Iris Recognition under Non-ideal Imaging Conditions and CCD Noise

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Abstract. Iris recognition is the most reliable and dependable biometric system as the features of human eye are invariant and distinctive for every individual. Present iris recognition algorithms are tested using the bench mark databases which are assumed to be almost ideal except for eyelid and eyelash occlusions and rotational inconsistencies. It has been discussed elaborately by Daugman in [3] that, non-ideal imaging conditions affect the "authentics" distribution in the decision environment graph. Getting motivation from this observation, all possible non-ideal imaging conditions and Charge Coupled Device (CCD) noise are simulated and applied on the available databases. Legendre moments, introduced by Teague can achieve translation and scale invariance and also, close to zero value of redundancy measure, so that the moments correspond to distinct and autonomous features of the image. In the proposed method it is proved that, they can also work very well on noise affected features when trained and tested using SVMs. The performance of the Exact Legendre Moments (ELM) on UBIRIS and CASIA datasets proves to be very good with Correct Recognition Rate (CRR) = 99.6% under non-ideal imaging conditions and CCD noise.

Keywords: Iris recognition, Exact Legendre Moments, SVMs, CCD noise, Non-ideal imaging.

1 Introduction

Iris recognition is well accepted by public even though the imaging procedure requires the subject's cooperation, because it is unobtrusive, safe and accurate. Iris is the annular segment amid dark pupil and white sclera in the human eye which is an internal organ yet externally visible and has an unusual texture that is exclusive for each individual [2]. The textural features like freckles, ridges, corona and collarette region are alike all over the life time and do not alter at all. Iris biometric is well acknowledged by the public as the imaging technique is non-invasive and it also gained the interest of researchers as the iris prints

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are stable and unique. Several international airports have set up the iris scan systems to recognize their passengers and facilitate quick processing.

In CASIA database [6], the iris image is captured using Near Infra Red (NIR) wavelength camera, which is almost ideal except for the eyelash and eyelid occlusions where as in UBIRIS database [9], the iris image is captured using visual wavelength imaging device. In WVU data set, eye image is acquired using NIR illumination but iris images undergo rotational discrepancy. Visible wavelength illumination is not harmful to eye, but the images suffer from noise terms like poor contrast, low brightness, specular reflections and problems like blinking of the eye due to involuntary reaction, contraction of pupil to adjust to the illumination etc. NIR illumination is not safe but the images have good contrast and no specular reflections. It is observed that all the iris datasets available suffer from one of the issues of imaging conditions mentioned above but not all. The later versions of CASIA and UBIRIS databases are obtained under non ideal conditions like poor contrast, low brightness, motion blur and eye lash and eye lid occlusions but not CCD noise, hence making them suitable for testing the robustness of the segmentation method.

It was illustrated with proofs that the quality of the imaging strongly influences the "authentics" distribution in decision environment graph by Daugman in [3]. The camera gain, tilt, illumination, contrast, CCD noise etc., affect the image quality. The imaging devices are CCDs. During acquisition and conversion of photons in to digital signals by CCD sensors, various noise components like Thermal noise, Read-out noise, Fixed pattern noise, photon Shot noise are added to the signal, all as a whole called as CCD noise. Phase codes were used rather than amplitude information in multi scale quadrature method in [3] to encounter the imaging quality issues.

Legendre moments were used for scale invariant and translation invariant textural feature extraction in [14]. Hence, by creating non ideal iris database in which the images suffer from all possible irregularities like, blur due to camera motion and defocus, low contrast and brightness and mainly CCD noise, the robustness of the new feature extraction method with ELMs for iris recognition is tested. In the method proposed the CCD noise, simulated using the model proposed in [10] at various levels of variance along with camera motion blur is added to the CASIA and UBIRIS iris databases. The noise corrupted iris region is segmented normalized and the textural features are extracted using ELMs. The coefficients of all noisy iris images of different classes are picked out and then given ranking based on their entropies. The optimal ranked feature vectors are then classified using Support Vector Machines (SVM).

The rest of the paper is as follows. The CCD noise simulation, segmentation, normalization, textural attribute collection and feature vector generation using ELMs is explained in section 2. Section 3 is dedicated to the explanation about classification using SVMs. In section 4 the experimental results, comparisons and discussions are illustrated and in section 5, the conclusions and scope of future work are furnished.

1.1 Related Work

A detailed survey on iris recognition algorithms is presented in [1]. Zero crossing method with dissimilarity functions for matching was employed by Boles. The iris textural data were extracted using 2D Haar transform by Lim. Multi channel Gabor filtering for the extraction of iris features was used in [5]. Hilbert transform for iris feature extraction was used by Tisse in his method. Levelsets were applied for segmentation and wavelet features were extracted in [7]. In the proposed method a new feature extraction concept using ELMs is proposed and evaluated on the simulated non ideal databases.

1.2 Proposed Algorithm

A series of steps to generate non-ideal imaging conditions, applying them on available iris datasets, extracting features from images and finally classifying the data presented by the algorithm is as follows:

- **Step 1:** First the iris image from the database is taken, scaled to 1024 levels, after which its irradiance image is generated using Inverse Camera Response Function (ICRF).
- **Step 2:** Simulation of non-ideal imaging conditions in MATLAB
  - The intensity independent and intensity dependent CCD Noise is generated using two random noise sources of three different combinations with normal distribution of standard deviations chosen to be $\sigma_{independent} = 6\%$ and $\sigma_{dependent} = 5\%, 10\%$ & 16%. and applied on the image.
  - Camera motion blur and poor contrast are also simulated and applied on the image.
- **Step 3:** The intensity image is generated from the noisy and blurred irradiance image using Camera Response Function (CRF) and then it is rescaled to 256 levels. The resulting image is corrupted with simulated CCD noise and camera motion blur.
- **Step 4:** The pre-processing, segmentation and normalization of iris region are done to facilitate feature extraction.
- **Step 5:** Then feature extraction using ELMs is used to generate feature vectors.
- **Step 6:** Finally classification of feature vectors using SVMs is done to evaluate the performance of ELMs on CCD noise and camera motion blur affected features in terms of % CRR.

2 Segmentation and Feature Extraction

The noise model of a CCD camera is proposed in [10] is used to generate synthetic CCD noise.

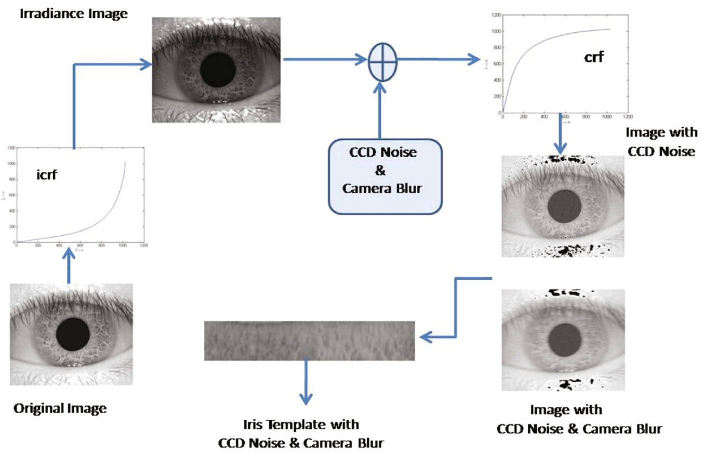

Fig. 1. CCD noise & blur simulation procedure

2.1 Iris Segmentation

In any biometric system, preprocessing of the image and extraction of distinct features from it, play vital role in deciding the recognition rate. The segmentation is done using Integro differential operator and normalization using the Rubber sheet model proposed in [2].

2.2 Feature Extraction with Exact Legendre Moments

Legendre moments generated with Legendre polynomials as kernel function, were first introduced in [13]. The 2D ELMs proposed by Hosny [12] are of order $(p+q)$ for an image intensity function $f(x, y)$, are defined as follows:

$$L_{pq} = \sum_{i=1}^{M} \sum_{j=1}^{N} I_p(x_i) I_q(y_j) f(x_i y_j) \tag{1}$$

where,

$$I_p(x_i) = \frac{(2p+1)}{(2p+2)} [xP_p(x) - P_{p-1}(x)]_{U_i}^{U_(i+1)} \tag{2}$$

and

$$I_q(y_j) = \frac{(2q+1)}{(2q+2)} [yP_q(y) - P_{q-1}(y)]_{V_j}^{V_(j+1)} \tag{3}$$

In the proposed method, ELMs are extracted from noisy and blurred iris images, the computation of which are fast and accurate.

3 Iris Classification with SVMs

In Iris recognition several researchers applied Hamming distance for pattern matching [1]. Conventional SVMs and Non symmetrical SVMs were applied by some researchers to differentiate the False Positive and False Negative cases and asymmetrical adaptive SVMs were used in [7] to reduce the matching times of the test samples.

SVMs have been an excellent tool for data classification. The fundamental idea is to map the data points in to a high dimensional space and separating them by a hyper plane with maximal margin. In the proposed method the iris feature vectors made up of ELMs are first ranked based on their entropies and then trained and tested using traditional SVMs with Linear kernel.

ELMs have least redundancy measure. Also ranking is given to the features according to their entropies. The entropy of the configuration which is in an order is lower than the entropy of the configuration with disorder. Therefore the irrelevant feature vector has higher entropy than the relevant feature vector. The feature with least entropy is given first rank and so on as proposed in [8], The entropy is calculated as follows. Entropy,

$$E = -\sum_{i=1}^{N}\sum_{j=1}^{N} d_{i,j} \times \log(d_{i,j}) + (1 - d_{i,j}) \times \log(1 - d_{i,j}) \tag{4}$$

where $d_{i,j}$ is the distance between features of N different samples in the same class. The features that have least entropy are more significant for classification.

3.1 Classification Evaluation

The classification of iris feature vectors is carried out using OSUSVM package available at `http://kaz.dl.sourceforge.net/project/svm/svm/3.00/osu-svm-3.0.zip`. Once the features are ranked according to their entropies, the class label is appended to each feature vector and the samples are classified based on supervised learning method. The proposed method is checked using 3-fold cross validation also, with 70% of the sample data used as train set and 30% of the data set as the test set. The multi class SVMs operated in One-against-All approach and are tuned with linear support vector classifier kernel. The $\%CRR$ is defined as

$$\%CRR = \frac{Correctly\ Recognized\ Users\ Number}{Total\ Number\ of\ Users\ Enrolled} \times\ 100 \tag{5}$$

4 Experimental Results

The experiments are conducted on a PC with Pentium i3, 2GHz processor and 2 GB RAM in MATLAB 7.10 environment. The evaluation of the proposed method is carried out on CASIA and UBIRIS databases under different non-ideal conditions. CASIA version-1 database consists of 756 iris images taken in two sessions from 108 subjects. Each iris image is of 8-bit gray scale and resolution of 320×280. The UBIRIS version-1 database contributes 1205 iris images from 241 subjects with 5 samples from each subject with resolution of 150×200.

4.1 Discussion on Results

The performance of Legendre moments is already proved in terms of scale invariance and translation invariance in [14]. It is empirically proved by the results that the ELMs can work very well on CCD noise corrupted and blurred images. Experiments are carried out under three sets of different non ideal conditions, high CCD noise and camera blur ($\sigma_{dependent} = 5\% + \sigma_{independent} = 4\%$), medium CCD noise and blur ($\sigma_{dependent} = 10\% + \sigma_{independent} = 4\%$), and low CCD noise and blur($\sigma_{dependent} = 16\% + \sigma_{independent} = 6\%$) and motion blur of length 9 pixels and angle 5^o. Before extraction of ELM features, preprocessing step is

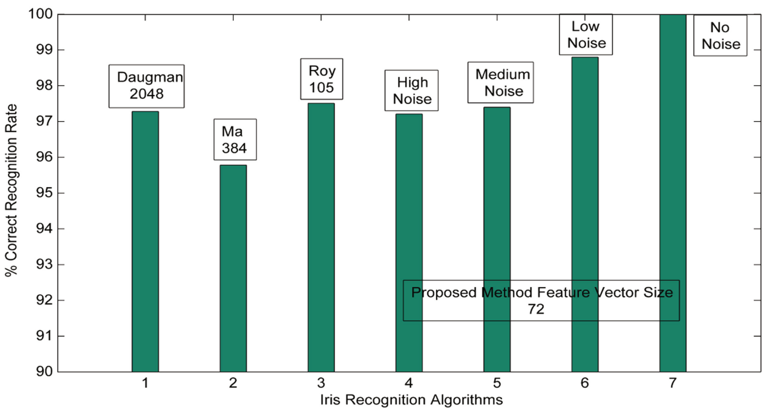

Fig. 2. Results of iris recognition algorithms on UBIRIS database: A comparison of % CRR and feature set size. The proposer's name, and feature set size is given in the boxes.

performed to enhance the contrast and highlight the blurred edges in the image by applying high boost filtering. Then iris region is segmented and normalized to get a 20×240 size noisy and blurred template. It is made into two blocks of size 20×120 for which ELMs of level-5 are extracted and resulting coefficients are arranged into a row forming a feature vector. The number of coefficients generated depends on the degree of Legendre polynomial. The higher the degree of polynomial, the more the number of coefficients and the better the performance of the proposed method. As there is a constraint regarding the feature set size, the degree of the polynomial chosen is 5, and the resulting feature vector length is 72. The performance of the proposed method is investigated in terms of % CRR and feature set size .

The classification of iris images is carried under different train:test ratios such as 6:1, 5:2, 4:3, 3:4, 2:5 and 1:6 in CASIA dataset and 4:1, 3:2, 2:3 and 1:4 in UBIRIS. The results on both datasets are shown in figures 3 and 4. It is found that the CRR is 100% for all train versus test ratios in UBIRIS and CASIA except for 1:6, under ideal, no noise conditions. It is also observed that the % CRR is slightly decreased as the number of samples for training is decreased as against the number of samples for testing. Another observation is that the % CRR is very good when compared to other methods even in high noise and blurred environment which proves the robustness of ELMs against CCD noise and blur and the number of features is also very small when compared with other methods which is shown in figure 2. The % CRR is $\geq 99.6\%$ for UBIRIS and $\geq 99\%$ for CASIA in the 3-fold cross validation test under all sets of CCD noise and blur conditions.

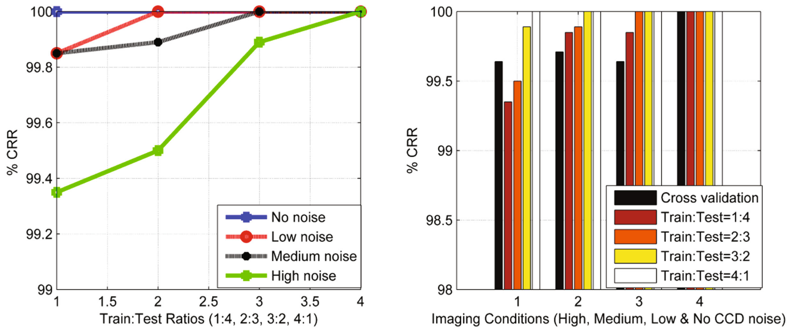

Fig. 3. Result of UBIRIS database for various non ideal conditions

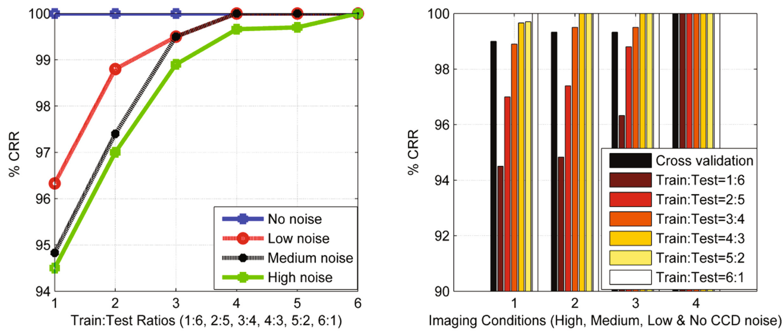

Fig. 4. Result of CASIA database for various non ideal conditions

5 Conclusions

It is observed from the experiments that, even in presence of high levels of noise also the % CRR is very high and it can still be improved with perfect segmentation. The ranked ELM feature set size is very small (72) when compared to other methods. In future, feature extraction using ELMs will be evaluated on higher versions of UBIRIS and CASIA databases.

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