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Iris Identification using Multiclass Support Vector Machine based on Five Regions for Iris Segmentation

Identificación de iris utilizando la máquina de vectores de soporte multiclase basada en cinco regiones para la segmentación de iris

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ABSTRACT/ Personal identification using Iris has been stabilized as efficient technology. In this paper, a new framework of iris segmentation based on five regions has been employed. A set of features will be deriving from these regions after treatment them by different filters. Finally, the derived features will be used to identify each iris using multiclass support vector machine. The proposed system used only 50% of Iris information to extract the features of it. The system performs with an identification rate 97% for training phase and 91% for test phase on 350 images (50 person, 7 images for each person) from CASIA V 1.0 database.
Keywords:Iris identification, segmentation, multiclass support vector machine, Sequential Minimal Optimization, Chi-square
RESUMEN / La identificación personal con Iris se ha estabilizado como tecnología eficiente. En este trabajo, se ha empleado un nuevo marco de segmentación del iris basado en cinco regiones. Un conjunto de características se derivará de estas regiones después de tratarlas con diferentes filtros. Finalmente, las características derivadas se utilizarán para identificar cada iris utilizando una máquina de vectores de soporte multiclase. El sistema propuesto usó solo el 50% de la información de Iris para extraer sus características. El sistema funciona con una tasa de identificación del 97% para la fase de entrenamiento y del 91% para la fase de prueba en 350 imágenes (50 personas, 7 imágenes para cada persona) de la base de datos CASIA V 1.0.
Palabras clave: Identificación de iris, segmentación, máquina de vectores de soporte multiclase, Optimización mínima secuencial, Chi-cuadrado

1. Introduction

Automated techniques will be used by biometric technology to recognize and identify any person from its characteristics either behavioral (voice, signature, gait, etc.) or physical (fingerprint, iris, smell, geometry of hand, retina, face, ear, etc.). Iris, among these biometrics technologies, has been found to be the most accurate, stable and also over the life period has unique characteristics [1]. Structure of Iris has a quite a bit of features such as ridges, furrows, corona, freckles and crypts. The iris has a high generality, distinctiveness, performance and permanence and remain consistent over a human lifetime[2]. The algorithms of Iris recognition have demonstrated very high matching efficiency and very low false match rates in large databases. Thus, in the large-scale of identification systems, the iris is appropriate to play an important role in the next generation[3].

The Iris, a ring protected by the cornea between the region of black central pupil and the region of white sclera in the eye of human. Also the iris, has a texture (complex fiber) that can striped to shape a template of biometric [2].

The system of iris identification is typically including the acquisition of image, segmentation of iris, the extraction of the features, and matching and identification[4]. However, among the pervious modules, the segmentation of iris plays a vital role in the accuracy of overall system, because its results will be followed by all the subsequent modules [1].

2. Related Work

There are two types of iris segmentation most broadly: boundary-based segmentation methods and pixel-based segmentation methods. The first type is finding the boundary inner of iris firstly (i.e., base element pupil) then the other parameters will be found based on it. The methods of first type include Hough transform (HT) that finds within the given range of the radius the circularity by edge-map voting, and using an integral derivative the boundary will be found by Daugman's integro-differential. Singh and et al[5], used Hough Transform and a Canny Edge to detect the boundaries of iris then extract the deterministic patterns by applying the Haar wavelet that represented a feature vector and comparing them using the Hamming Distance to determine the similarity.

Hilal and et al[6], propose a method that used active contour with Hough transform to detect the outer iris boundary and the inner iris boundary is segmented in its real shape which iris textures are closer to the pupil than to the sclera.

While Tisse and et al[7], implements gradient decomposed Daugman's integro-differential with Hough transform combination to locate the iris and extract pertinent information from iris texture using 2-D Hilbert transform.

Pixel-based segmentation is the second type of methods. In this type, the classifier of iris is created to identify the boundary of the iris based on the discriminating features using information of illumination and color texture between a pixel of iris and its neighborhood.

Thornton and et al[8], candidate multiple filter and compare the information discriminated by measuring them on a set of images (i.e., irises) from different datasets then search for the pattern representation of best possible iris by conducting the parameters of a selected filter bank to give some results of recognition. Krichen and et al[9], presented a method of verification based entirely on the information of color, and for matching they used the modified Hausdorff distance and minimum variance principle.

In other side, many researchers used multiclass support vector machine with or without other techniques to recognitions.

Salve and Narote[10], used support vector machine and ANN as a classifier of iris pattern for feature that extracted of 1D Gabor wavelet of segmented iris.

Bansal and et al[11], identify a gender using wavelets of texture features that extracted from iris then developed a gender classification based on Support Vector Machine .

Rana and et al[12], normalized the image of iris using DWT into four sub bands (LL, LH, HL and HH), then finding the most discriminating information that presented in LL sub-band using PCA to form the matrix of features, while the classification of iris was using Support Vector Machine.

3. Multiclass Support Vector Machine

Vapnik proposed a support vector machine that has been extensive for estimation of density, regression and classification. Support vector machine designed originally to classify a two classes (binary classification). Support vector machine can be extended to classify multi classes rather (multiclass classification). There are currently two approaches of multiclass SVM, either and combined multi binary classifiers or directly constructed in single optimization formulation considering in all data and has a number of variables proportionate to the classes. Therefore, for both methods of multiclass SVM, a larger optimization is needed to solve a multiclass problem and it is computationally more expensive[13]. The training in SVM is a quadratic-optimization (QP) problem that is a maximizing a margin between a hyperplane and nearest point. The hyperplane is constructed as Eq. 1:

$$w^T x + b = 0 \qquad (1)$$

where w and b are hyperplane vector coefficients and bias term[14]. The training of M-SVM will be used a simple algorithm Sequential Minimal Optimization (SMO), was proposed by John C. Platt in 1998. SMO can be quickly solve the SVM quadratic programming (QP) problem without using numerical QP optimization steps or any extra matrix storage at all. A standard normal deviate is a random sample from the standard normal distribution[15]. The Chi Square (written as $\chi 2$) is distribution of the summation of squared standard normal deviates. Similarity of χ2 is widespread used in machine learning, especially on these features that generated from computer vision, natural language processing[16]. The formula of the chi-square is (see Eq. 2):

$$X_c^2 = \sum_{i=0} (O_i - E_i)^2 / E_i \qquad (2)$$

Where c, O and E are freedom degrees, observed value and expected value. Furthermore, the χ2 is very efficient for a nonlinear and take advantage of modern linear algorithms. There are many parameters that effect on multiclass support vector machines. Two parameters that have been focused on this work for their impact on the training and test identification rates: Epsilon (ε) and Tolerance (T). In M-SVM a value of loss function (ε-insensitive) should be selected, where ε has an effect on SVM's smoothness and the number of support vectors. The generalization capability and complexity of a network depend on ε-value. Also there is some relationship between noise observation of the data in the training and the value of ε. Figure 1 show the ε-value in the support vector machine models.

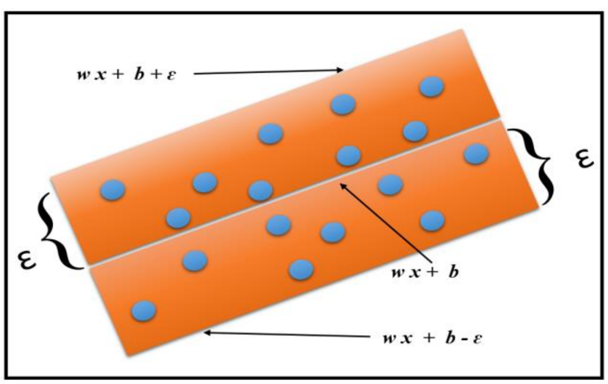

Figure 1. ε-value in M-SVM model

4. Materials of Testing

The training and testing used a database that consists of different iris samples which be attributed for fifty different persons; and seven iris samples will be used for each person. The samples, in this work, were downloading from the standard database (CASIA v 1.0). The images of irises have BMP, 24 bit/pixels and 320×280 pixels as a type, bit depth and the size for each iris image. For improving getting probability and for more accurate knowledge for the necessary representation features behaviors, the system will be used number of samples in the training phase more than those which used in the testing phase. For each person, number of samples (7 irises) will be divided into two groups: the training group (first group) has 4 irises are used as training samples while the remaining irises (3 irises) used to test the samples in test group.

5. The Model of System

The proposed system of iris identification has a general structure shown in Figure 2. The three main stages of the system include: stage of preprocessing stage followed by Features extraction stage and ending with matching stage. The first stage consists of the following modules: pupil detection, segmentation and filtering. The image file is the input of the system. After the loading of image, the system is passed it into the Detection pupil step to find out a center of iris. The segmentation step is cutting up the image into five regions (pieces) around the center of iris. The previous pieces are manipulation by multiple filters to extract a set of features. At matching stage, the extracted features of each piece either matching with those features stored in database or adding for iris database.

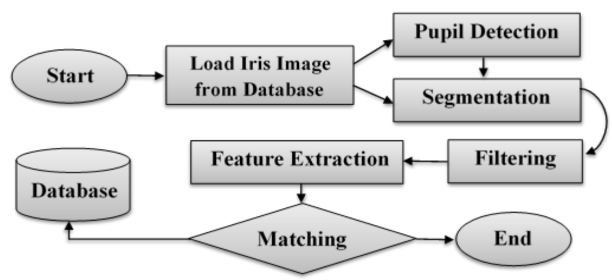

Figure 2. The System Model

5.1 Pupil Detection

In this stage, the iris image is converted into binary image (using threshold equal to 70). The system is counting to all black regions (blobs) inside the binary image, to extract the largest region (blob). The largest blob, will be extracted throughout the previous operation, used as a pupil of iris. Figure 3 illustrates the steps of detection of pupil.

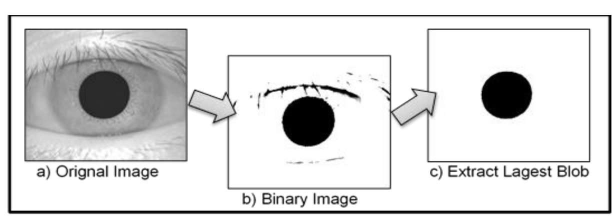

Figure 3. Pupil Detection

5.2 Segmentation

The proposed segmentation process can be outlined as follows: the center of pupil of image, that represented the output of the previous process, is used to construct five elliptic regions around it, which will be used as masked regions[18][19][20]. The original image is segmented into five regions based on those masked regions, i.e., the result regions are extracted using masked images around the center of pupil of that iris (see Figure 4).

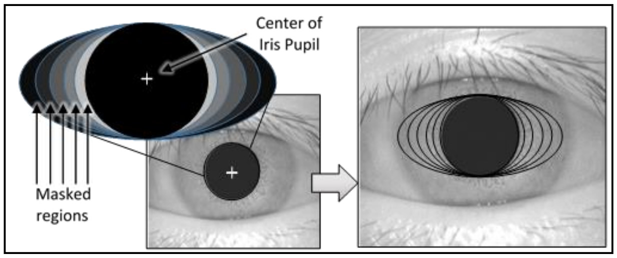

Figure 4. Extract regions around Iris pupil.

5.3 Filtering and Features extraction

The regions, that have been extracted from segmentation stage, are manipulating by several filters (Mean, Median, Variance and Sharpen) to produce a set of arrays (matrices). Four arrays will be constructed for each region (named as MFAR, DFAR, VFAR and SFAR), Table 1 illustrates description for each.

Table 1. Description of each region array

No.	Region Array	Description
1	MFAR	Mean Filter Array
2	DFAR	Median Filter array
3	VFAR	Variance Filter array
4	SFAR	Sharpen Filter array

The system produced twenty arrays for each iris (5 regions × 4 filters)[21][22][23]. These arrays are manipulating to produce two features for each array. The features are extracting by applying two steps on the arrays. First step is multiplying each value in each array by its location. While in the second step, compute a mean and median of the new array to extract one features for each. The features are selecting depending on mean and median because they least affected by the sampling fluctuation. The output of this stage will be forty features (2 features × 20 arrays) that will be used in the next step (matching) to either store those features in the database (during enrollment phase) or compare them with another iris (during recognition phase) see Figure 5.

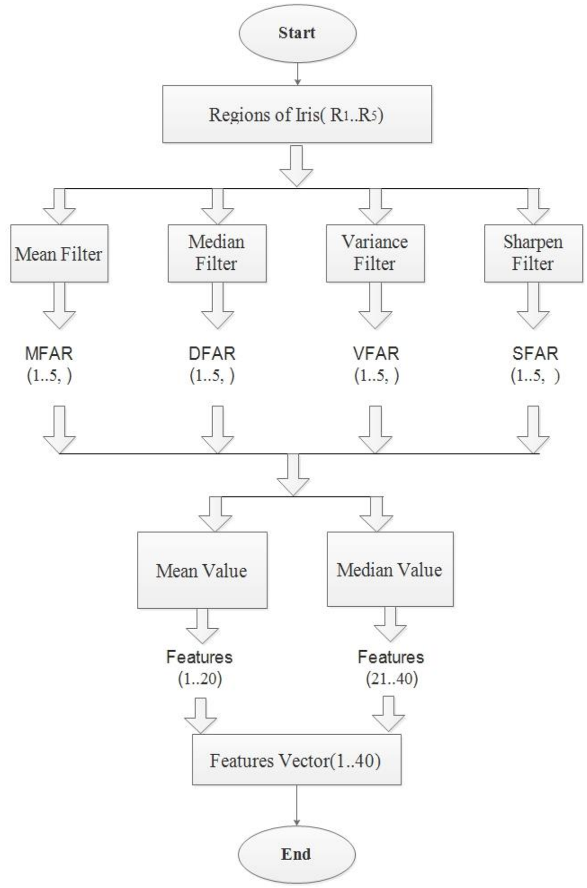

Figure 5. Applying filtering and extracting features

5.4 Matching

In this stage, multiclass support vector machine (M-SVM) [17] will be used for matching on two phases (i.e. training phase and test phase). The collected iris samples in this work are classified into two classes: training samples and testing samples. For improving getting probability and for making the training result more stable, the system will be used number of samples in the training phase more than those which used in the testing phase. This will make the system more accurate knowledge for the necessary representation features behaviors. Therefore, number of samples (7 irises) , for each person, will be divided into two groups: the first group (training group) has 4 irises are used as training samples. The remaining irises (3 irises) will be used for testing the samples in second group. So, the total irises in our system are 350(50×7) which are divided into 200 (50×4) irises which belong to training phase; while the remaining 150(50×3) irises are used for testing phase. Figure 6 showed M-SVM in the system that used chi-square as a kernel and sequential Minimal optimization as a teacher.

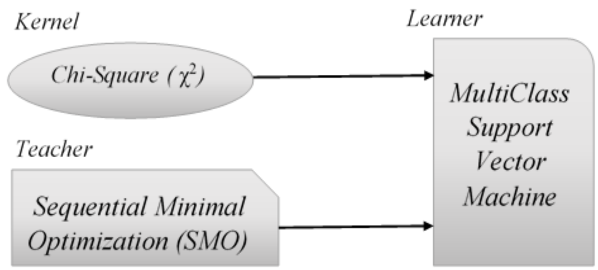

Figure 6. Kernel and Teacher of M-SVM

A module of iris matching computes the score of match (i.e., the degree of similarity) between different two irises by extracting the features vectors from them. The similarity for irises which belong to the same iris should be high score and low for those belong to different iris. In our project, the forty features (2 Features × 4 Filters × 5 Regions) which have been extracted in previous stage, have been used either matching with those features stored in database previously or adding for iris database.

6. Experiments

The performance of the established identifiers of iris firstly tested on the training data. All the feature vectors corresponding to each person belong to the training data have been used to test the efficiency of the identifier in test data. For the evaluation of system identification accuracy, the correct identification rate (ID_{Rate}) was adopted (see Eq. 3):

$$\mathrm{ID}_{\mathrm{Rate}} = \frac{Corr}{Tot} \times 100\% \quad (3)$$

Where Corr and Tot are a number of correctly samples and a total number of tested samples. In this work we used part of the iris instead of the entire iris, which our goal is to reduce the data extracted from the iris and try to discriminate using them.

In this work, we soon extracted 50% of the information and obtained good result where, the highest rate of identification is (97%) in the set of training, while corresponding rate of identification for the same features in the test set was (91%). Two factors have been taken into consideration and their direct impact on the rate of identification. The first factor is the Epsilon (ε) and Figure 7 illustrating its effect on the rate of identification in the range ($0.0001 \leq \varepsilon \leq 0.0081$) . The best identification rate was (97.00% in training and 91.00% in testing) at ($\varepsilon = 0.0001$)

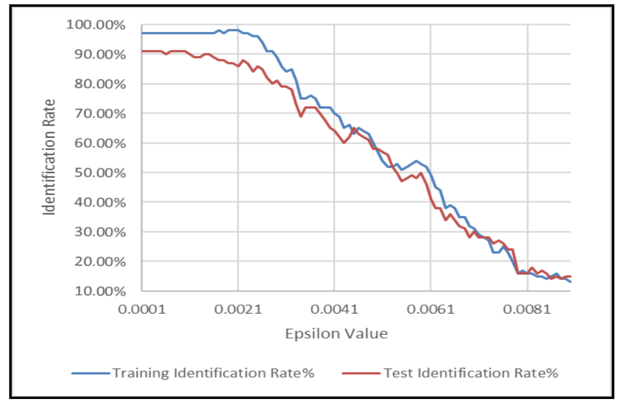

Figure 7. The effect of Epsilon on Identification Rate

The second factor is the Tolerance (T) and Figure 8 illustrating its effect on the rate of identification in the range ($0.009 \leq T \leq 0.999$). The best identification rate was (97.00% in training and 91.00% in testing) at ($T = 0.009$)

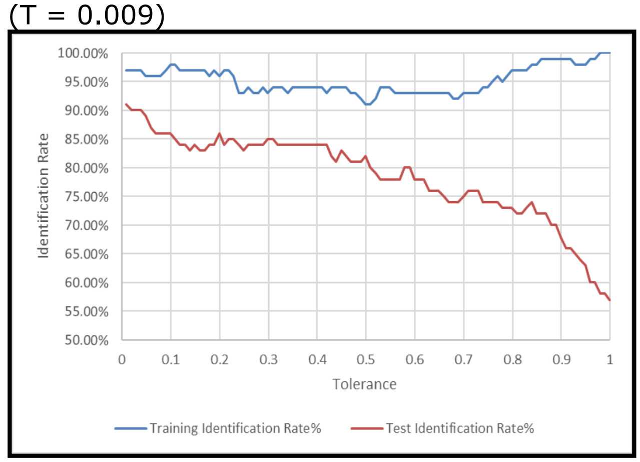

Figure 8. The effect of Tolerance on Identification Rate

7. Conclusions

Iris identification system based on multiclass support vector machine is designed and implemented. The study proposes a five regions for iris segmentation rounded the pupil of iris as elliptic regions. One of the objectives of this work is to reduce the amount of data extracted from the iris as much as possible. The features are extracting by manipulating the previous five regions by several filters (Mean, Median, Variance and Sharpen). Also SVM quadratic programming (QP) problem solved the by using Sequential Minimal Optimizations (SMO) algorithm that can be run quickly and without any extra matrix storage. The proposed method obtained good result depending on the amount of data that extracted from iris, where the final highest identification rates are (97% and 91%) in the training and test sets.

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