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A NOVEL MULTI-BIOMETRIC IMAGE PRE-PROCESSING USING DYNAMIC CLIP-VALUE BASED IMAGE PRE-PROCESSING TECHNIQUE

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ABSTRACT

Fingerprint, Retina and Iris based Unimodal biometrics contributes a lot in today's information security and unique identification for the process of user authentication in various domains in which the individuality of human beings has to be ensured. However Unimodal systems are not perfect when deployed to real-world applications due to non-ideal conditions such as off-angle gaze, illumination, occlusion and variation in posing. These limitations have led to an increase of research in multimodal biometrics. In recent times, researchers have worked on multimodal biometrics by combining Unimodal templates with different methods with each having to compensate for the shortcomings of the Unimodal systems. In this work present a mash-up biometric recognition strategy that incorporates a new dynamic clip-value based image pre-processing technique (WFI-CLAHE) with a novel amalgamated fusion strategy which employs decision level fusion rules to combine three classifiers based on feature and score level fusion. Here, compare the recognition rate of the proposed method with other existing fusion methods in use. It is shown that the multimodal biometric system based on the proposed mashed-up new pre-processing with a novel amalgamated fusion scheme provides the best performance. The proposed have obtained a recognition accuracy of 99.75%.

Keywords: Multimodal biometrics; Unimodal biometrics; WFI-CLAHE; Score fusion, feature fusion and decision fusion.

1. INTRODUCTION

Biometrics is the computerized process of recognizing individuality of human beings in terms of their physiological traits such as the iris, retina, face, hand geometry, vein and finger print and this has attracted interest in security technology. Biometrics has wide range of applications in various sectors of the economy especially in high risk security areas, with emphasis placed on the accuracy of the system. Fingerprint, Retina and Iris biometrics have become popular over the years but a couple of setbacks have made these Unimodal systems less effective for real-world applications [2], Common problems encountered include: varying illumination conditions, off-angle gaze, occlusion, noise and spoof attacks. Multi-modal biometrics has been identified as one way to overcome most of the shortcomings faced by Unimodal systems. multi-biometric systems can be classified into four categories namely: i) multi-sample that collate different samples of the same biometric trait; ii) multi-instance that collate different instances of traits e.g. using right and left iris images for recognition; iii) multi-algorithm that use two or more feature extraction methods for recognition; iv) multi-modal that combine biometric traits from two or more modalities for recognition [1].

Furthermore, there are two stages in multimodal biometric fusion process which are organized as follows: i) pre-matching fusion ii) post- matching fusion. Fusion methods before matching process are sensor and feature based. While the sensor based fusion involves capturing of images using one or more sensors and then stitching images before matching, the fusion level fusion is carried out by extraction of features from every modality and then the parallel or series level concatenation is applied to obtain single feature vector for the formation of a high dimensional feature vector. In this case feature selection methods are applied to reduce the dimensionality of the feature vector. Post matching fusion methods include the score, rank and decision level fusion [4].

In case of fusion at score level, transformation, density, classification methods are used to combine matching scores obtained from different modalities. Usually the normalization methods such as Z-Score, Min-Max, and Tan h are employed to transfer matching scores obtained from various modalities into a single domain. Matching scores are received as features by classifier based methods which detects whether user is genuine or not. Statistical distribution estimation methods are employed in density based methods that involves combination of scores for making the final decision. Both rank and decision level fusion are under studied in literature due the loss of information during the recognition process. However, decision level of fusion involves combining output labels from different modalities to make a final decision either using Boolean operations or voting rules [5].

In this proposed work an assortment biometric recognition strategy that imbibe a new WFI-CLAHE the image pre-processing technique based on dynamic determination of clip-value with a novel amalgamated fusion strategy which employs decision level fusion rules to combine three classifiers based on feature and score level fusion for an enhanced recognition accuracy. The five feature extraction procedures: modular Principal Component Analysis (mPCA) Local Binary Pattern Histogram (LBPH), sub-pattern Principal Component Analysis (sp-PCA), Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) [2] are applied to each modality (Fingerprint, Retina and Iris) where the first three are local methods and the last two are global methods [3]. Feature level fusion is then performed for each modality on the feature vectors obtained from the five methods to form the first two classifiers. Next to perform weighted score-level fusion using matching scores obtained from LDA for Fingerprint and LBPH for Iris and Retina to form the third classifier. Outputs obtained from each of the classifiers are then fused at decision level using the majority voting rule to obtain the final decision.

The rest of the paper is organized as follows: Section 2discusses related work, the proposed preprocessing method and the local and global feature extraction methods described in Section 3, Section 4 discusses recognition process of fingerprint, retina and iris with normalization methods. In Section 5 discuss feature fusion for fingerprint, retina and iris vectors and score level fusion of global and local features. Section 6presents proposed amalgamated fusion strategy. Section 7 deals with experiments and result and Section 8conclude the work.

2. RELATED WORKS

Yang, W., et al., (2018), proposed a fingerprint and finger-vein based cancelable multi-biometric system, which provides template protection and revocability [14]. The proposed multi-biometric system combines the minutia-based fingerprint feature set and image-based finger-vein feature set. The proposed work develops a feature-level fusion strategy with three fusion options. Matching performance and security strength using these different fusion options are thoroughly evaluated and analyzed. Moreover, compared with the original partial discrete Fourier transform (P-DFT), security of the proposed multi-biometric system is strengthened, thanks to the enhanced partial discrete Fourier transform (EP-DFT) based non-invertible transformation.

Hassan, R., et al., (2017), investigated the effectiveness of image enhancement technique that able to solve the abovementioned issue [15]. A comparative study has been conducted in which three image enhancement techniques namely Histogram Equalization (HE), Adaptive Histogram Equalization (AHE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) were evaluated and analyzed. UBIRIS.v2 eye image database was used as a dataset to evaluate those techniques. The effectiveness of the enhancement techniques on the different distance of image captured was evaluated using the False Acceptance Rate (FAR) and False Rejection Rate (FRR). As a result, CLAHE has proven to be the most reliable technique in enhancing the eye image which improved the localization accuracy by 7%.

Ammour, B., et al., (2020) proposes a new feature extraction technique for multimodal biometric system using face–iris traits [16]. The iris feature extraction is carried out using an efficient multi-resolution 2D Log-Gabor filter to capture textural information in different scales and orientations. In this study, SSA is applied and combined with the normal inverse Gaussian (NIG) statistical features derived from wavelet transform. The fusion process of relevant features from the two modalities is combined at a hybrid fusion level. The best recognition rate is obtained with min-max normalization and max rule fusion, with higher recognition rates up to 99.16% and 99.33% for CASIA-ORL and CASIA-FERET databases, respectively.

Xiong, Q., et al. (2021) proposes to improve the recognition rate of the biometric identification system; the features of each unimodal biometric are often combined in a certain way [17]. However, there are some mutually exclusive redundant features in those combined features, which will degrade the identification performance. To solve this problem, this work proposes a novel multimodal biometric identification system for face-iris recognition. It is based on binary particle swarm optimization. The face features are extracted by 2D Log-Gabor and Curvelet transform, while iris features are extracted by Curvelet transform. In order to reduce the complexity of the feature-level fusion, propose a modified chaotic binary particle swarm optimization (MCBPSO) algorithm to select features. It uses kernel extreme learning machine (KELM) as a fitness function and chaotic binary sequences to initialize particle swarms. After the global optimal position (Gbest) is generated in each iteration, the position of Gbest is varied by using chaotic binary sequences, which is useful to realize chaotic local search and avoid falling into the local optimal position.

3. PROPOSED METHODOLOGY

3.1. The Proposed Image Pre-processing

Pre-processing is needed prior to extracting features from biometric images. In fact, most biometric images are corrupted with noise such as the specular light, light produced by illumination during acquisition. The Wedge Fuzzy Integrated Clip Limited Adaptive Histogram Equalization (WFI-CLAHE) pre-processing method is described below:

WFI-CLAHE presents the spontaneous mechanism that involves dynamic determination of clip-limit for limiting contrast for the output of a better enhanced image. The proposed work employs Wedge Fuzzy Integration (WFI) Function which is capable of calculating the clip limit on the basis of input image characteristics and handles the clipping process very effectively and dynamically. It involves uniform distribution of the clipped region of histogram that exceeds the clip limit among all histogram bins. The upper, lower and mean value of an image pixel intensities belongs to focused window are given as inputs to wedge fuzzy integration function (WFI) which in turn undergoes determination of clipping limit of the image I by calculating the fuzzy number $\mu_I(Pr_\beta)$. There are three arguments named a, b, and c. The value returned by WFI ranges between 0 and 1 and clipping is done accordingly. Those intensity values that exceed the calculated clipping limit are redistributed as in CLAHE, thus resulting in a smoothened histogram. A triangular fuzzy number computed by the membership function is denoted by $T_M = (a, b, c)$. The mathematical formulation of WFI is given by the following equation.

$$\mu_I(Pr_\beta) = \begin{cases} 0 & Pr_\beta < a \\ \dfrac{Pr_\beta - a}{b - a} & a \le Pr_\beta \le b \\ \dfrac{c - Pr_\beta}{c - b} & b \le Pr_\beta \le c \\ 0 & Pr_\beta > c \end{cases}$$

Where the parameters {a, b, c} (with a < b < c) determine the Pr_β coordinates of the three corners of the underlying WFI. Here Pr_β denotes the image dependent clipping parameter. The point b, with membership value of 1, is the mean value and 'a' and 'c' are left hand spread and right hand spread of Pr_β. The WFI-CLAHE algorithm computes the fuzzy clip-limit by using the following equation, thus is a replacement of pre-defined crisp clip-limit with a WFI calculated fuzzy clip limit.

$$WFIclp = \left\lfloor \frac{w}{256} \right\rfloor + \left[\mu_I(Pr_\beta) . \left(w - \left\lfloor \frac{w}{256} \right\rfloor \right) \right]$$

Where $\mu_I(Pr_\beta)$ is the WFI clipping parameter ranging from '0' to '1'. This WFI lets areas of lower local contrast to attain a higher contrast and limits noise in high contrast regions. After computation of clip-limit, the calculation of probability of occurrence of pixel is given as follows:

$$\mathbf{P_{WFI}^{(i)}}=\mathbf{P_{WFI}^{(x=i)}}=\frac{\mathbf{n_i}}{\mathbf{n}},\mathbf{0}\leq\mathbf{i}\leq\mathbf{L}$$

Cumulative Distribution Function (CDF) corresponding to $P_{WFI}^{(i)}$ is given as

$$cdf_{WFI}(x_k)=\sum_{j=0}^{k}P_{WFI}(x_j)\ \ for\ k=0,1,\dots,L-1$$

This becomes the image's accumulated histogram. The transformation function is given by

$$T_{f_{WFI}}(x)=x_0+(x_{L-1}-x_0)cdf_{WFI}(x_k)$$

The resultant of enhanced image EI_{WFI} (i, j) using WFI-CLAHE is as follows:

$$EI_{WFI}(i,j)=T_{f_{WFI}}(x)=x_0=\{T_{f_{WFI}}(x(i,j))|\forall\ x(i,j)\in X\}$$

Where i and j are the co-ordinates of enhanced image.

3.2. Feature Extraction

By not taking the whole image, extraction of features within an image only on a defined sub-region is carried out in this work by the local feature extraction methods. All of the sub-region is extracted one by one by the same procedure. Global feature extraction on the other hand operates on the image as a whole to extract features for recognition. One of the main advantages of using local feature extractors is that features obtained have lower dimensionality and a reduced error rate due to partial illumination that may occur in some parts of the image. Below a description of the two categories of the feature extraction methods.

A. Global methods

1) **Principal component analysis***:* It aims to reduce the total scatter of the centered images in the training set. It minimizes the dimensionality of the training set to a one-dimension vector space. All test images are projected to this space to obtain feature vectors with the same dimension. Matching scores are obtained by finding the Euclidean distance between the feature vector of the test image and feature vectors obtained from the training set [6].

2) **Linear discriminant analysis:** *It* tries to project data into a vector space and magnifies the inter-class variance as well as degrades the intra-class variance [7]. However, it explicitly tries to model the difference between classes in the data. Matching scores are obtained by finding Euclidean distance between the feature vector of the test image and feature vectors obtained from the training set.

B. Local Methods

1) **Local Binary Pattern Histogram:** It involves assignment of a binary value either 1 or 0 to pixels according to the evaluation of pixel values. Pixels with greater value than the centre pixel's value are assigned with binary number 1, all of the other pixels are assigned with 0 [8]. For this purpose, it uses the 8-bit or 16-bit operator on a specific area of the image. The proposed work used the circular LBPH with extended neighborhood. A circle with specified radius is defined within every block in the image in which the sampling points (neighbors) are located at the edge of the circle. Matching scores are obtained by finding the Chi-square distance between the feature vector of the test image and feature vectors obtained from the training set.

2) **Sub-Pattern Principal Component Analysis:** Before performing this analysis at initial, the images are turned as row vectors and subjected to division results in k sub-patterns. And consequently, the analysis is performed on each sub-pattern group of the training set [9]. Matching scores are obtained by computing the average Euclidean distance between the feature vector of a test image and feature vector of images in the training set from each *k* sub-pattern.

3) **Modular Principal Component Analysis:** It involves division of image to form blocks and then application of principal component analysis on the set of blocks [7]. These blocks are converted into row vectors and the number of images in the training set is increased to ($N \times d$). Where N and d are number of blocks and d is the number images in the training set. Matching scores are obtained by finding the Euclidean distance between feature vector of the test image and feature vectors obtained from the training set [9].

3.3. Proposed Amalgamated Fusion Methodology

In our proposed method preferred to amalgamated feature, score and decision level fusion by combining classifiers based on the prior two fusion strategies. The proposed work have applied this process as feature level fusion contains more information about each biometric template and ability of score-level fusion to combine different noise levels from both templates. While decision level fusion has the ability to combine outputs from the two fusion levels [13]. Different decision level techniques have been proposed including maximum, minimum and average voting. The proposed work has chosen to use majority voting technique. In majority voting, each classifier outputs its own class and the class with the highest occurrence amongst all the classifiers is chosen. If there is a tie, then the classifier with the highest matching score is chosen as the identified class as in eq 1. In maximum voting the classifier output with the highest value is chosen as the identified class [18] as in equ. 2.

$$\boldsymbol{H(x) = argmax_{i=1}^{k}(y_i)} \qquad (1)$$

Where y and x are output and input respectively. In average voting involves finding the mean of the output confidence for each class across the entire ensemble. The class highest mean value is identified as the correct class [13].

$$\boldsymbol{H(x) = argmax_{i=1}^{k}\left(\frac{1}{k}\sum_{i}^{k} y_{ij}(x)\right)} \qquad (2)$$

Where y and x are output and input respectively.

7. EXPERIMENTS AND RESULTS

Intel (R) Core (TM) i3-7100U processor with 8 GB RAMS with 64-bit OS, x-64 based processor is employed for the purpose of conducting a well-equipped experiment of proposed methodology. The CASIA Iris Image Database version 1.0, the CASIA Retina Image Database for Testing version 1.0, and the CASIA Finger Image Database version 5.0 are the three databases from which the images for our experiment are acquired The Iris database has a total of 756 images which are captured from 108 eyes with 7 images for each eye. Retina database has a total of 1000 classes with 4 images in each class. The fingerprint database has a total of 500 classes with 400 samples in each of the class.

In order to test the effectiveness of the proposed system at first will compare the recognition rate obtained with it from the individual classifiers and other fusion methods in literature. Results obtained show that proposed method out performs other multi-biometric classifiers shown in table 7.1.

$$\textbf{Recognition Rate \%} = \frac{\textbf{No. of Correctly Predicted Labels}}{\textbf{No. of Tested Labels}} \times 100$$

Table 7.1: - Performance Comparison of Proposed Method with Other Multi-Metric Classifiers

Method	Performance %
Fingerprint fused vector	90.25
Iris fused vector	93.25
Retina fused vector	93.50
Weighted score fusion	98.50
Proposed	99.75

The proposed method performs better than many other feature or score-level fusion techniques because it combines information from three different classifiers using the voting method to make the final decision. While other methods make decision based on either feature-level fusion or score-level fusion.

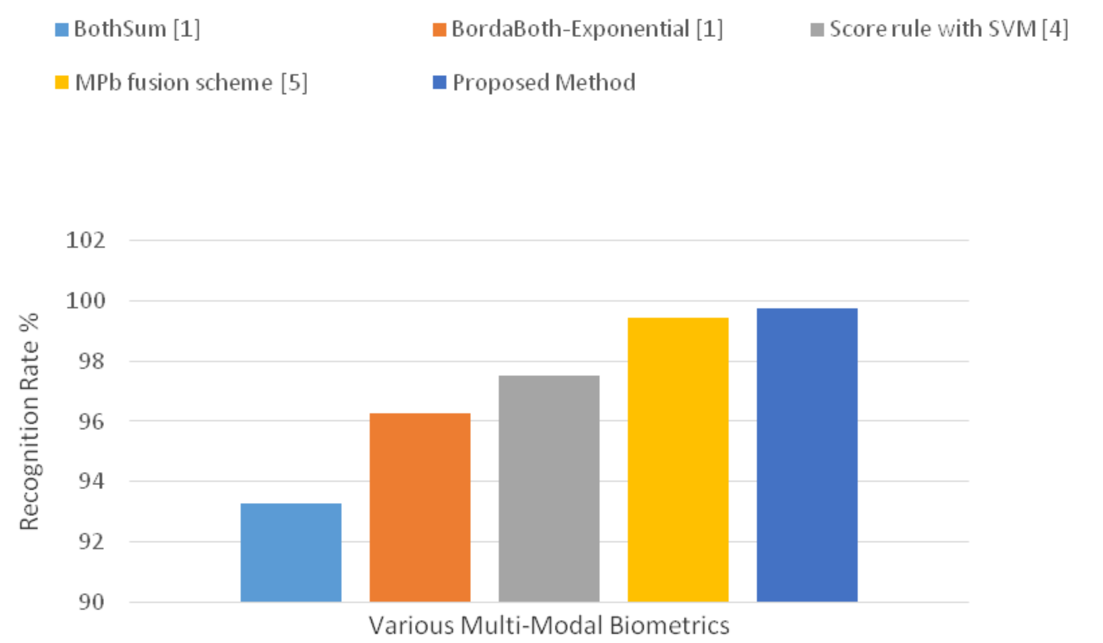

Fig.7.1.Comparison with Various Multi-Modal Biometrics

It is seen from the Fig.7.1. that the proposed mash-up multi-modal biometric system that integrates the novel amalgamated fusion strategy with effective WFI-CLAHE, provides highest recognition rate among various existing multi-modal biometric recognition scheme.

8. CONCLUSION

The proposed work implemented a mashed-up strategy that incorporates amalgamated fusion scheme based on feature, score and decision level of fusion by combining three fusion classifiers with a decision rule with a new WFI-CLAHE based image pre-processing technique. First it used both global and local feature extraction methods on Fingerprint, Retina and Iris biometric template. Then we performed feature-level fusion individually for all the three traits to form the fused Fingerprint, Retina and Iris classifiers. Followed weighted score fusion between LDA method for Fingerprint and LBPH method for Iris and Retina as both produced the highest recognition rate for the individual modalities. It combined three classifiers with a popular decision level fusion rule in order to obtain the final decision. As shown previously, results obtained from the proposed strategy outperform other fusion systems.

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