A Decision-level Fusion Strategy for Multimodal Ocular Biometric in Visible Spectrum Based on Posterior Probability

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Abstract

In this work, we propose a posterior probability-based decision-level fusion strategy for multimodal ocular biometric in the visible spectrum employing iris, sclera and peri-ocular trait. To best of our knowledge this is the first attempt to design a multimodal ocular biometrics using all three ocular traits. Employing all these traits in combination can help to increase the reliability and universality of the system. For instance in some scenarios, the sclera and iris can be highly occluded or for completely closed eyes scenario, the peri-ocular trait can be relied on for the decision. The proposed system is constituted of three independent traits and their combinations. The classification output of the trait which produces highest posterior probability is to consider as the final decision. An appreciable reliability and universal applicability of ocular trait are achieved in experiments conducted employing the proposed scheme.

1. Introduction

Among biometric traits, ocular traits have enjoyed significant attention by researchers from industry, government and academia due to its social, economic and scientific impact. With the rising popularity and urge for the security of smart phones and mobiles application, it's certain that the application of biometric scenario in mobile biometrics will be of great significance. Ocular trait is found to be highly reliable therefore very promising for mobile environment as well. The challenges in ocular traits is a fundamental problem in biometrics with broad economic (upcoming market growth of mobile biometrics will enjoy an annual growth rate of over 150%), social (secure mobile banking applications) and scientific impact (development of detection, segmentation, characterization, identification algorithm in computer vision). Therefore, significant attentions have also been received by researchers and several commercial application and mobile are been launched since last few decades.

Eye offers offer several stable and robust traits with high population coverage. Among the eye traits, the iris is the most popular and promising trait [7]. For a large population iris biometric can be considered as more effective for authentication purpose. But there are some limitations in using iris biometric applicability in a mobile environment. Traditionally iris traits are acquired in Near Infra-Red (NIR) spectrum. The sensors of mobile cameras capture eye traits in the visible spectrum. Although iris recognition works in the visible spectrum for lighter irises, for dark irises, such sensor fails to acquire enough information. It makes the iris images inappropriate for implementing mobile biometrics application.

Therefore alternative supportive trait like sclera [8, 9, 10] and peri-ocular are combined to increase iris biometric applicability. Sclera or conjunctival vasculature is the opaque [12], white area and acts as a protective covering of the human eye. The vein patterns visible in the sclera region are unique for each person and it is prominent in visible wavelengths. The small neighbourhood region of the eye including the eyebrows is known as peri-ocular [1]. Various works have been proposed in the literature in peri-ocular in [2-6]. It is combined with iris, vein patterns of the eye or with the partial facial features for identification or authentication. Excluding the iris, both upper and lower eyelids, eye folds, and eye corners, detailed skin texture, fine wrinkles, colour, or skin pores are considered as the biometric features of peri-ocular. The features can also be classified based on geometry (shape of the eye, eyelids, eye folds and various lines), texture, or colour.

Therefore, a fusion of above-mentioned eye traits can be a scope for establishing security and better authentication purposes. Moreover, the low-resolution cameras in mobile can be the added barrier for having intense information from each of the traits. Therefore, exploring best utilization of these eye traits either separately or in combination is required to carry out.

Several attempts have been made in the literature to

combine this trait and to make the best utilisation of the traits. All these trait and combination have achieved respectable performance. But each of them also has their pitfall. For example, when an eye is completely closed the sclera or iris trait cannot be used but peri-ocular trait can work in this scenario. Therefore, optimal utilisation of this trait is possible if all of them are employed in a system and decision technique can be used to choose the best result for the each instance. To fulfil this gap this research is conceived.

Organisation of the rest of the paper, in Section 2 the proposed decision-level fusion strategy is enumerated, in section 3 the experimental results and their analysis are summarised and in section 4 the conclusion of the work is drawn.

2. Proposed Decision Level Fusion Strategy

The proposed decision level fusion strategy, preprocessing technique and feature extraction, and classification technique used in this research are explained as below.

2.1. Proposed Decision Level-Based Fusion Algorithm

We found that the presence of the best information on the each trait were varying for a different scenario. Therefore a single trait or combination of might be successful in one scenario and might not for universal scenario. Therefore, a fusion technique or a trait might not be robust for all scenario. Therefore we proposed a decision-making scenario based on posterior probability. A flow diagram of the proposed scheme is in Figure1.
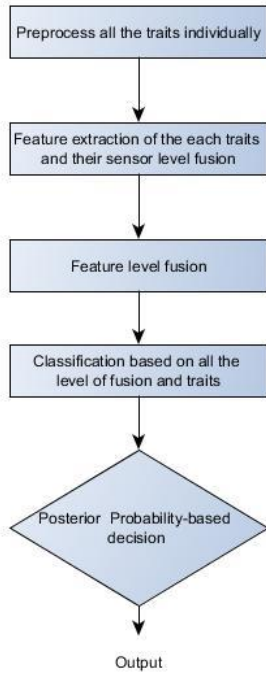

Figure1: A flow diagram of the proposed scheme.

In a biometric system requires 1 to 1 or 1 to n match as it intended to verify or recognise the claimers identity by matching the presented biometric property with the enrolled biometric knowledge base. This scenario can be mathematically formulated by:

Let f be a mathematical representation of the biometric property or feature vector extracted from the presented biometric image and e be the enrolled representation feature vector stored for the claimed identity I.

The task is to determine if the pair (I, f) belongs to class I which is to accept (genuine) the user or class else which is to reject (imposter) the user.

Let S(f, e) denote the distance matching score computed by matching e and f and T denotes the threshold determined at the learning stage. Then the verification/ recognition is defined as:

$$(l, f) \in \frac{I, \text{if } S(f,e) \quad\quad <T}{class\ else, \quad\quad otherwise} \tag{1}$$

According to Bayesian statistics, the posterior probability of a classification is the conditional probability that is assigned by the classifier after the relevant statistics is taken into account. Similarly, the posterior probability distribution is the probability distribution of an unknown population, treated as a random variable, conditional on the evidence obtained from an observation. Posterior means after taking into account the relevant evidence related to the particular case being considered.

Hence, the posterior probability is the probability of the parameters β given the evidence X: $p(X|\beta)$. Hence for each classification, the classifier will have a prior belief that the probability distribution function is $p(\beta)$ and observations x with the likelihood $p(x|\beta)$, then the posterior probability is defined as:

$$p(\beta | x) = \frac{p(x|\beta)\ p(\beta)}{p(x)} \tag{2}$$

Hence, the posterior probability of the classification result is the confidence score of classifying the sample to a given sample space. Therefore, depending on the availability of the information the posterior probability will be assign.

Therefore, the distance matching score computed for each class the probability of sample belonging to the each class can be calculated. We have employed this probability for decision level fusion. The detail steps of the proposed algorithm are explained as below.

Enrollment:
Step 1: Pre-processed the traits individually and combine the traits for sensor level fusion.
Step 2: Featuring the each trait and the sensor level fused trait.
Step 3: Feature level fusion of the individual trait extracted.

Step 4: Build a training model for each trait and each level of fusion and keep a separate representation for each.

Verification and recognition:
Step 1: Pre-processed the traits individually
Step 2: Featuring the each trait by SPMS-LDP.
Step 3: Classify respective feature representation of each trait w.r.t training model for each trait and obtain the posterior probability Cs for each.
Step 4: Find the scenario (trait or its combination) where the posterior probability is highest represented by C_{sh}.
Step 5: The decision of the trait corresponds to C_{sh} assign as the recognition or verification result.

We have used SVM as classifier therefore, we tried a property of the SVM i.e. the confidence score for decision making.

2.2. Pre-processing

For pre-processing of the trait we used the separate pre-processing technique. Peri-ocular traits were segmented manually and no further pre-processed was required as the trait visible were quite prominent.

(a)   (b)   (c)

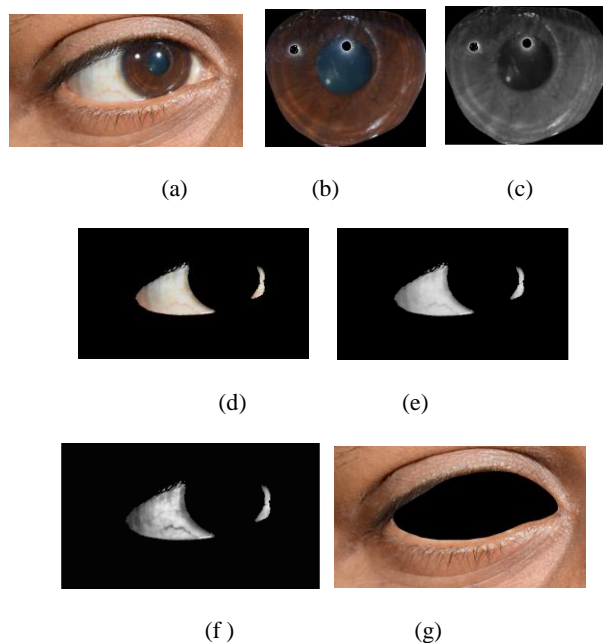(d)   (e)

(f)   (g)

Figure 2: (a) original eye image, (b) segmented iris image (c) preprocesses iris image, (d) segmented sclera image, (e) preprocesses sclera image with channel selection (f)) preprocesses sclera image with histogram equalization, (g) segmented periocular region .

Whereas, sclera and iris information was not visible with enough clarity. Therefore we assume they required to be preprocessed to extract more appropriate information. For sclera pre-processing algorithm proposed in [11] is used. In the case of iris the patterns in the iris are not prominent, so in order to make them clearly visible, image enhancement

is required. Adaptive histogram equalisation is performed with a window size of 2 x 2 at a clip limit of 0.01, with full range and distribution, exponential to get the best result on the red channel of the iris image (as the iris patterns were best visible in the red channel of the colour image).

2.3. Employed Feature and Classifier

For featuring the traits of these information's we considered Multi-Scale Local Derivative Pattern (SPMS-LDP). We found from our observation that the eye traits are rich in both global and local feature. The feature SPMS-LDP is both reach in the local and the global feature as the total image and the image divided into different plane are considered for the scenario. A multi-scale of four and third order of the LDP is employed here. Ten different spatial planes are considered for the featuring. Each histogram distribution of bin size of 256 is calculated for each plane, order and spatial plane and concatenated to get the total feature of dimension 30720. This can be calculated as below.

$$FD = Ns * No * 256 * Nsp \qquad (3)$$

Where, FD= feature dimension; Ns= number of scale, No= number of order, Nsp= number of spatial plane. The Spatial plane division of the image to divide the image into dense sampling is explained in the following image.
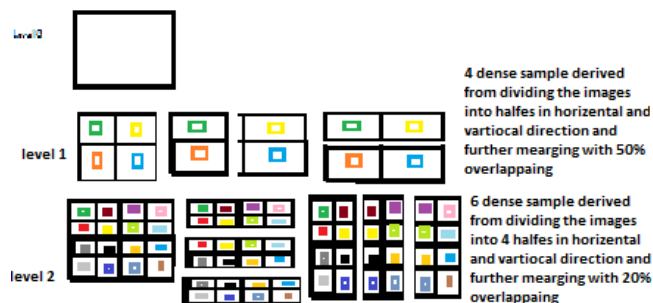

Figure 3: The Spatial plane division to divide the image into dense sampling is explained in the following image.

The various level of the spatial division incorporates the local and the global feature of the traits.

Support Vector Machines (SVMs) are employed in this experiment for classification purpose. The Library for Support Vector Machines (LIBSVM) is used here for the SVM implementation. Following are the details of the SVM employed.: svm_type-- C-SVC, kernel type – linear, cost function - 0.07, Wi weight for C-SVC (default 1) - (total training sample - training sample of one class)/training sample of one class.

3. Experimental Results and Discussion
The experimental results of the above mention investigation are as below.

3.1. Dataset

This dataset employed in this work is MASD version1. In this dataset, a multi-angled iris and sclera database that contains images in the visible spectrum was taken at a distance are presented. This is in contrast with existing databases that do not contain multi-angled images.

The proposed multi-angled dataset consists of 2624 RGB images taken in one session from 82 individuals where each channel of RGB colour space is represented in grey-scale. The individuals were comprised of both male and female, with different ages and the different colour was considered, a few of them were wearing contact lenses and images were taken at the different time of day.

The database contains images with occluded eyes, closed eyes and blurred eye images, images with high resolution are provided in the database. All images are in JPEG format. Here for each individual image in four multi-angle were considered. For each angle, eight images were acquired. For each individual both left and right eye was captured.

Different lighting conditions were considered during the image accusing. An NIKON D 800 camera and 28300 lenses were used for image acquisition. Different quality images were used here and some of the sample images are shown below in Figure 4.

(a)   (b)
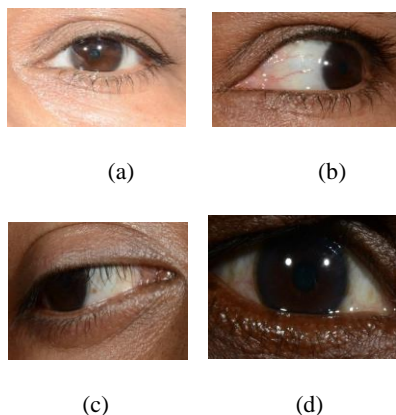

(c)   (d)

Figure 4: Different quality of eye images used in the experiments

Some of them are not occluded having a good quality of sclera regions visible, some of them are of medium quality and the third type was of poor quality with respect to sclera region visibility. In the experiments some closed eye images were also used, examples of such images are provided below in Figure 5.

The images were captured in an indoor lighting condition so noise factors such as reflection, luminosity, and contrast were minimised. The database contains blurred images and images with blinking eyes as shown in Figure 5.

(a)   (b)

(b)   (d
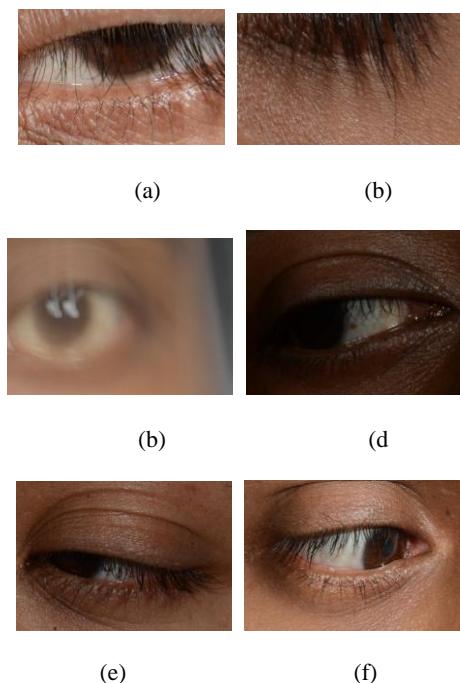

(e)   (f)

Figure 5: Examples of closed and blurred eyes.

In the experiments, all the images were considered for experimentation. For the experiment, 2 images from each angle, each class are randomly chosen and utilised for training and the remaining 2 set images for testing performance. So all together 8 images for testing and 8 images for training. Therefore, False Rejection Rate (FRR) statistics will be 164*8 score and False Acceptance Rate (FAR) score is 164*163*8.

3.2. Details Result and Discussions

The result of the experiments are summarized in table 1. It can be infrared the table the result of the each scenario is not robust for any traits or its combination. It can be concluded form the result that the verification performance was better than the recognition accuracy. The verification was ~10% better in each scenario. Performance of the periocular trait was found to attend the best verification accuracy and for recognition iris was found to attend the best accuracy. They have huge amount of gap in regards to recognition and as well as verification accuracy in different environment (acquiring and lighting condition) and with respect to the different trait. An improvement of ~1% was found in the fusion of each trait in verification scenario and ~0.75% for recognition scenario.

Although single trait or its combination do not worked stable or robustly but if we condition the total subset of the traits and its combination at least one trait or its combination is able to reach an appreciable recognition accuracy. Therefore, a decision-making technique considering the proposed algorithm will help to recover the pitfall highlighted. The accuracy after applying the above-

mentioned decision making have improved by ~2%. It is quite clear from the above table 1 that the use of the proposed decision mechanism for feature fusion has produced a robust result for different lighting environment Moreover it has also lead to an increase in accuracy. The reason for this increase in the accuracy is because of the variability of the information of the traits depending on lighting condition mainly. The decision algorithm not only increased the overall accuracy of the system but also help in optimizing the FAR and FRR. Moreover, it also worked for closed eye scenario.

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Table 1: The results of the recognition and verification.

Trait	Recognition accuracy in %	Verification Accuracy in %
Iris	88.95	96.55
Periocular	80.26	98.56
Sclera	78.92	91.85
Iris + Sclera Feature level	91.34	97.62
Iris + Periocular Feature level	90.95	98.92
Sclera + Periocular Feature level	84.33	95.86
Iris+ Sclera+ Periocular Feature level	85.56	98.88
Iris + Sclera image level	91.78	98.01
Iris + Periocular image level	91.52	99.01
Sclera + Periocular image level	85.14	96.78
Iris+ sclera+ periocular image level	86.79	99.11
Proposed decision-based fusion	**96.53**	**99.56**

5. CONCLUSIONS

In this work, we proposed a more realistic ocular biometrics that can be employed in visible spectrum using. We have experimented and analysed the three traits (sclera, iris and peri-ocular), individually and also fusing their information and investigated the best trait or level of fusion that can be used in regards to ocular biometrics. As the performance was not robust and stable, for any of the trait or fusion technique, we proposed a new decision algorithm based on the posterior probability of SVM for judging the best level of fusion. Analyzing the confidence score and the classification result of the different trait the decision making was perfoarmed. We have used texture based feature namely Special Pyramid based overlapping Multi-Scale Local Derivative Pattern (SPMS-LDP). The result achieved by experimenting the different traits and their combination infers that a single trait or its combination is

not capable of producing a universal result. Therefore a decision-making algorithm is required to handle the problem and choose the best trait or the level of fusion depending on the instance. The experimental result achieved and the analysis made solicits the viability of the proposed fusion based decision-making technique.

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