

Fusion of Multispectral Palmprint Images For Automatic Person Identification using Correlation Filter Classifier

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Abstract—Automatic personal identification has become an important issue in several applications, such as physical buildings and information systems. Nowadays, biometric techniques are an important and effective solution for automatic personal identification and palmprint identification is one of the emerging technologies. This paper presents biometric technique to automatic personal identification system using multispectral palmprint technology. In this method, each of spectrum images are aligned and then used to extract palmprint features using Minimum Average Correlation Energy Filter (MACE) method (for matching). These features are then examined for their individual and combined using the concept of data fusion at matching score level. The experimental results show the effectiveness and reliability of the proposed system, which brings high identification accuracy rate.

Index Terms—Biometrics, Identification, Multispectral, palmprint, MACE, UMACE, PEAK, PSR, Data fusion.

I. INTRODUCTION

Biometrics, which deals with identification of individuals based on their biological or behavioral features, has been emerging as an effective identification technology to achieve accurate and reliable identification results and provides advantages over Traditional personal identification approaches [1] which use something that you know such as PIN, or something that you have, such as an ID card are not sufficiently reliable to satisfy the security requirements which may be faked or cracked [2]. Although no single biometrics is expected to effectively satisfy the requirements of all identification purposes, the use of such unique, reliable, and stable personal features has invoked increasing interest in the development of biometrics-based identification systems for various civilian and forensic applications.

Biometrics is an emerging field of research in recent years and has been devoted to the identification of individuals using one or more intrinsic physical or behavioral traits (also known as traits or identifiers). Among these biometric technologies, hand-based biometrics, including fingerprint, two-dimensional and three-dimensional palmprints, hand geometry or hand shape, finger-vein-print, fingerknuckle-print. These features are relatively stable and the hand image from which they are extracted can be acquired relatively easily. Furthermore, the

identification systems based on hand features are the most acceptable to users. Palmprint identification is one kind of hand-biometric technology and it has proven to be a unique biometric identifier due to its stable and unique traits [3].

Biometric systems based on uni-modal biometrics are often not able to meet the desired performance requirements for large user population applications [4], due to problems such as noisy data, non-university, spoof attacks, and unacceptable error rates. . Therefore, multimodal biometric methods have been developed to overcome those problems, which combine multiple biometric samples or characteristics derived in the hope that the supplementary information between different biometrics might improve the identification performance [5]. The design of a multi-modal biometric system is strongly dependent on the application scenario. A number of multimodal biometric systems have been proposed in literature that differ from one another in terms of their architecture [6], the number and choice of biometric modalities [7], the level at which the evidence is accumulated, and the methods used for the integration or fusion of information [8]. In this paper we use the palmprint images captured under visible light (gray level and color images), the multimodal biometric identification based on feature of color spectrum images are fused at matching-score levels. In this system, we propose to use (Unconstrained) Minimum Average Correlation Energy Filter (U)MACE method (for matching). The iris and palmprint images are used as inputs of the matcher modules. The outputs of the matcher modules {Max peak size or peak-to-sidelobe ratio (PSR)} are combined using the concept of data fusion at matching score level.

The remainder of the paper is organized as follows. The proposed scheme for uni-modal biometric identification system based on MACE filter is exposed in section 2. Section 3 Present the matching technique used. This section includes also an overview of (U)MACE filter. The similarity measurement used is detailed in section 4. The fusion technique used for fusing the information is detailed in section 5, A sections 6 is devoted to describe the evaluation criteria. The experimental results, prior to fusion and after fusion, are given and commented in section 7. Finally, section 8 is devoted to the conclusion and future work.

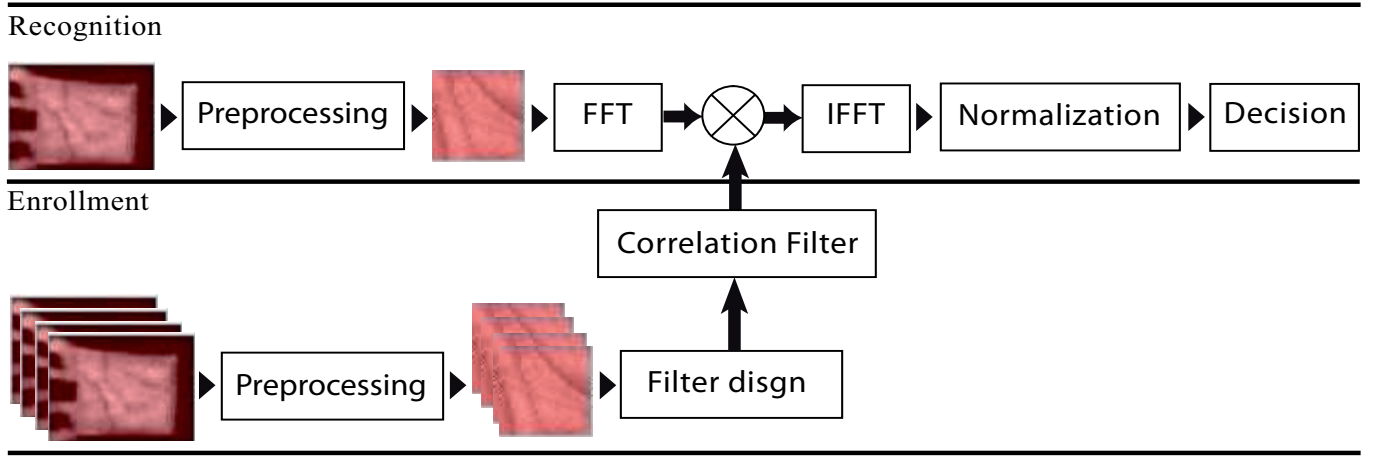


Fig. 1. The block-diagram of the proposed uni-modal biometric identification system based on PCA technique.

II. PROPOSED SYSTEM

The proposed system is composed of two different subsystems exchanging information at matching score level and feature level. Each uni-modal biometric system (for example Fig. 1 show a uni-modal biometric identification system based on one of color spectrum images (RED, GREEN, BLUE and NIR) consists of preprocessing, matching (correlation process), normalization and decision process. the first algorithm identification with correlation filters is performed by correlating a test image transformed into the frequency domain via a discrete Fast Fourier Transform (FFT) with the designed filter (enrollment) also in the frequency domain. The output correlation is subjected to an Inverse Fast Fourier transform (IFFT) and reordered into the dimensions of the original training image, prior to being phase shifted to the center of the frequency square. The resulting correlation plane is then quantified using performance measures (peak-to sidelobe (PSR) ratio or max peak size ratio). Based on this unique measure, a final score matching is made.

III. MATCHING PROCESS

For each class a single MACE filter is synthesized. Once the MACE filter $H(u, v)$ has been determined, the input test image f is cross correlated with it in the following manner:

$$c(x, y) = IFFT\{FFT(f(x, y)) * H^*(u, v)\} \quad (1)$$

Where the test image is first transformed to frequency domain and then reshaped to be in the form of a vector. The result of the previous process is convolved with the conjugate of the MACE filter. This operation is equivalent with cross correlation with the MACE filter. The output is transformed again in the spatial domain. Essentially MACE filter is the solution of a constrained optimization problem that seeks to minimize the average correlation energy while at the same time satisfy the correlation peak constraints. As a result the output of the correlation planes will be close to zero everywhere except at the locations of the trained objects that are set to be correct where a peak will be produced. MACE filter, H ,

is found using Lagrange multipliers in the frequency domain and is given by [9]:

$$H = D^{-1}X(X^*D^{-1}X)^{-1}u \quad (2)$$

D is a diagonal matrix of size $d \times d$, (d is the number of pixels in the image) containing the average correlation energies of the training images across its diagonals. X is a matrix of size $N \times d$ where N is the number of training images and $*$ is the complex conjugate. The columns of the matrix X represent the Discrete Fourier coefficients for a particular training image X_n . The column vector (u) of size N contains the correlation peak constraint values for a series of training images. These values are normally set to 1.0 for images of the same class.

The UMACE filter like the MACE filter minimizes the average correlation energy over a set of training images, but does so without constraint (u), thereby maximizing the peak height at the origin of the correlation plane. The UMACE filter expression, H , is given by [10]:

$$H = D^{-1}X \quad (3)$$

IV. SIMILARITY MEASUREMENT

Typically, the height of this peak can be used as a good similarity measure for image matching (Fig. 5.(a)). Another parameter, PSR, can be used for measuring the similarity between tow samples. PSR is a metric that measures the peak sharpness of the correlation plane. For the estimation of the PSR the peak is located first. Then the mean and standard deviation of the 40×40 sidelobe region (excluding a 5×5 central mask) centered at the peak are computed. PSR is then calculated as follows [11]:

$$PSR = \frac{peak - mean(Slidelobe\ region)}{\sigma(Slidelobe\ region)} \quad (4)$$

$Peak$ is the maximum located peak value in the correlation plane, $mean$ is the average of the sidelobe region surrounding the peak and σ is the standard deviation of the sidelobe region values (Fig. 2.(b)).

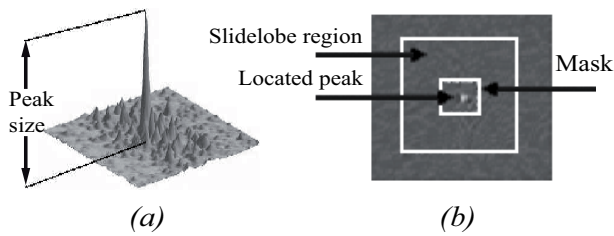


Fig. 2. Similarity matching. (a) Max peak size and (b) Peak-to-sidelobe ratio

V. FUSION PROCESS

Multimodal biometric systems can increase robustness and enhance the accuracy of recognition system, when the information from different modalities are fused. However, in the multimodal system design, these modalities operate independently and their results are combined using an appropriate fusion scheme. Thus the fusion can be performed at different levels [12]. These are: (i) Fusion at the feature extraction level, where the features extracted using two or more sensors are concatenated; (ii) Fusion at the matching score level, where the matching scores obtained from multiple matchers are combined; (iii) Fusion at image level, Image fusion is the process by which two or more images are combined into a single image; (iv) Fusion at the decision level. In this paper we combined the modalities at matching score level. The fusion in score level is realized using four simple rules [13]. These rules consist of the WeighTted-sum (WHT) of the two similarity measures, their MINimum (MIN) and MAXimum (MAX) of both and finally their MULTiplication (MUL). The final decision of the classifier is then given by choosing the class, which maximizes the fused similarity measures between the sample and the matching base.

VI. EVALUATION CRITERIA

The measure of any biometric recognition system for a particular application can be described by two values [10]. The False Acceptance Rate (FAR) is the ratio of the number of instances of pairs of different palmprints found to match to the total number of match attempts. The False Rejection Rate (FRR) is the ratio of the number of instances of pairs of the same palmprint is found not to match to the total number of match attempts. FAR and FRR trade off against one another. That is, a system can usually be adjusted to vary these two results for a particular application, however decreasing one increase the other and vice versa. The system threshold value is obtained based on the Equal Error Rate (EER) criteria where $FAR = FRR$. This is based on the rationale that both rates must be as low as possible for the biometric system to work effectively. Another performance measurement is obtained from FAR and FRR which is called Genuine Acceptance Rate (GAR). It represents the identification rate of the system. In order to visually depict the performance of a biometric system, Receiver Operating Curves (ROC) are drawn. The ROC curve displays how the FAR changes with respect to the GAR and vice-versa [14]. Biometric systems generate matching scores that represent how similar (or dissimilar) the input is compared to the stored template.

VII. EXPERIMENTAL RESULTS AND DISCUSSION

In the identification mode, the biometric system attempts to determine the identity of an individual. A biometric is collected and compared to all the templates in a database. Identification is closed-set if the person is assumed to exist in the database. In open-set identification, the person is not guaranteed to exist in the database. In our work, the proposed method was tested open set identification.

A. Experimental database

To evaluate the performance of the proposed Multimodal identification scheme multi-spectral palmprint database from the Hong Kong polytechnic university (PolyU) [15]. The database contains images captured with visible and infrared light. Four palmprint images for each person, including Red, Green, Blue and near-infrared spectrum, are collected. . These images were collected from 400 persons, each person provide 12 image in two session. In the all experiments three randomly samples, of each plam image is selected to construct the training set (enrollment). The rest of the samples are taken as the test set (identification). Thus, the number of training and test images is 1200 and 3600. Thus, we have a total of 3600 genuine matching and the remaining, 718200, impostor matching.

B. Single spectrum palmprint image

In this section we compare the performance of all spectrum images by applying MACE ,UMACE filters and performance measures PSR and peak matching. From Fig. 3, and Table 1. It can safely be see that the best results in this experiment by applying MACE filter with the PSR measure in different spectrums palmprint image with an EER equal 0.000 %. Thus, the bad result in this experiment if applying UMACE filter and PSR measure. For example, if only the Red spectrums are used, we have $EER = 0,111 \%$ at the threshold $To = 0,629$, PSR. In the case of using the Green spectrums, EER was 0,001 % at $To = 0,991$, the Blue spectrums done an EER equal to 0,012 % at $To = 0,715$, Thus, the bad result in this experiment if UMACE filter and PSR measure, the NIR spectrums done an EER equal to 0,069 % at $To = 0,772$.

C. Multiple spectrum palmprint image

A robust identification system may require fusion of several spectrums (RED, GREEN, BLUE AND NIR) for the reason that the limitation presented in one spectrum may be compensated by another spectrum. Therefore, information presented by different modalities is fused to make the system efficient using fusion at matching score level.

1) *Fusion at matching score level:* At the matching score level fusion, the matching scores output by multiple matchers are integrated. In this step two experiment are done, the first experiment, we fused the Red, Green and Blue spectrums (RGB), in the second experiment, we combined the Red, Green, Blue spectrums and NIR (RGBN). From Table 2, the results demonstrate that in the both experiment the EER are equal 0.000% for all fusion rules. The ROC curve of GAR against FAR for various fusion rules in the both experiment is shown in Fig.4.

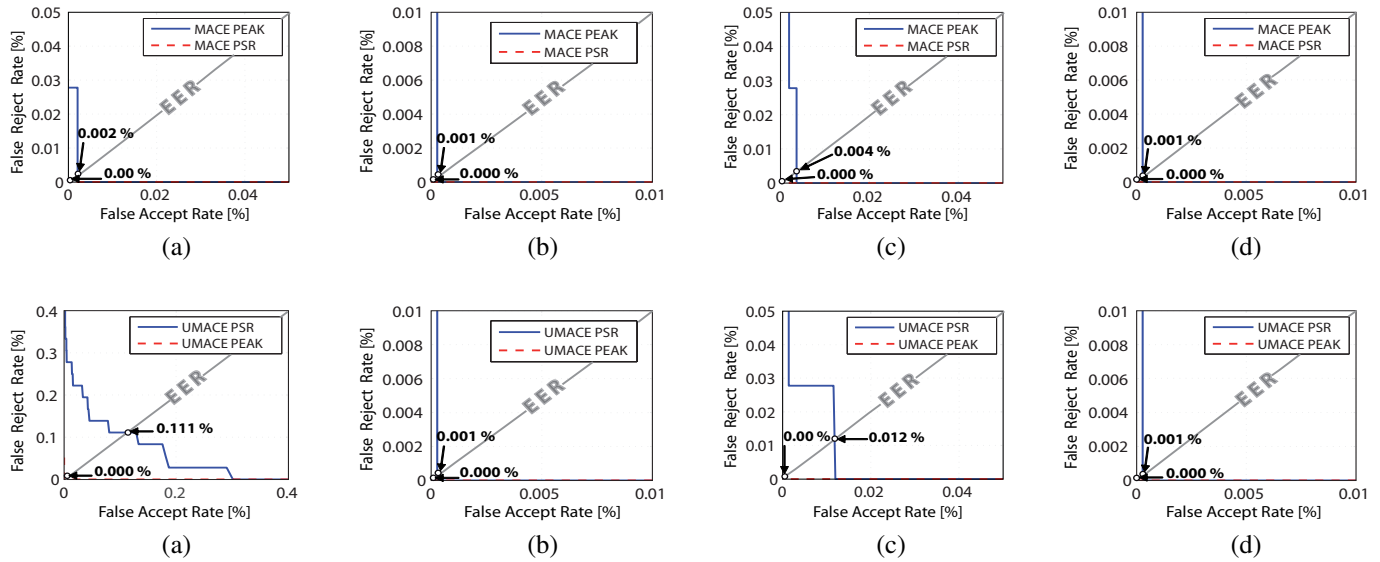


Fig. 3. Uni-modal system identification test results. (a), (b), (c), (d) and (e), (f), (g), (h) ROC curves of spectrum palmprint (RED, GREEN, BLUE and NIR) by applying MACE filter and UMACe filter respectively.

TABLE 1 : UNI-MODAL SYSTEM IDENTIFICATION TEST RESULTS

	MACE				UMACE			
	PEAK		PSR		PEAK		PSR	
	T_0	EER	T_0	EER	T_0	EER	T_0	EER
RED	0.735	0.002	0.855	0.000	0.968	0.000	0.629	0.111
GREEN	0.915	0.001	0.689	0.000	0.821	0.000	0.991	0.001
BLUE	0.765	0.004	0.618	0.000	0.771	0.000	0.715	0.012
NIR	0.774	0.001	0.745	0.000	0.912	0.001	0.772	0.069

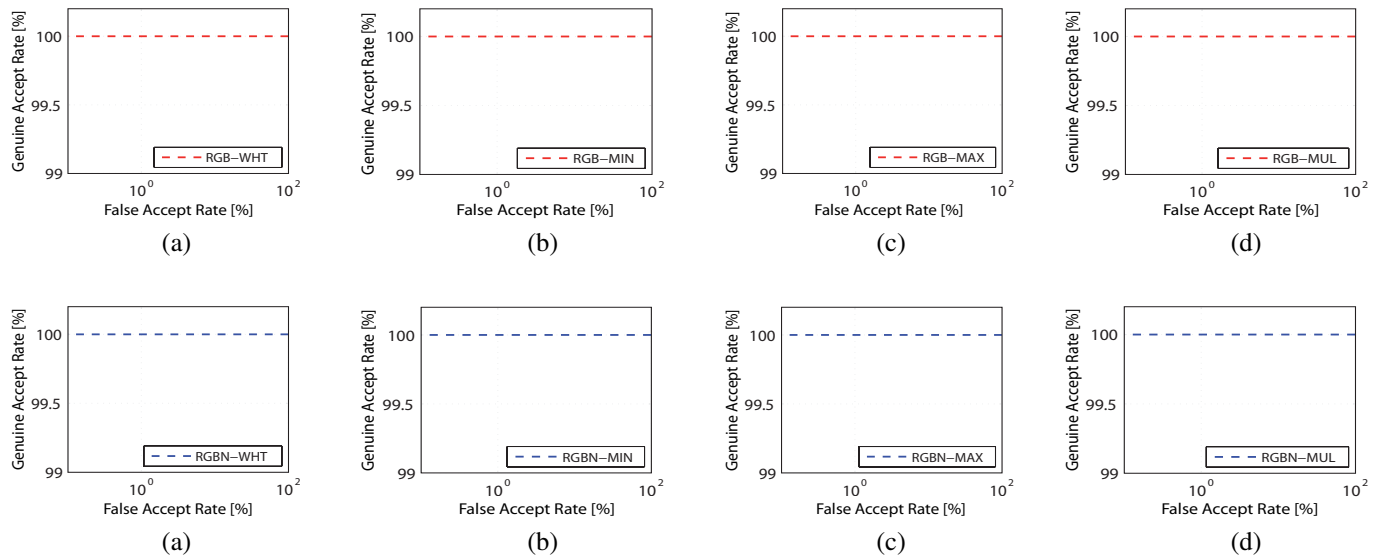


Fig. 4. Multimodal test results of fusion at feature level. (a-d) ROC curves of all fusion rules for RGB, (e-h) ROC curves of all fusion rules for RGBN.

TABLE 2 : MULTIMODAL IDENTIFICATION SYSTEM TEST PERFORMANCE AT SCORE LEVEL

	WHT		MIN		MAX		MUL	
	T_0	EER	T_0	EER	T_0	EER	T_0	EER
RGB	0.528	0.000	0.436	0.000	0.921	0.000	0.147	0.000
RGBN	0.505	0.000	0.391	0.000	0.925	0.000	0.022	0.000

VIII. CONCLUSION

In this paper, a multi-modal biometric identification system based on fusion of palmprint spectrum images, has been proposed. Fusion of these spectrum images is carried out at the matching score level and image level. The proposed system use minimum average correlation energy filter for matching process. To compare the proposed Multiple spectrum palmprint image with Single spectrum palmprint image, a series of experiments has been performed in open set identification and it has been found that the proposed multi-modal system gives a considerable performance gain over the uni-modal systems.

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