9)}$$

Measure the distribution of high gray level values. The HGRE is expected large for the image with high gray level values.

- Long Gray Level Run Emphasis

$$GRE = \frac{\sum_{i=1}^{G}\sum_{j=1}^{R}\left(\frac{P(i,j)}{i^2}\right)}{\sum_{i=1}^{G}\sum_{j=1}^{R} P(i,j)} \qquad \text{,……… (10)}$$

Measure the distribution of low gray level values. The LGRE is expected large for the image with low gray level values.

Generation of Iris Code: In this step, the RLM matrix is computed for each iris block separately, then the features list of values derived from the iris block are collected and assembled in the feature vector. Then, for each class (person) the iris template, T, is created from the feature vectors belong to different image samples belong to that class. Beside to template vector (T) the degree of variability of each collected feature is represented by computing the standard deviation vector ( ); where each element of this vector represents the degree of scattering of the corresponding feature within a class. To compute the template vectors, the mean and standard deviation values for each feature from different blocks belong to different image sample are determined. The mean and standard deviation vectors are determined using the following equations:

$$t_{ip} = \frac{1}{n_p} \sum_{j=1}^{n_p} f_{ijp} \quad \omega_{ip} = \sqrt{\frac{1}{n_p} \sum_{j=1}^{n_p} \left(f_{ijp} - t_{ip} \right)^2} \text{ ,.................(11)}$$

Where, f_{ijp} is the value of the i^{th} feature extracted from j^{th} sample image belong to person p, np is the number of images samples taken for p person,   is the mean value of the i^{th} feature for person (p), ω_{ip} is the standard deviation of the i^{th} feature for p person. The collection of {tip| i=1 to m} represent the template vector, T(p), for person (p), and the collection of {ω_{ip}| i=1 to m} represent the standard deviation vector, (p), for person p. It is noticed some features, f_{ijp}, have high deflection values relative to their averages. To handle this problem the values of the features which are relatively far from the mean value have been excluded in order to enhance the computation of the template vector. The applied exclusion criterion is:

If $|f_{ijp}$ - tip | > 2.3ω_{ip} then exclude f_{ijp}& recalculate t_{ip} and ω_{ip}

As a last step, the lowest possible combinations of the features can lead to good recognition is searched for. The test of finding best feature combinations were started using single feature and gradually increased to double, third and so on till reaching the highest recognition rate.

Pattern Matching

In this step the enrolled iris image will compare against all templates in database. Normalized Euclidian distance will use as measurement; the template that give minimum value will represent the class of enrolled image.

$$Ecludien\ Didtance\ (test, template) = \sum_{i=1}^{m} \frac{\sqrt{(testi - template)^2}}{\sigma_i} \text{,.. (12)}$$

Where
m represent length of features vector.
$\boldsymbol{\sigma_i}$represent standard deviation for test image *i*.

Experimental Results

This paper presents a new method for identifying individuals from an iris image sequence. We thus perform a series of experiments to evaluate its performance. The proposed method was tested on MMU ver.1[Multimedia University] which contains 450 images from 45 people. Each image has 320*240 pixels resolution in gray scale. The accuracy of recognition rate (R) was evaluated using the following formula:

$$R = \frac{Number\ of\ correct\ identfied\ iris\ images}{Total\ number\ of\ iris\ images} \times 100\% \ ,\ldots\ldots \quad (13)$$

In order to select best value for *Qstep* parameter number of tests were done at different *Qstep* values for RLM feature set as shown from Figure (3).

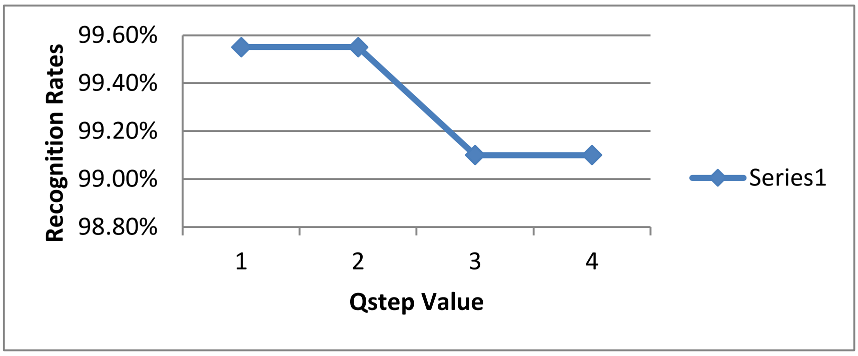

Figure 3. Recognition Accuracy Rates at different *Qstep* Values

Figure (3) shows that the best *Qstep* value is 4 and recognition accuracy decrease while *Qstep* value increase. So all experiment will depend on *Qstep* value =4.Figure (4) presents the attained recognition rates when only one feature is used for representing each iris block. The horizontal axis in the figure represents the index number of the used feature, while the vertical axis represents the attained recognition rate.

Figure 4. The discernment Power of each feature

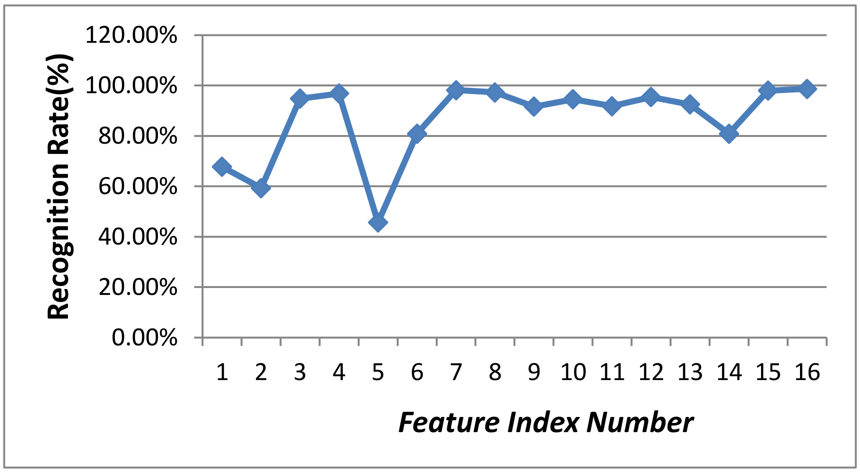

Figure (4) shows that the index number of best feature *is sixteen* because it led to highest recognition rate (98.64%), while feature number *five* led to the lowest recognition rate (45.68%). Tests on various combinations of two features have been made. The best attained recognition rate for the pairs two features was (99.09%); which is consist of feature (8)with (15).The best recognition rate for combinations of triple features was (99.09%) from combine feature number (1, 10 and 15).The best recognition rate for combinations of fourth features was (99.3%) from combine feature number (1, 4, 9 and 10).

To prove the efficiency of our proposed system, the accuracy of our proposed based texture features and some other methods on MMU1 database are reported in table 1.

Table 1. Comparison of the proposed method with other methods

Method	Classes Number	Recognition Rate
K. Masood[2007]	82	93.7%
Our Proposed Method	88	99.3%

CONCLUSION

In this paper, a new method was proposed for iris recognition using texture features. The RLM proved to be good techniques as it provides reasonable accuracy. The iris will divided into overlap blocks and each of these blocks will be assigned weight value .For matching weighted Euclidian distance was used. It is found that

- the proposed method gives well results and this proves the accuracy of each stage because the efficiency of each stages effect accuracy of recognition rates.
- Sequential forward features selection method was apply to depreciate the performance of single, double, third and so on for companions of features. For future work, more sophisticated feature selection method can be used.
- Determine the important degree to each block by assigning weight according to sigmoid function will increase recognition accuracy.
- Texture features such as RLM gives high recognition rates as compared with other methods.

REFERENCES

Albregtsen, F. (1995), "Statsical Texture Measures Computed from Gray Level Run Length Matrices", Image Processing Laboratory, Department of Informatics, Oslo University.

Anil K. Jain, Patrick Flynn, Arun A. Ross(2007)," Handbook of Biometrics", springer.

Boles, W.W., and Boashash (1998), "A Human Identification Technique Using Images of The Iris and Wavelet Transform", IEEE trans. Signal Processing, Vol.46, No.4, pp.1185-1188.

Daugman J.(1993), "High Confidence Visual Recognition of Person by a Test of Statistical Independence", IEEE Transaction on Pattern Analysis and Machine Intelligence, No 11, pp. 1148-1161.

K. Gulmire, S. Ganorkar (2012), " Iris Recognition Using Independent Component Analysis", International journal of emerging technology and advance engineering, Vol. 2, Issue 7, PP.433-437.

K.Masood, Dr M. Y. Javed and A.Basit (2007),"Iris Recognition Using Wavelet", International Conference on Emerging Technologies (ICET 2007), pp. 253-256.

L. Ma, Y. Wang, and T. Tan (2002), “ Iris recognition based on multichannel Gabor filtering,” in Proceedings of the 5th Asian Conference on Computer Vision (ACCV ’02) , vol. 1, pp. 279–283, Melbourne, Australia.

L.Birgale, M. Korkare (2012), "Iris Recognition Using Ridgelets", journal of Information Processing System, Vol.8, No.3.

Manikandan, P. and Sundararajan, M.(2010), "Discrete Wavelet Features Extraction For Iris Recognition Based Biometric Security", International Journal of Electronic Research, Vol.2, No.2, pp.273-241.

Multimedia University, Iris database," http://www.persona.mmu.edu.my/~.

S.F.Bahget, S. Ghomiemy, S. Aljahdali, M. Alotaibi (2012), "A Proposed Hybrid Technique for Recognizing Arabic Characters", International Journal of Advanced Research in Artificial Intelligence, Vol. 1, No. 4.

S.J. Sheeba, S.S. Jeya, S. Veluchamy (2013), "Security System Based on Iris Recognition", Research Journal of Engineering Sciences, Vol. 2, No. 3, Pp. 16-21.

Suhad A. Ali, Dr. Loay E. George (2013), "New Method for Iris Localization for Personal Identification", International Conference on Information Technology in Signal and Image Processing-itSIP, India.