Fusion of Multi-Representation Iris Images For Automatic Person Identification

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***Abstract*—The single biometric system may be inadequate for passive authentication either because of noise in data samples or because of unavailability of a sample at a given time. In order to overcome the limitation of the single biometric, a multi-representation biometric are used. In this paper, we propose a multi-representation biometric system for person identification using Iris modality. This work describes the development of a multi-representation biometric personal identification system based on Minimum Average Correlation Energy Filter (MACE) method (for matching) (fisrt algorithm) and 1D Log Gabor filter (second algorithm). The outputs of each algorithm are combined using the concept of data fusion at matching score level. The experimental results showed that the designed system achieves an excellent identification rate and provides more security than uni-modal biometric system.**

***Index Terms*—Biometrics, Identification, Multi-representation, Iris, MACE, UMACE, 1D Log Gabor Filter, Data fusion.**

I. INTODUCTION

Biometrics refers to the technologies that can automate the identification of persons by one or more of their distinct physical or behavioral characteristics. Biometric system is essentially an automatic pattern recognition system that recognizes a person by determining the authenticity of their specific characteristics possessed by that person. Single biometric systems are not perfect and problems like noise in the sensed biometric data, non-universality and lack of distinctiveness of the chosen biometric trait lead to unacceptable error rates in recognizing a person [1]. Some of the limitations imposed by simple modal biometric systems can be overcome by using multi-representation modalities. The multi-representation systems are expected to be more reliable due to the presence of multiple templates security. The design of a multi-representation system is dependent on the application. A number of these systems has been proposed in literature. They differ from one another in terms of their architecture, the number and the choice of the biometric modalities and the methods used for the integration or fusion of information. In this work we proposed a robust multi-representation authentication system. The proposed multi-representation scheme integrates two algorithms identification using the Iris modality. In the first algorithm, the feature vectors are created by using 1D Log-Gabor filter and then compared to the enrollment templates, the matching score is obtained by the hamming distance. The second algorithm use the (Unconstrained) Minimum Average Correlation Energy Filter (U)MACE method (for matching), the outputs of the matcher modules Max peak size or peak to- sidelobe ratio (PSR) are used as matching score. This is referred to as biometric fusion‘[2]. In our method, matching scores from both authentication modules are combined into a unique matching score using fusion at the matching-score level. Based on this unique matching score, a decision about whether to accept or reject a user is made.

The remainder of the paper is organized as follows. The proposed scheme for uni-modal biometric identification system based on MACE filter and 1D Log Gabor Filter is exposed in section 2. Section 3 gives a brief description of the preprocessing process for iris modality. Section 4 and 5 present the matching technique used. 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.

II. SYSTEM DESIGN

The proposed system is composed of two different algorithm exchanging information matching score level. Each algorithm exploits iris modality. Fig. 1 show (the first algorithm) a uni-modal biometric identification system based on Iris modality, 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. Fig. 2 show (the second algorithm) a uni-modal biometric identification system

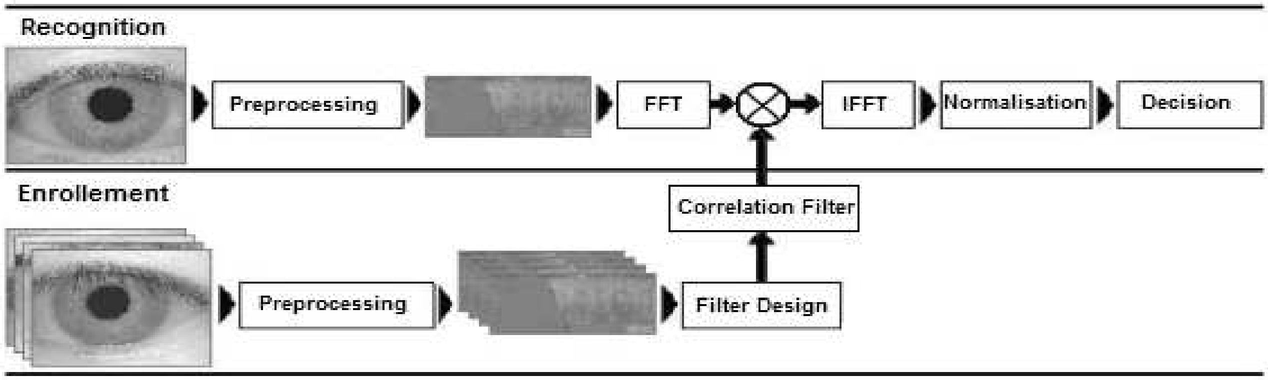


Fig. 1. The block-diagram of the proposed uni-modal biometric identification system based on minimum average correlation energy.

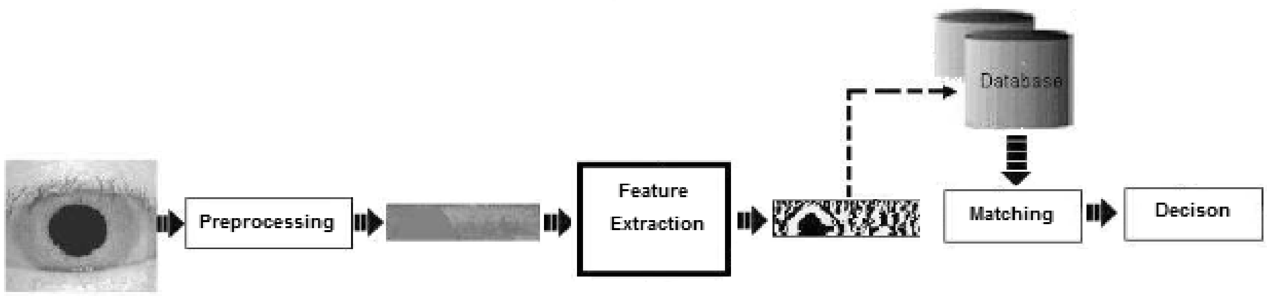


Fig. 2. Block-diagram of a uni-modal biometric identification system based on 1D Gabor Filter.

based on iris modality, consists of preprocessing, feature extraction and matching process. The two score matching from both algorithm authentication systems are combined into a unique matching score using fusion at the matching-score level. Based on this unique matching score, a final decision is made (the user is identified or rejected). This enhanced structure takes advantage of the proficiency of each individual biometric and can be used to overcome some of the limitations of a single representation modality.

III. Preprocessing Process

The iris is the annular region of the eye bounded by the pupil and the sclera (white of the eye) on either side. The iris pattern is a promising biometric characteristic because it is thought to be unique to each eye, with a high degree of discrimination ability [3]. Therefore, the iris pattern is the most important biometric feature candidate, which can be used for differentiating the individuals. Compared to other biometric technique, iris recognition has many merits.

Image preprocessing is a necessary and crucial step in multi-representation authentication system before the feature extraction process. Therefore, the image acquired is prepared for feature extraction.

A. *Iris Preprocessing*

The input eye contained images need to be processed so that the characteristic iris features can be extracted for comparison. During the preprocessing steps [4], the actual iris region in a digital eye image is to isolate. The iris region, can be approximated by two circles, one for the iris/sclera boundary and another, interior to the first, for the iris/pupil boundary. The eyelids and eyelashes normally occlude the upper and lower parts of the iris region.

*1) **Segmentation**:* After the boundaries of both the outer and inner circles are defined, the iris region is then located (Fig. 3). The circular Hough Transform is adopted to search for the boundaries. Eyelids are detected by fitting two lines using the linear Hough Transform, and eyelash is isolated by a simple threshold technique [5].

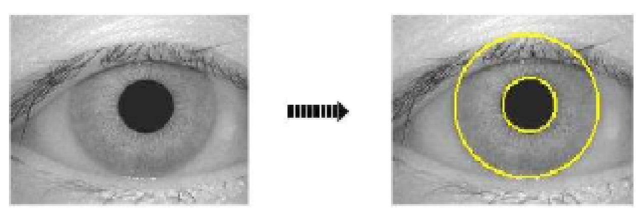


Fig. 3. Image of the eye and its iris segmentation.

*2) **Normalization**:* In order to perform comparison between irises, the segmented iris region needs to be aligned to a fixed size. Normalization is performed using Daugmans rubber sheet model [6], where the circular region is mapped to a rectangular. During the normalization, the center of the pupil is considered as the reference point, while the radial vectors circle through the iris region. The encoding process produces a bitwise template containing a number of bits of information, and a corresponding noise mask which corresponds to corrupt areas within the iris pattern, and marks bits in the template as corrupt. Fig. 4 shows an iris with boundaries, iris normalization, and its mask.

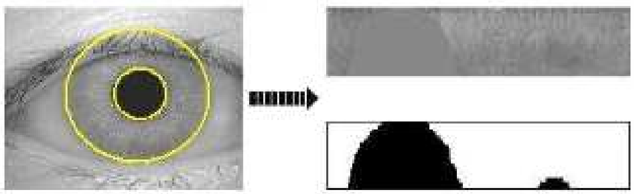


Fig. 4. Image with boundaries (right), iris normalization (top left) and its mask (bottom left).

IV. MACE AND UMACE FILTER IDENTIFICATION BASED SYSTEM

A. *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:

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

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 [7]:

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

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 [8]:

$$H = D^{-1}X \tag{3}$$

B. *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 [9]:

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

$Peak$ 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. 5.(b)).

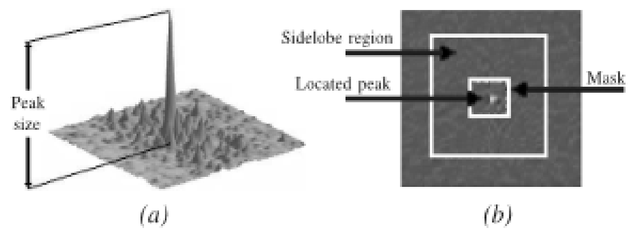


Fig. 5. Similarity matching. (a) Max peak size and (b) Peak-to-sidelobe ratio

V. 1D GABOR FILTER IDENTIFICATION BASED SYSTEM

A. *Feature extraction and encoding process*

The most discriminating information present in an iris pattern must be extracted. Only the significant features of the iris must be encoded so that comparisons between templates can be made. 1D Log- Gabor filter is able to provide optimum conjoint representation of a signal in space and spatial frequency [10]. The features is generated from the normalized iris by filtering the image with 1D Log-Gabor filter.

1) ***Log-Gabor Filter****:* Gabor features are a common choice for texture analysis. They offer the best simultaneous localization of spatial and frequency information. One weakness of the Gabor filter in which the even symmetric filter will have a DC component whenever the bandwidth is larger than one octave [11]. To overcome this disadvantage, a type of Gabor filter known as Log-Gabor filter, which is Gaussian on a logarithmic scale, can be used to produce zero DC components for any bandwidth. The frequency response of a Log-Gabor filter is given as:

$$G(f) = \exp\left[\frac{-(log(f/f_0))^2}{2(log(\sigma/f_0))^2}\right] \tag{5}$$

where f_0 represents the center frequency, and σ gives the bandwidth of the filter. In the experiments, The parameters of Log-Gabor filter were empirically selected as $f_0 = 1/2$ and $\sigma = 0.0556$. are used in all calculation. The ROI sub-images (rows) were unwrapped to generate 1D vector for feature extraction. These signals were convolved with 1D Log-Gabor filter. The resulting convolved form of the signal is complex valued. We then apply the following inequalities to extract binary response templates for both, real and imaginary part.

$$\begin{array}{ll} b_r = 1 & \text{if } Re[\bullet] \geq 0 \; b_r = 0 \text{ if } Re[\bullet] < 0 \\ b_i = 1 & \text{if } Im[\bullet] \geq 0 \; b_i = 0 \text{ if } Im[\bullet] < 0 \end{array} \tag{6}$$

Feature extraction method stores the real and imaginary part in the feature vector.

B. *Matching process*

Feature extraction in our system is based on a binary template derived from the application of log-Gabor filters to the image data and binarized the result. Matching the obtained and the stored features (iris) is based on normalized Hamming Distance between both representations. The Hamming distance algorithm employed also incorporates noise masking, so that only significant bits are used in calculating the hamming distance between two iris templates. Now when taking the Hamming distance, only those bits in the iris pattern that correspond to 1 bits in noise masks of both iris patterns will be used in the calculation [12].

*1) **Hamming Distance**:* Let $T_1[i,j]$ and $T_2[i,j]$ be the two images arrays of size $N_1 \times N_2$ and let M_1; M_2 be their Mask. Then the Hamming Distance (HD) between T_1 and T_2 can be defined as [13]:

$$HD = \frac{\sum_{i=0}^{N_1} \sum_{j=0}^{N_2} M_1(i,j) \cap M_2(i,j) \cap \{T_1(i,j) \oplus T_2(i,j)\}}{\sum_{i=0}^{N_1} \sum_{j=0}^{N_2} M_1(i,j) \cap M_2(i,j)} \tag{7}$$

It is noted that HD is between 1 and 0. for perfect matching, the matching score is zero. When the hamming distance of two templates is calculated, one template is shifted left and right bit-wise and a number of hamming distance values are calculated from successive shifts.

VI. Evaluation criteria

The measure of utility of a palmprint system for a particular application can be described by two values [13]. 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

A. *Experimental database*

To evaluate the performance of the proposed multi-biometric identification scheme, a database containing iris images was required. In this work, we construct a multi-representation database for our experiments based on CASIA Iris database [15]. The multi-representation database consists of six iris images images per person with total of 100 persons. Two samples, of each iris, are randomly selected to construct a training set and the rest of the samples are taken as the test set.

B. *Uni-modal test result*

The goal of this experiment was to evaluate the system performance when we using information from each algorithm. There are a total of 200 training images and 400 test images for each modality, respectively. Therefore, there are totally 400 genuine comparisons and 39600 impostor comparisons are generated. MACE and UMACE filters are applied to evaluate the identification performance for the first algorithm, the PSR and the peak matching are determined. The 1D Log-Gabor filter is applied to extract features and use the hamming distance to evaluate the identification performance for the second algorithm.

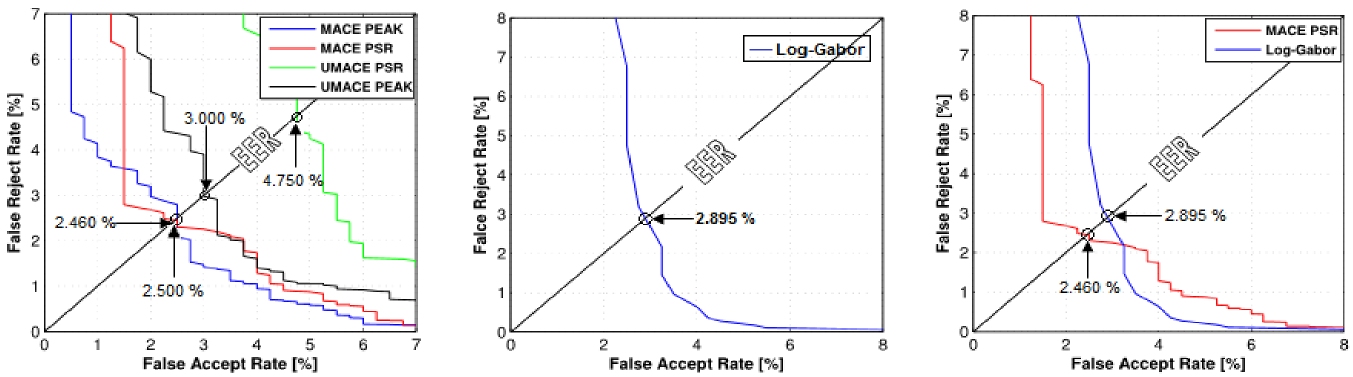
*1) **First Algorithm test result**:* Fig. 6.(a) compares the performance of iris identification system under the two filters (MACE and UMACE) and the two performance measures (Peak size and PSR). The experimental results indicate that the MACE filter and PSR matching perform better result than the other cases in terms of Equal Error Rate (EER). For example, if the MACE filter with peak matching is used, we have an EER = 2.500 % at the threshold To = 0.5079. In the case of using the UMACE filter with peak matching, EER was 3.000 % at To = 0.5560. The UMACE filter with PSR matching done an EER equal to 4.750 % at To = 0.5433. The use of MACE filter with PSR matching improves the result (2.460 % at To = 0.4624) for a database of 100 persons. The system was tested with different thresholds and the results are shown in Table. 1.

*2) **Second Algorithm test result**:* Fig. 6.(b) depicts the performance of iris identification system by using the 1D Gabor Filter. The EER of this experiment is about 2.895 % while the corresponding threshold is To = 0.425.

In Fig. 6.(c), we compare the performance of the two Algorithm. The results show the benefits of using the first Algorithm.

C. *Multi-modal test result*

The goal of this experiment was to investigate the systems performance when we fuse multi-representation information from iris modality. Therefore, information presented by different multi-representation is fused to make the system efficient.

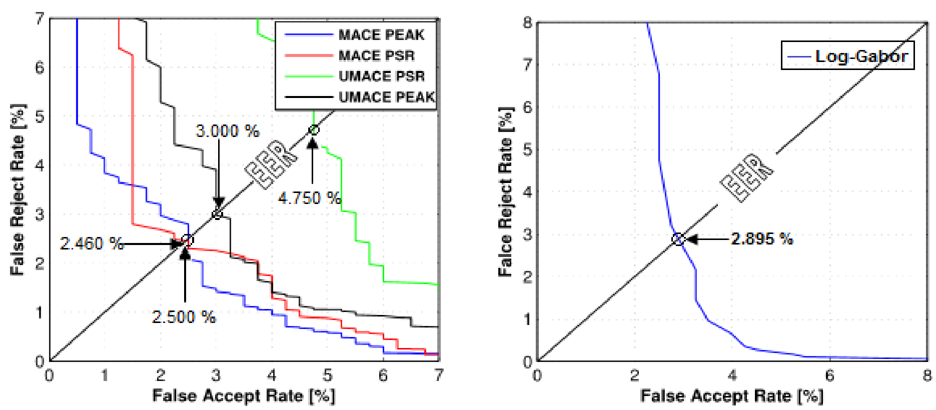


(a) (b) (c)

Fig. 6. Uni-modal open set system identification test results. (a) The ROC curves for the first algorithm, (b) The ROC curves for the second algorithm and (c) Performance comparison.

TABLE 1 : UNI-MODALE IDENTIFICATION SYSTEM TEST PERFORMANCE

MODALITY	MACE						UMACE					
	PEAK			PSR			PEAK			PSR		
	FAR	FRR	GAR	FAR	FRR	GAR	FAR	FRR	GAR	FAR	FRR	GAR
	5.776	0.500	94.278	3.584	1.500	96.473	9.970	0.750	90.123	13.01	2.500	87.100
Iris	2.500	2.500	97.500	**2.460**	**2.460**	**97.713**	3.000	3.000	97.000	4.750	4.750	95.250
	0.669	5.250	99.285	0.462	6.000	99.483	1.053	4.500	98.913	1.482	6.000	98.473



(a) (b)

Fig. 7. Multi-Modal test results. (a) The ROC curves for the fusion at matching score level , (b) The ROC curves for the best system

TABLE 2 : MULTI-MODALE IDENTIFICATION SYSTEM TEST PERFORMANCE

SUM		MUS		MAS		MIS		SWS	
T1	EER	T2	EER	T3	EER	T4	EER	T5	EER
0.4661	2.000	1.760	0.4588	**0.119**	**1.750**	0.781	1.907	0.468	2.009

Fusion at the matching-score level is preferred in the field of biometric recognition because there is sufficient information content and it is easy to access and combine the matching scores [7]. In our system we adopted the combination approach, where the individual matching scores are combined to generate a single scalar score, which is then used to make the final decision. During the system design we experiment five different fusion schemes: Sum-score, Min-score, Max-score and, Mul-score Sum-weighting-score [8]. Suppose that the quantity D_{0i} represents the score of the i^{th} matcher $(i = 1, 2)$ for the txo algorithms and D_F represents the fusion score. Therefore, DF is given by:

- SUm-Score (SUS): $D_F = \sum_{i=0}^{n} D_{0i}$
- MIn-Score (MIS): D_F =min$\{D_{0i}\}$
- MAx-Score (MAS): D_F =max$\{D_{0i}\}$
- MUl-Score (MUS): $D_F = \prod_{i=0}^{n} D_{0i}$
- Sum-Weighting-Score (SWS): $D_F = \sum_{i=0}^{n} w_i D_{0i}$

*1) **Fusion at the matching score level**:* The information presented by two the algorithm is fused at the matching score level to make the system efficient. For that, a series of experiments were carried out to selection the best fusion rule that minimize the EER using the best unimodal result (MACE filter with PSR matching) for the first algorithm and combined with the score matching obtained by the second algorithm. Thus, to determine the best fusion rule, a graphical relationship (ROC) can be established (see Fig. 7.(a)). We can observe that the MAS rule based fusion has the best performance. Thus, the best result of EER is given as $1.750\ \%$. The performance of the identification system is significantly improved by using the fusion. Finally, The performance of the identification system under different fusion rule and a database size equal to 100 is shown in Table 2.

VIII. **CONCLUSION**

In this Paper, we present two algorithms to fuse the information from Iris modality where fusion is performed at the matching score level to generate a unique score which is used for recognizing a Iris image. The features extracted from Iris images are obtained using Minimum Average Correlation Energy Filter (MACE) method and 1D Log Gabor Filter using the multibiometric database for our experiments based on CASIA which consists of Iris images from 100 person. To compare the proposed multi-representation system with the uni-modal systems, a series of experiments has been performed in the two algorithm, and it has been found that the proposed multi-rpresenation system gives a considerable performance gain over the uni-modal systems in the two algorithms. Experimental results also show that these proposed methods give an excellent identification rate.

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