# An Intelligent Decision Combiner Applied to Noncooperative Iris Recognition

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***Abstract – In despite of successful implementation of iris recognition systems, noncooperative recognition is still remained as an unsolved problem. Unexpected behavior of the subjects and uncontrolled lighting conditions as the main aspects of noncooperative iris recognition result in blurred and noisy captured images. This issue can degrade the performance of iris recognition system. In this paper, to address the aforementioned challenges, an intelligent decision combiner is proposed in which prior to perform decision fusion; an automatic image quality inspection is carried out. The goal is to determine whether captured decisions based on visible light (VL) and near infrared (NIR) images have enough reliability to incorporate into final decision making. Experimental results on the UTIRIS confirm the superior performance of the proposed combiner in comparison with other common non-trainable decision combiners whereas in all cases, the effectiveness of fusion approach makes it a reliable solution to noncooperative subjects' behavior and uncontrolled lighting conditions.***

**Keywords:** Decision fusion, non cooperative iris recognition, quality inspection, visible light and near infrared images

## 1 Introduction

In despite of the existence of so many proposed iris verification and identification systems, it seems that all aspects of such authentication systems have been solved and there are no challenging issues prior to mass-scale deployment on national and international levels. However, it must be noted that aforementioned viewpoint is only because the iris images must been taken under several controlled conditions such as properly arranged illumination and the cooperative behavior of person. For example, to make a correct decision, the user must look in a guided direction, from a short and narrow distance range.

New challenges in human authentication systems such as noncooperative behavior have attracted researchers' attention in recent years [1, 2, and 3].

Some advantages of a non-cooperative iris recognition system have been shown as below [3]:

- Security: Since there is no need to user cooperation, it is possible to recognize the individuals' identity when and where the user is not aware of identification process. This achievement is suitable to identify subjects in terrorist attacks.
- User commodity: The less cooperative behavior leads to more user commodity in image capture process ad reduce the time which is necessary to capture an appropriate image.
- Functioning Radius: Noncooperative recognition enables us to perform identification process in larger distance than that of cooperative systems (usually less than 1 m).

In despite of mentioned advantages, noncooperative behavior in an authentication system results in low quality captured images which caused by user motions during the image acquisition process. In the iris recognition systems, the image quality is considered as a critical issue which directly affects the overall performance of identification process. Thus, it seems that the need to determine the image quality prior to perform identification process is an invaluable task which can prevent rejection of genuine or acceptance of imposter attempts. The former may happen and can be addressed by another user attempt to validate whose identity. But, the later is not allowed in biometric systems and occurs when the threshold or related features have not been appropriately chosen. Therefore, an automatic inspection of image quality must be regarded as an essential part of biometric systems to avoid making a decision when the noncooperative recognition is a crucial issue. In this paper, we propose a novel approach to check the quality of captured images and determine to what extent must be incorporated in final decision making.

We showed in [4], integration of visible light and near infrared features led to a quite considerable improvement of recognition rate. Here, our aim is to propose a decision fusion framework based on the quality inspection of visible and near infrared captured images to achieve a biometric system which utilizes advantages of both kinds of acquired images in an intelligent manner. It should be stressed that our main contribution is to recommend the idea of combining decisions derived from VL and NIR and not concerned on quality assessment stage. Experimental results show that employing proposed approach lead to a significant improvement in recognition rate and also can be considered as a worthful achievement toward noncooperative iris recognition.

The remainder of this paper is organized as follows: Section 2 briefly summarizes the most cited iris recognition methods. An overview on decision combiners is brought in section3. Detailed description of the proposed decision fusion approach is given in Section 4. Preprocessing and feature extraction are briefly explained in section 5. Section 6 reports the experiments and the results and, finally, Section 7 presents the conclusions.

## 2 State of the art

Various algorithms for iris feature extraction have been proposed by many researchers since 1990s.

As a pioneering work, Daugman proposed to extract the iris features with complex valued 2D Gabor wavelet and quantized local phase angles to yield the final iris representation [5]. A desirable recognition results are achieved using Daugman's method.

In the view of the Wilds et al., Daugman's system yields a remarkably parsimonious representation of the iris via the Gabor filters [6]. Wilds used an isotropic band pass decomposition derived from application of Laplacian of Gaussian filters to the iris texture. This method preserves more available iris information.

Both systems of Daugman and Wildes employ carefully designed image acquisition devices to get equal high quality iris images [5, 6, and 7]. Therefore, many challenges such as deformation of the iris pattern and low quality captured images are relaxed. However, these conditions are not simply satisfied in many fields of applications particularly where the system faces with uncontrolled lightening condition and noncooperative user' behavior.

Recently, some researchers [1,2, and 3] endeavor to achieve a desirable recognition rate in spite of mentioned conditions. In [3], the authors demonstrate the new challenges of iris recognition when extended to less cooperative situation and describe some initial work into this area. The authors in [2] propose a new and robust iris segmentation methodology based on the well-known fuzzy-clustering algorithm which yields high segmentation accuracy in noncooperative image acquisition. In [1] a new classification method based on partitioning the iris texture into six regions is proposed. In each region, an independent feature extraction and comparison is performed and finally through a classification rule, the combination of dissimilarity values result in the final decision. Nevertheless, noncooperative recognition challenges have been still remained unsolved and it seems that immense amount of work needed to address these challenges.

## 3 Decision Combiners

The possible ways of combining the outputs of the L classifiers in an ensemble depend on what information we obtain from the individual members.

In [8], three types of classifier outputs are distinguished as follow

Type 1 (The Abstract level): The output of each classifier is a label for each input feature and there is no information about plausibility of other class labels, so the abstract level is the most universal one.

Type 2 (The Rank level): The output of each classifier is a subset of class labels which ranked in order of plausibility of being the correct label [9, 10]. Type 2 is especially suitable for problems with a large number of classes e.g. character, face, speaker recognition, and so on.

Type 3 (The Measurement level): Each classifier produces a vector for a given observation in which $i^{th}$ entity represents the support for $i^{th}$ hypothesis.

Since the nearest neighbor classifier is known as a most reliable and accurate one in iris recognition and regard to the fact that number of classes in such an application might be very large, here, we only consider the methods proposed in two last categories. Majority voting and its weighted version, Label Ranking, Naïve Bayesian (NB), Behavior Knowledge Space (BKS), and singular value decomposition (SVD) are the most well-known decision combiners classified into the second category. Except majority voting and label ranking methods, the other mentioned approaches need to be trained on a large amount of training samples which restricts the application domains (e.g. iris recognition) of these decision combiners. For example, in NB a confusion matrix must be calculated by applying each expert to the training data set or in BSK a look-up table must be designed using a labeled data set.

In the third category, combination methods are classified in two subcategories including class-conscious and class-indifferent combiners. Class-conscious consists of trainable and non-trainable classifiers. Non-trainable ones make the ensemble ready for operation as soon as the base classifiers are trained. In these methods, the ensemble support for a class label is achieved as a result of a combination function on individual classifier supports. Simple and generalized average rule, minimum rule, maximum rule, median rule, and product rule are considered as a combination function in this framework. Trainable Class-conscious and class-indifferent combiners need to be learned on a large amount of train samples and as mentioned are restricted to special domains. Linear regression, fuzzy integral, decision template, and dempster-shafer combiners are most common approaches in two later categories.

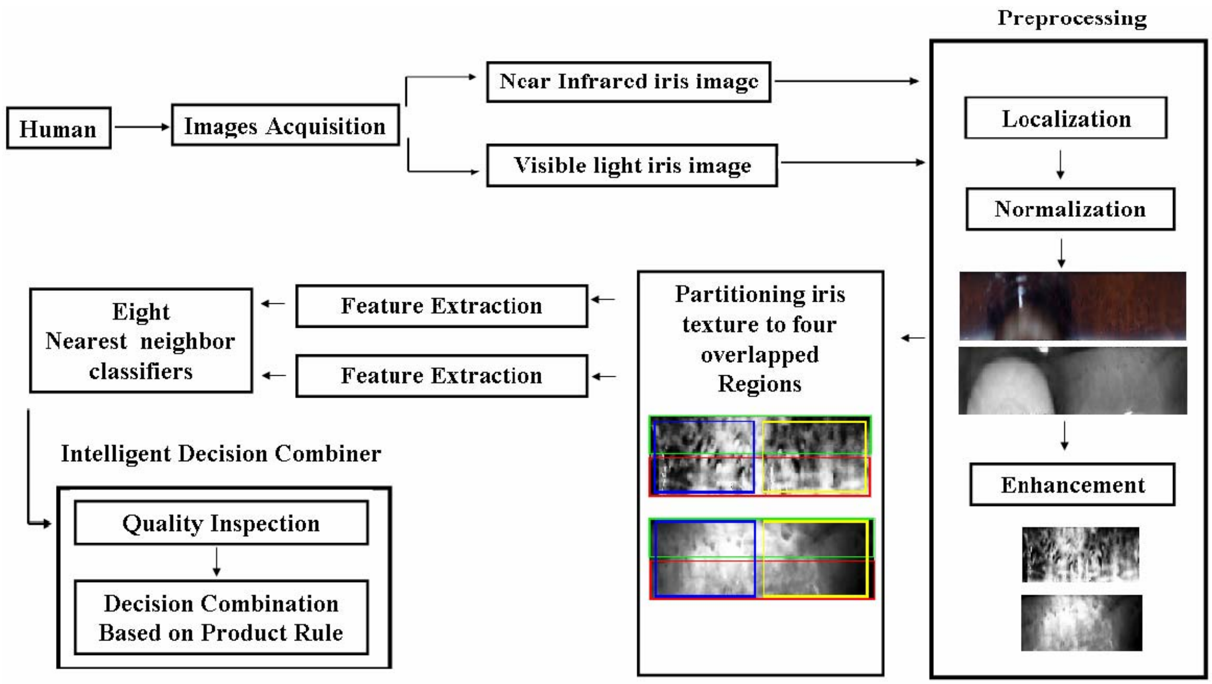


Fig. 1 Overview of the proposed method.

In [11], profound theoretical analysis is performed to determine in which situations ensembles can improve or degrade classification results.
It is shown that small learning sets increase classification error of the expert classifiers and damage correlation structure between their outputs. Moreover, if the training samples used to develop the expert classifiers are too small, non-trainable fusion rules can outperform more sophisticated trainable ones.
Since the samples belong to an individual iris in current databases are very small in comparison with other databases such as face, using non-trainable combiners like weighted majority voting and label ordering can be found more reasonable and practical than trainable decision combiners. In this paper, we propose a novel intelligent decision combiner based on automatic image quality inspection and compare resultant achievements with common non-trainable decision combiners.

# 4 The Proposed approach

As demonstrated in [4, 12], near infrared and visible light iris images have their own complementary features. Here, we briefly explain these features and relate this issue to decision fusion approach.
Visible light images are widely affected by environmental illuminations and reflections; therefore the performance of such systems basically depends on the lighting conditions. In spite of such shortcoming, a useful property of these images is the capability of preserving fine details and worthful information of iris texture while such property does not exist in the near infrared ones.

In this paper, aforementioned approach is employed in an intelligent decision fusion framework which uses image quality inspection before information obtained from captured images incorporated into decision making process. As depicted in Fig. 1. , for each individual, visible light and near infrared images are captured and then iris segmentation, normalization, and enhancement are performed. Next, the iris texture is portioned into four overlapped regions. The redundant portions are embedded in overlapped regions to increase the consistency between the decisions derived from each region. Furthermore, since UTIRIS database consists of high level noisy images, the information obtained from smaller sub regions will not lead to a correct decision and larger regions consequently result in more reliable achievements. However, if the regions related to a captured image failed to reach a relative consensus on what class label must be chosen, the captured image either visible light or near infrared is considered as a low quality one due to corrupted informative iris regions. Therefore, if a captured image does not satisfy the proposed quality measure, the authentication system will not permit the image to affect the decision making process and throw it out automatically. In the case which both captured images satisfy the quality measure, if the resultant decisions achieved from visible light and near infrared images confirm each other, the final decision will be made undoubtedly. If both captured images are inferred as low quality ones, class scores will be computed based on the predetermined method (here product rule) and then the maximum one will be compared with a predefined threshold. The authentication system assigns a class label provided that the maximum score exceeds the threshold, otherwise, no decision is made, and the image acquisition process is carried out another time. The last case is applicable in practical situations and in our simulations is neglected. It is important to note that one of the major advantages of this intelligent decision combiner over the traditional approaches is to prevent from decision fusion when one of the captured images corrupted by noise or blurred due to user motion during the image acquisition process. This achievement enables us to overcome a very crucial challenge in noncooperative iris recognition. In other words, we relate our proposed approach to noncooperative iris recognition via its ability to deal with noisy and blurred captured images. Unlike popular trainable decision combiners such as dempster-shafer (DS) theory, Fuzzy Integral (FI) and Decision Template (DT), our approach is applicable in domains where due to small training samples, those seem inapplicable.

The proposed approach cannot categorized into a pure classifier fusion or selection categories and can be considered as hybrid one. If the both visible and infrared captured images have similar quality either high or low, classifier fusion using product rule will be performed if not, a classifier selection will be carried out which discards a set of decisions obtained from low quality captured image.

# 5 Preprocessing & Feature Extraction

An iris image contains not only the region of interest (ROI) but also some useful part such as eyelid, pupil etc. So, a captured iris image cannot be used directly.

Prior to extract unique features from the iris texture, three steps must be performed including localization of the iris, image normalization, and ROI enhancement in the iris image. These procedures are called image preprocessing. The preprocessing is described in the following.

- Iris localization: boundary detection (pupil, iris and eyelid) to find the region of interest in iris image;
- Image normalization: converts uniform ROI from different iris scale to a normalized template, which reduces the distortion of iris caused by the variation of the illumination, distance from camera and other factors;
- Iris enhancement: enhances ROI contrast degree for improving contrast of iris features (such as freckles, coronas, strips, furrows, crypts, and so on).

In this paper, our aim is not to focus on preprocessing and feature extraction steps. Here, we briefly explain how image enhancement and feature extraction are performed to provide information fed into classifiers and decision combiners.

After iris localization and normalization, on account of asymmetry of pupil (not being a circle perfectly) and probability of overlapping outer boundaries with sclera or eyelids in some cases and due to the safety chosen radius around pupil, we select 5:250 pixels from 256 along r and 513:1024 pixels from 1024 along $\theta$ in normalized iris. To enhance the contrast of cropped images, histogram equalization followed by wiener filter is carried out.

A two-dimensional adaptive wiener filter is applied to remove high frequency noises and histogram equalization is used to improve the contrast of projected iris. Wiener filter adaptively tailors itself to the local image variance.

Where the variance is large, the filter performs little smoothing. Where the variance is small, it performs more smoothing.

The most important step in human identification system based on iris biometric is the ability of extracting some unique attributes from iris which help to generate a specific code for each individual. In this paper, discrete cosine transforms was used to extract the iris features and to analyze the human iris patterns.

In [13], a new approach to human iris recognition based on the 1D Discrete Cosine Transform (DCT) has been proposed. Their experimental results indicate the good performance of DCT based features on both BATH and CASIA datasets. Although the main application of DCT is in image compression, recently it has been used as a feature extraction method in face recognition [14]. In the following, the main feature extraction algorithm is briefly explained and further details can be found in [13].

At first, the normalized iris texture must be partitioned into several overlapped patches which the sizes in vertical and horizontal directions can be determined using extensive experiments to achieve a higher performance rate. Thereafter, using ¼ hanning window, resolution of horizontal direction is degraded and consequently every patch reduced to a column vector which called 1D patch vector. In order to reduce spectral leakage during the transform, every 1D patch vector is windowed by means of a hanning window. The differences between the DCT coefficients of adjacent patch vectors are then calculated and a binary code is generated from their zero crossings.

# 6 Experimental Results

In this section, at first, we describe our own data collection at the University of Tehran and next, the experimental results on this database are reported.

## 6.1 Data Collection

Recently, in our biometric research team at University of Tehran, we gathered a new database (UTIRIS) consists of two sessions with 1540 images, 770 captured in visible light and 770 in NIR illumination.

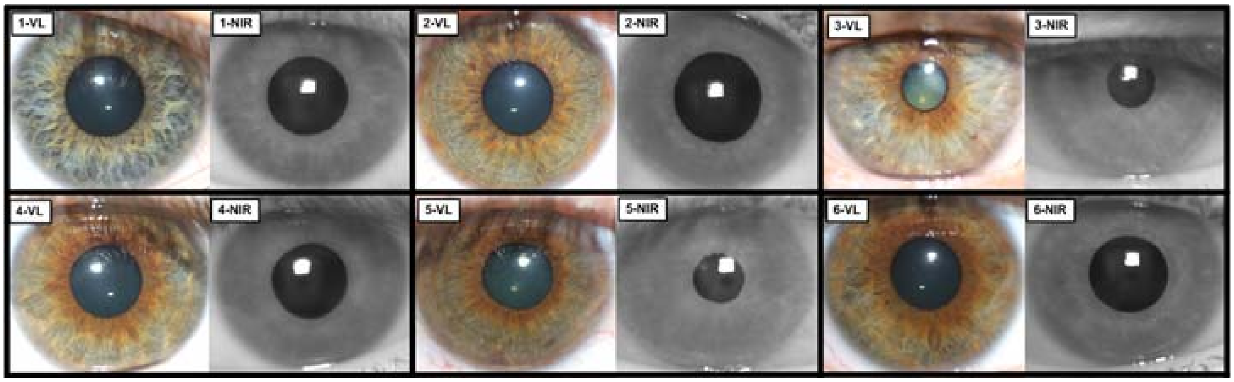


Fig. 2 some samples from UTIRIS database.

Both sessions hold 158 eyes relating to 79 subjects (Right and Left eyes). Images in visible light session have been captured in high resolution with 3 mega pixels where they have been downsampled by a factor of 2 in each dimension to have the same size as near infrared captured images [15]. Despite of high resolution captured images; both visible and near infrared iris images are highly noisy due to focus, reflection, eyelashes, eyelids and shadows variations which make the UTIRIS a challenging iris database. In despite of highly noisy images, it is clear that the UTIRIS can not cover the all aspects of noncooperative iris recognition; but it can be considered as the first iris database which contains VL and NIR images captured from same persons to address the situations where the cooperative behavior is not expected. Fig. 2 shows some samples of UTIRIS database.

## 6.2 Description of Experiments

Among total UTIRIS database, we specifically consider iris images of 114 individuals and evaluate the accuracy of the system in different possible numbers of test and train samples. Although using only one train sample may appear meaningless at first, our aim is to highlight the effectiveness of the fusion approach to improve the obtained results in this configuration based on only visible or near infrared datasets.

Firstly, the performance of DCT Based features [13] was evaluated on both parts of the database separately. Next, to assess our proposed approach, extracted features derived from different regions of visible light and near infrared images are fed to correspondent nearest neighbor classifiers. For each person, the inspection of visible and near infrared iris images is performed, followed by an intelligent decision fusion in next step.

To compare the proposed fusion approach, traditional combining pattern classifiers such as majority voting [16], borda count method [17], maximum rule, minimum rule, and average rule and product rule were employed to combine the decisions obtained from eight nearest neighbor classifiers. In borda count method, only the first ten labels are incorporated into decision making process since in most cases the true class label for each nearest neighbor classifiers is laid in this range. Experimental results as shown in Table 1 indicate the superior performance of proposed decision combiner.

Comparing the fusion results with the cases which only visible light or near infrared images are applied, indicate advantages of decision fusion approaches specially in the small training samples. The later achievement can be found as a practical way to develop human system authentication with low capacity mass storage device.

Although the performance of proposed combiner is more remarkable than the traditional fusion approaches, but it is important to note that even using these approaches a quite considerable improvement is achieved (as depicted in Table1) which implies that the decision combiners can play an important role in authentication system based on iris biometric. In other words, it seems that feature[] and decision fusion approaches are more efficient solutions rather than choosing complex and time-consuming feature extraction processes to achieve a robust and accurate authentication system.

TABLE I
UTIRIS CLASSIFICATION RESULTS USING DIFFERENT CLASSIFIER FUSION APPROACHES

| Fusion Method | Error rate (mean±std.) | | | |
|---|---|---|---|---|
| | Number of Training Samples | | | |
| | 1 | 2 | 3 | 4 |
| Only VL | 14±1.3% | 7. 9±1% | 6.5±.1.1% | 3.6±1.3% |
| Only NIR | 18±2.2% | 8.9±.1.2% | 5.5±1.2% | 4.6±.1% |
| Proposed | 3.7±.7% | 1.4±.6% | 1.2±.7% | 1±.4% |
| Product | 5.7±1% | 2.1±.7% | 1.6±.65% | 1.1±.7% |
| Max | 5.7±1% | 2.6±.6% | 1.8±.4% | 1.2±.7% |
| Min | 27±1.4% | 15±1.6% | 10±1.2% | 8.9±2.5% |
| Average | 5.9±.9% | 2.28±.5% | 1.3±.7% | 1.1±.8% |
| Majority | 16±2.1% | 7.3±.9% | 4.6±1% | 2.9±1.5% |
| borda count | 10±1.4% | 3.54±.7% | 2±.5% | 2.9±1.5% |

By considering the obtained results in Table1, it is observed that increasing the number of training samples lead to a little improvement in recognition rate. This is because a considerable amount of iris images have very low quality or damaged partially with eyelid or eyelash occlusion. After putting out these kinds of occluded and blurred images and using more than two training samples, 100% recognition rate is achieved.

## 7 Conclusion

In this paper, an intelligent decision combiner for iris recognition was proposed. In this method, prior to combine classifiers implemented on overlapped regions, an automatic image quality inspection is carried out to determine whether captured decisions have enough reliability to incorporate into final decision making.

The capability of the proposed method enables the biometric systems to deal with noisy and blurred captured images for identification of the subjects where a cooperative behavior is not expected. Experimental results on the UTIRIS database indicate superior performance of the intelligent decision combiner in comparison with the most common non-trainable decision combiners. The performance of the proposed approach in facing with low quality captured images makes it as a reliable approach toward noncooperative iris recognition.

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