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Analysing Biometric system based on Score Level Fusion of Palmprint and Iris

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Abstract— Biometrics is a highly used technology which is earning research interest for many years due to its applications in access control, identification, forensic investigation, and surveillance. There are typically two types of biometric systems: Unimodal and multimodal, depending on the presence of biometric modality. In this work, due to the inherent advantages of a multimodal system over a unimodal system, a multimodal system is proposed. Two or more biometric modalities, when combined, offer more reliable identification and verification system. Here, palmprint and iris are used in identification due to their high robustness. For feature extraction, we have used three statistical methods: Average absolute deviation (AAD), a histogram of gradients (HOG), and Gaussian membership feature (GMF) over both the modalities. K-nearest neighbor (KNN) classifier is used for matching with Euclidean distance. Finally, the Fusion scheme is employed to compare the unimodal and multimodal biometric systems. Score level fusion is performed using frank T-norm, Schweizer-Sklar, Hamacher norm, and Dubois-Prade fusion rules.

Keywords— Biometrics; Palmprint; Iris; Recognition; Score level fusion

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I. INTRODUCTION

Biometrics is a field of pattern recognition which is used to identify/verify human on the basis of their physiological or behavior traits [1]. Physiological traits are mostly static for many years, such as palmprint, face. They may vary due to aging or tears and scratches. Behavioral traits are not visible traits. They are hidden and can be observed in their own speech; they can be judged through their walking. The use of biometrics in different applications provides users high security, and they do not have to remember their password and personal identification number (PIN). The chance of losing and forgotten the PIN and ID cards motivated the researchers to investigate biometrics [18]. As biometrics using physiological and behavioral traits, so there is no need to keep cards for authentication. No man can forget their palmprint at home. Thereby biometric can be the reliable and easy use of passwords in security. So for a biometric modality, It should persist following properties that are desirable for the good performance of the system:

1. First is a high degree of acceptance: This means the system should clearly identify true and false tests.
2. Robust: System properties should be stable and robust in a sense; they must not vary depending on the presence of noise and disturbance.
3. Minimum Age Effect: The performance of the system should not vary with the age of the individual. However, biometrics modalities are stable within the age of 10-15 years. Beyond this gap, the system may suffer. But to nullify this effect, samples are updated on a continuous gap.
4. Fast and Easy: The system should be fast. It should rapidly capture data from a user. The procedure of taking samples should de easy also. For example-Face scan should be easy and fast; for fingerprints, the scanner should take samples easily and rapidly.
5. No Morphing: Morphing or copying should be difficult for any biometric system.

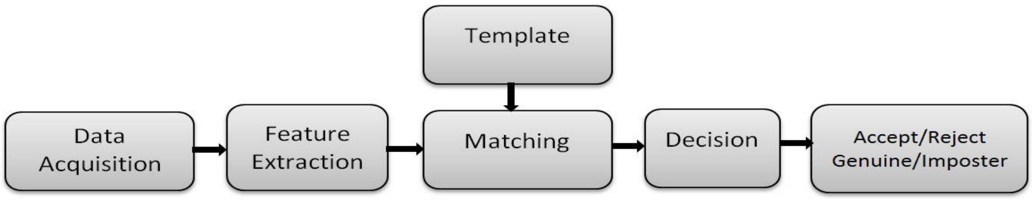

Fig. 1: Block diagram of a biometrics system.

A general biometric system consists of data acquisition to acquire the required database, followed by feature extraction to extract the unique information and then matching and decision making. Block diagram of a biometrics system is shown in Fig. 1. Generally, biometric systems are categorized as Unimodal and multimodal biometric systems. The unimodal system means the presence of one biometric trait, for example, face-print, palmprint, palm-phalanges, gate, hand geometry, dorsal hand veins, retina, and voice. From these biometrics, fingerprint-based biometrics are most common in offices for punching attendance. But these systems are not used in security applications because they do not provide high performance [3]. Palmprint based biometric system is found highly secure and give a high degree of performance [4], [5], [19]. In [19], a 2D Gabor phase encoding scheme is proposed for palmprint feature extraction and representation. Other than palmprint, Iris is also found to be very robust [20]. Also, iris-based biometric systems outperform palmprint, faceprint and give high robustness [2]. M. negin suggested biometric subsystems that identify the person using iris in personal and public locations and found that iris-based biometric systems are highly secure and efficient [17].

Although many biometrics provide good recognition systems, but their performance is affected by the presence of noise, different illumination, and they can be spoofed easily [7]. In [8], the disadvantages regarding unimodal biometrics system is investigated, and different techniques of improving the system performance are also suggested. A study of the biometric system is available in [6], [7], [16].

To guarantee the better potential of the biometric system, multimodal biometric systems are used in the place of the unimodal biometric system. The animals and birds inspire this multimodality to detect the location of their home. These bio-inspired features are used in Multimodal biometric systems. The multimodal system consists of more than one biometric modality. These are created by combining various unimodal systems such as palmprint and hand veins, face and palmprint, etc. Typically, there are four types of fusion strategies that belong to the sensor, classification scores, features, and matching. In sensor-based methods, data is captured from multiple sources and fused. In classification scores or score level fusion method, generally, score in the form of distance (ex.-Euclidian distance) are fused together. There are different methods of score level fusion like Sum, Product, frank T-norm, Schweizer-Sklar, and Hamacher t-norm [9]. In this, Sum and product are the simplest methods. These rules are arithmetic rules. Frank T-norm and Hamacher t-norm are fuzzy based rules. The literature of different fusion methods can be seen in [14, 15].

Here, palmprint and iris are used in identification due to their high robustness. Feature extraction methods used are histogram of gradients (HOG), average absolute deviation (AAD), and Gaussian membership feature (GMF) over both the modalities. Then matching scores are calculated using KNN with Euclidean distance. Finally, score level fusion is performed using frank T-norm, Schweizer-Sklar, Hamacher t-norm, and Dubois-Prade fusion rules. The faster convergence of receiver operating characteristics curves of score level fusion implies the importance of our fusion technique. Along with this, a high identification rate also proves the success of this method.

Various sections are as follows. A discussion of unimodal and multimodal systems is given in Section I. The techniques of feature extraction are explained in Section II. Section III demonstrates the method of score level fusion. Experiment and results are shown in section IV. The paper is concluded in section V.

II. FEATURE EXTRACTION

The technique of withdrawing distinctive information from the data samples by removing the unessential information is referred to as feature extraction. Different feature extraction techniques are investigated in literature [10], [11], [12].

A. Palmprint Feature Extraction

Matching scores are to be calculated from extracted features. To attain a similarity between features, palm samples must have similar postures. For this, pre-processing is required. For palmprint, fingertips can be extracted, which works as key-points—this key-points help in cropping the region of interest (ROI). IIT Delhi database is simulated in this work for palmprint, which contains left and right-hand anterior samples of approximately 230 persons in the age group 14-56 years. This database consists of 5 to 6 samples of each hand. So, 150 people are selected, having 6 samples for the experiments. Database acquisition is based on a contact-less type of scanning system with a digital CMOS camera. This type of system is effortless and highly useful in an office environment. There is no use of pegs for the placement of the hand. Due to this, the hand position is variant. Each sample of any single individual is slightly different. This makes the system more real. In any online system, whenever any individual test the system, a new sample is generated. After this procedure, we extract the ROI from these samples. This procedure is pre-processing, which involves basic steps like binarizing, thinning, cropping, and morphological changes. After cropping the ROI of size 180*180, these ROIs are divided into 100 sub-windows. Then feature extraction of each method is applied to each window.

After completing this step, some equalization is required. There are several methods of equalization in literature. Here we have applied adaptive histogram equalization (AHE). There are several variants of AHE also. The last step is feature extraction. This is the most important step, which removes redundant features keeping important features safe. Our system is mainly based on the comparison of unimodal and Multimodal systems. So we have used simpler feature extraction methods. We have used three types of feature extraction methods. The algorithm for extracting HOGs [13] counts occurrences of edge orientations in a local neighborhood of an image. The other two methods are Gaussian membership function (GMF) [12] and AAD [6]. These are statistical methods, and both are related.

B. Iris feature extraction

Iris is the inner mixed white portion of the eye surrounded by the black pupil. It consists of a unique pattern that is used as a biometric modality for last many decades. In literature, iris biometric recognition systems are found to be very efficient. The data acquisition process is also simple and only need a good quality camera. Although, eyelids sometimes seem to be problematic in ROI extraction. There are several ROI extraction methods for the iris. We have used the IIT Delhi iris database in our analysis. This database consists of 224 individuals, with 176 males and 48 females. Similar methods of pre-processing, enhancement, and feature extraction are used iris as in palmprint given in sec. II-A.

III. SCORE LEVEL FUSION

Score level Fusion is more common and easier than other schemes due to the easy handling of scores that are crisper and allow for easier mathematical testing. These scores are basically distance measures from the test and training vectors. The basic block diagram for this is shown in Fig. 2. This requires pre-processing, feature extraction, matching, and normalization. The final step is fusion. Normalization is an important step that involves scaling of score in a common range. There are different methods of score level fusion like Sum, Product, frank T-norm, Schweizer-Sklar, and Hamacher t-norm [9], [14]. In this, Sum and product are simplest methods. These rules are arithmetic rules. Frank T-norm and Hamacher t-norm are fuzzy based rules. The literature of different fusion methods can be seen in [14, 15]. To normalize the scores, Min-Max score Normalization is used.

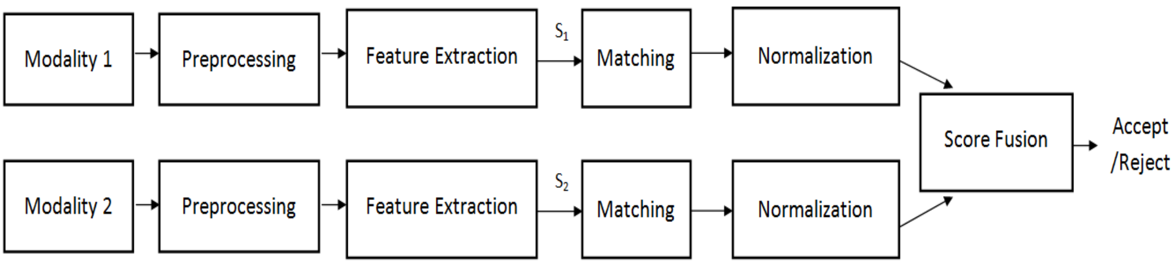

Fig. 2: Score level fusion

IV. EXPERIMENTS AND RESULTS

In this work, multimodal biometric system is designed. Firstly, palmprint and iris recognition is performed using HOG, AAD and GMF feature extraction. Identification results of HOG, AAD and GMF features of IITD palmprint database and IITD iris database is plotted in Fig. 3. With AAD, GMF and HOG, identification results for palmprint are 90.2%, 94.4% and 96.8%, respectively. With AAD, GMF and HOG, identification results for iris are 92.2%, 98.4% and 99.2%, respectively. It is clearly seen that both palmprint and iris identification results are comparable. However, HOG feature extraction outperform the other two methods.

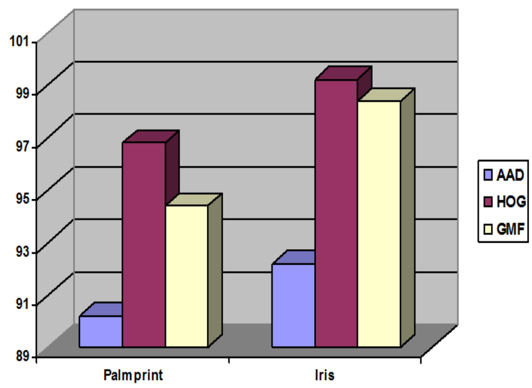

Fig. 3: Identification results of HOG, AAD and GMF features of IITD palmprint database and IITD iris database

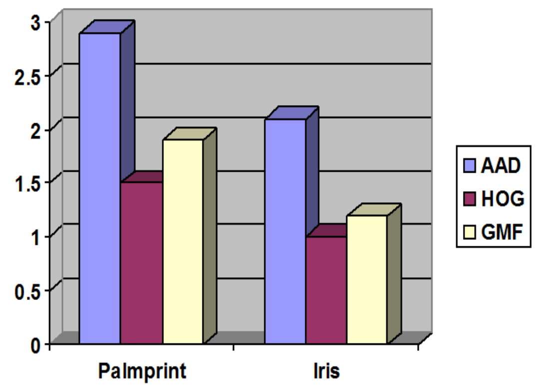

Fig. 4: Equal Error Rate of IITD Palmprint Database and IITD Iris Database

For verification, Equal Error Rate (eer) is chosen as a performance measurement quantity where its lower values show high performance of the system. There are other different methods of verification in literature also [9]. “*EER is calculated where FAR equals FRR. FAR is false acceptance rate, which shows the acceptance of imposters as genuine and FRR is False Rejection Rate which is rejection of true subjects. While genuine acceptance rate (GAR) is ‘100-FRR’*”. Equal Error Rate of IITD Palmprint Database and IITD Iris Database is plotted in Fig. 4. It is again clear here, that HOG has the lowest error rate of 1.01 with iris and 1.5 with palmprint. With AAD, eer is 2.9 and 2.1 for palmprint and iris, respectively. For GMF, eer is 1.9 and 1.2 for palmprint and iris, respectively.

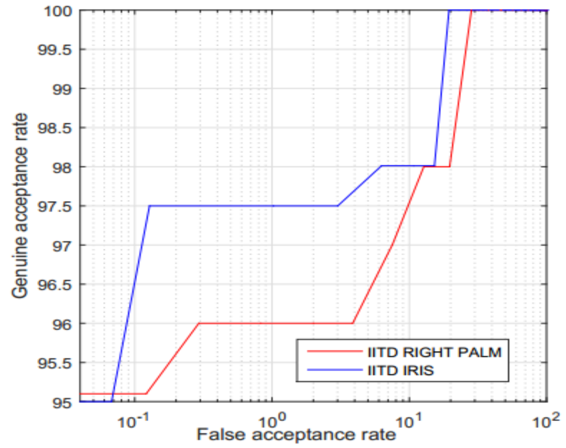

Fig. 5: ROC curves of IITD Palmprint Database and IITD Iris Database

To further evaluate the results of HOG for palmprint and iris, receiver operating characteristics curves (ROC) are drawn in Fig. 5. From the ROC curve, it is seen that iris recognition reaches 100% GAR earlier as compared to the palmprint. From the Table I, at FAR=0.1, GAR is 95.1% and 96.53% and at FAR=1, GAR is 96% and 97.5% for palmprint and iris, respectively.

Finally, eer’s are calculated for score level fusion using frank T-norm, Schweizer-Sklar, Hamacher t-norm and Dubois-Prade fusion rules. Receiver operating characteristics of HOG for both the modalities and their fusion are shown in Fig. 6. It shows that Frank T-norm fusion rule gives better performance to other fusion rules. It is clear from ROC that Frank T-norm fusion converges even more rapidly as compared to other rules.

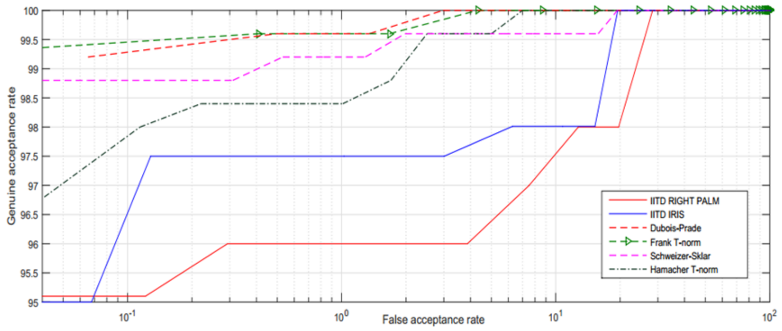

Fig. 6: ROC of score level fusion of IITD Palmprint Database and IITD Iris Database

Table I: Identification results of individual modalities using HOG feature

Rules	Hamacher T-norm		Schweizer-Sklar		Dubois-Prade		Frank T-norm	
False Acceptance Rate (FAR)	0.1	1	0.1	1	0.1	1	0.1	1
Identification results (%)	97.84	98.2	98.8	99.2	99.28	99.6	99.46	99.6

Table II: Score level fusion of IITD Palmprint Database and IITD Iris Database

Modality	False acceptance rate (FAR %)		Identification results
	0.1	1	
Palmprint	95.1	96	96.8
Iris	96.53	97.5	99.2

From Table II, it can be seen that frank T-norm performs better in score fusion rule than the other three. While Dubois-Prade also gives good performance than Hamacher t-norm and Schweizer-Sklar fusion rule.

CONCLUSION

In this paper, it is shown that HOG features perform well with iris and palmprint recognition. Identification results using HOG for iris and palmprint are 99.2% and 96.8%, respectively. However, the performance of these unimodal systems may be improved by fusing them. Here, information fusion is performed by score level fusion to overcome the limitations of the unimodal systems. Through experiments, it is clear that ROC of multimodal fusion converges faster hence outperform the unimodal system. Iris gives very good performance alone, but when it is fused with palmprint, it further enhances the performance. However, HOG feature extraction outperforms AAD and GMF feature extraction methods. It is also clear the iris-based on HOG features can also give modest biometric system. And from score level fusion rules, frank T-norm and DuboisPrade perform better than Schweizer-Sklar, Hamacher T-norm.

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