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Biometric Image Recognition by Fusion of Multiple Parameters with Latest Trends

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ABSTRACT: This research investigates the comparative performance from three different approaches for multimodal recognition. The scores from the different biometric traits of iris, face and fingerprint are fused at the matching score and the decision levels. The scores combination approach is used after normalization of both scores using the min-max rule. Our experimental results expected for the matching scores combinations at the decision level is the best followed by the classical weighted sum rule. The performance evaluation will done for each terms of matching time, error rates, and accuracy after doing comprehensive tests on the various standard Iris databases, Face dataset and fingerprint database. Experimental results will also compare prior to fusion and after fusion with related works in the current literature. The fusion of the human biometric images may be passing through neural network for improved results using train and testing methods.

KEYWORDS: Multimodal Biometric, Neural Network, fusion, Energy efficient algorithm; Manets; total transmission energy; maximum number of hops; network lifetime

I. INTRODUCTION

Biometrics refers to identity verification of persons according to their physical or behavioural characteristics. Many physical body parts and personal features have been used for biometric systems: fingers, hands, feet, faces, irises, retinas, ears, teeth, veins, voices, signatures, typing styles, gaits, odors, and DNA. Person verification based on biometric features has attracted more attention in designing security systems [1]. However, no single biometrical feature can meet all the performance requirements in practical systems [2]. Most of biometric systems are far from satisfactory in terms of user confidence and user friendliness and have a high false rejection rate FRR.

There is a need for development of novel paradigms and protocols and improved algorithms for human recognition. Unimodal biometric systems use one biometric trait to recognize individuals. These systems are far from perfect and suffer from several problems like noise, non-universality ,lack of individuality, and sensitivity to attack. Multimodal biometric systems use multiple modalities to over come the limitations that arise when using single biometric trait to recognize individuals. Multiple biometric systems perform better than unimodal biometric systems. The use of only one biometric trait susceptible to noise, bad capture, and other inherent problems makes the unimodal biometric system unsuited for all applications.

Many works in the literature have demonstrated that the drawbacks of the unimodal biometric systems are mainly genuine and imposters identification failure due to the intra class variations and the interclass similarities, while the drawbacks associated with multimodal biometrics are increased complicity of the system with two or more sensors[2–6]and thus higher cost, as well as inconvenience of using several biometrics. So, identification of person with high accuracy and less complexity of the system is becoming critical in a number of security issues in our society. Iris and fingerprint biometrics are more simple, accurate, and reliable as compared to other available traits. These properties make their fusion particularly promising solution to the authentication problems today. Moreover, fusion of iris and fingerprint is more reliable than fusion of each one with an other biometric like face [7]. However, iris biometric hasmorefeaturesandstabilityandresistancetoattacksthanfingerprint biometric; despite this, the conventional fusion methods still use the same weight in fusion for each single biometric, and this is the reason for why their best error rates are far from perfect. False accept rate identifies the number of times an imposter is classified as a genuine user by the system and false reject rate pertains to misidentification of a genuine user as an imposter. Although ideally both FAR and FRR should be as close to zero as possible in real systems, however, this is not the case [8]. For an ideal

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authentication system, FAR and FRR indexes are equal to0. To increase there lated security level, system parameters are then fixed in order to achieve the FAR = 0% point and a corresponding FRR point[9].

In this paper a novel combination of iris and finger print biometrics is presented in order to achieve best compromise between a zero FAR and its corresponding FRR; in our approach, iris trait has more weight in fusion with finger print and the system decision is made to have more intermediate values between bad and good recognition; the weight is simply an appreciation we assign to the matching distance for each single biometric set by fuzzy membership function andwe use major concepts of fuzzy logic introduced by Zadeh[10] which are fuzzy sets, fuzzy membership function, and fuzzy inference system. The fuzzy inference system mimicsour human thinking and this is mainly the reason we get enhanced results.

II. MULTIMODAL BIOMETRICS SYSTEMS

Multi-biometric systems have five different methods to address problems associated with single biometric systems [52]. Figure 1 show these types

a) Multi sensor: Two or more sensors are used to obtain data from one biometric trait such as fingerprint image with optical and ultrasound sensors and facial image by visible light camera or infrared camera.

b) Multi representation: Several sensors capturing several similar body parts(multi fingerprint image from multi finger but from one person).

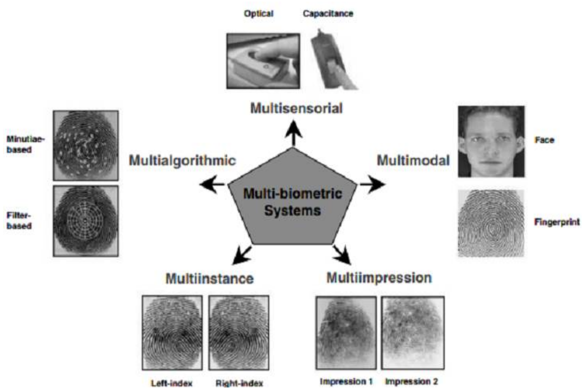

Fig.1.Multimodal types

c) Multi instance: The same sensor captures several instances of the same body part. For example, system capturing images from multiple fingers are considered to be multi-instance.

d) Multi algorithm: Two or more of different algorithms are used for the same trait. Maximum benefit would be derived from algorithms that are based on different and independent principles.

e) Multi modal: It is method that use two or more of different biometric traits which were captured from different sensors and employ them in the variety fusion strategies.

A. *Fusion Strategies*

Many fusion strategies can be executed at different levels as follow:

Feature level: The data obtained from sensor is used to extract the feature vector from one biometric trait which is independent from those extracted from the other; these feature vectors are concatenated to produce a single new vector.

This process is difficult when feature vectors are heterogeneous.

Matching score level: Each system provides a matching score indicating the nearness of the feature vector with the template vector. These scores can be combined to assert the veracity of the claimed identity. While the information contained in matching scores is not as rich as in images or features, it is much richer than ranks and decisions. Further, itis easier to study and implement than image-level and feature-level fusion. It can also be used in all types of biometric fusion scenarios.

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Decision level: Each individual biometric system gives its own binary result. The fusion process fuses them together to outputs single binary decision accepts or reject.

III. RELATED WORK

A. *Parallel Fusion*

The parallel fusion mode has been investigated more intensively and for longer than the serial fusion mode. As early asin 1998, Hong and Jain [11] proposed the parallel fusion mode by using fingerprint and face simultaneously for identification. Since then, many papers concerning parallel fusion have been published. Most of them have focused on the study offusion methods. The currently available fusion methods can be divided into three major classes according to the level where the fusion is conducted. Some methods [12]–[14] combine features of all the biometric traits into a new feature, which are categorized as feature level fusion methods. Some other methods [15], [16] study how to make a final decision based on the recognition results given by all the biometric traits, which are categorized as decision level fusion methods. It has been noticed that to fuse at the feature level is sometimes tricky and even infeasible because of the incompatibility of features; also, to fuse at the decision level would inevitably lose useful detailed information. Consequently, as a com-promise, the majority researches have focused on the score level fusion which combines match scores of all the bio-metric traits to from a final match score [17]–[21]. Further, the score level fusion methods can be roughly classified into transformation based methods where scores are normalized into a common domain and then combined [17], [18], classifier based methods where scores are treated as a feature vectorand a classifier is constructed to discriminate genuine and impostor scores [19], [20], and density based methods whichare based on the estimation of genuine and impostor match score densities [21].

In the investigation of the fusion methods, several specialissues were particularly emphasized. Some works took the diversity of users into consideration and emphasized that user-dependent methods should be applied for better performance. Jainet al.[22] attested that setting the fusion weight and the decision threshold according to user-dependent information can promote the performance of the multimodal biometrics ystems. Uludag et al.[23] then proposed a user-dependent score normalization method and a user-dependent weighting method. Several other works [24]–[27] concerning classifierbased score level fusion were proposed to train differentclassifiers such as PM [24], Bayesian [25] and SVM [26], [27]for different users. In [24], [25], [27], the user-dependentand user-independent information were treated as local andglobal information, respectively. Based on this, methods thatadaptively combine local and global information were usedto achieve satisfactory performance. Besides the emphasisof user diversity, some other works concentrated on thequality of captured biometric traits in the investigation offusion methods. Julian et al. [27] set the fusion weightaccording to the quality of the corresponding trait. Someother works [28], [29] took the use of quantified qualityinformation directly in classifier training. Additionally, someworks [16] and [30] were proposed to choose fusion methodsadaptively according to the performance requirement of theapplication.

Besides, some works investigated how to deal with thegenerally existing intra-class variance problem which resultsin a performance decline in the multimodal biometric systems.Roliet al.[31], [32] proposed the template co-update method.It uses the mutual help of two biometric matchers to update the template of each trait on-line based on the concept of a semi-supervised learning method called co-training. Afterwards, Did aciet al.[33] extended this work to more than two biometric traits. In works [34]–[36], the authors analyzed and testified the effectiveness of the template co-update method empirically. Lately, some works [37], [38] investigated the feature level fusion by exploiting the technique of Multiple Kernel Learning (MKL). Yang et al. [39] proposed a novel supervised local-preserving canonical correlation analysis method to combine fingerprint and finger-vein features at the feature level. Shekharet al.[40] proposed a joint sparse representation of multimodal biometrics by the techniques of MKL and Sparse

Representation (SR), which addressed the difficulties in feature fusion and achieved recognition robustness. Besides fusing multiple main biometric traits, Jainet al.[39]proposed to combine auxiliary information such as gender,ethnicity, height and weight with the main biometric traits ina parallel mode to improve the performance. This auxiliary information is called “soft biometrics”. Many recent workstook use of the soft biometrics and obtained promising results in various applications such as face recognition [40], gaitre cognition [41] and new born recognition [42].

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B. *Serial Fusion*

Works have been published which investigated how to usebiometric traits sequentially for recognition. Zhouet al.[43]designed a serial fusion system in which a subset of candidate identities is provided by a gait matcher at first, anda face matcher is then used to pick the recognized identityfrom the candidate subset. Marcialis et al. [44] proposed aframework for the serial fusion of face and fingerprint traitsin which the acceptance and rejection thresholds for the corresponding matchers are set according to the zero FAR (False

Accept Rate) and the zero FRR (False Reject Rate) values.Further, some works studied how to arrange the processingchain of biometric traits from several different points ofviews. One earliest work was made by Takabashiet al.[45],which applied the sequential probability ratio test to a three-stage biometric verification system (face, iris, voice). Later,Marcialiset al.[46] proposed a model to find the processing chain of two traits allowing a trade-off between therecognition accuracy and the matching time. They extendedthis model to systems with more than two traits in [47].Allanoet al. [48] proposed a method to set the processingchain balancing between the user cost and the recognition performance. Presently, Akhtaret al.[49] studied the robustnessof the system under spoofing attack. They found evidence thatserial fusion multimodal systems may be more robust thanparallel ones.

C. *Serial Multimodal Biometrics Framework*

A novel framework forserial multimodal biometric systems based on semi supervisedlearning techniques given in paper [50]. The proposed framework addresses theinherent issues of user inconvenience and system inefficiency inparallel multimodal biometric systems. Further, it advances theserial multimodal biometric systems by promoting the discriminating power of the weaker but more user convenient trait(s) andsaving the use of the stronger but less user convenient trait(s)whenever possible. This is in contrast to other existing serialmultimodal biometric systems that suggest optimized orderingsof the traits deployed and parameterizations of the correspondingmatchers but ignore the most important requirements of common applications. In terms of methodology, we propose to usesemi supervised learning techniques to strengthen the matcher(s)on the weaker trait(s), utilizing the coupling relationship betweenthe weaker and the stronger traits. A dimensionality reductionmethod for the weaker trait(s) based on dependence maximization is proposed to achieve this purpose.

IV. PROBLEM STATEMENT

Generally the problem of feature analysis can be divided into two sub-problems, i.e. feature representation andfeature selection. Feature representation aims to computationally characterize the visual features of biometric images.Local image descriptors such as Gabor filters, Local Binary Patterns and ordinal measures are popular methods for feature representation of texture biometrics [51]. However, variations of the tun able parameters in local image filters (e.g. location, scale, orientation, and inter-component distance) can generate a large and over-complete feature pool. Therefore feature selection is usually necessary to learn a compact and effective feature set for efficient identity authentication. In addition, feature selection can discover the knowledge related to the pattern recognition problem of texture biometrics, such as the importance of various image structures in iris and palm print images and the most suitable image operators for identity authentication.

V. MULTI-MODAL IMAGE FUSION TECHNIQUES

A. *Simple Average*

T. Zaveri et al. (2009) [53] explained that the image fusion is a process of combining multiple input images of the same scene into a single fused image, which contains important information and obtain the important features from each of the original images and makes it more suitable for human and machine perception. A novel region based image fusion method is explained in this paper which shows that region based image fusion algorithm performs better than pixel based fusion method. Pixel level image fusion methods are affected by blurring effect which directly affect on the contrast of the image. Therefore the paper describes region based method which is less sensitive to noise, better contrast and less affected by mis-registration. The large number of registered images is applied by the proposed

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algorithm and results are compared using standard reference. The proposed method performs well compared to other methods because this method is less sensitive to noise.

B. *Simple Maximum*

Yijian Pei et al. (2010) [54] after studying the principles and characteristics of discrete wavelet framework, explained an improved discrete wavelet framework based image fusion algorithm. The improvement is considered of the high frequency sub band image region characteristic. The wavelet transform based algorithm can obtain less noise than weighted average algorithm. The useful information of each source image is retrieved from the multi sensor, if the algorithm is synthesized effectively. The multi focus image fusion results are more accurate and reliable. Therefore this method can result in less data size, more efficient target detection and situation estimation for observers. The proposed method efficiently fuses the features and information of each image and hence the feasibility of wavelet in image fusion is also verified. The multi focus image fusion experiments and medical image fusion experiments can verify that this proposed algorithm has the effectiveness in the image fusion. This paper illustrated the quality assessment of the image fusion and quantitatively analyzes the performance of algorithms. The proposed method synthetically corrects the quality by the subjective assessment method and the objective assessment method. The assessment result shows that the proposed algorithm can fuse the images information in better performance.

C. *PCA(Principal Component Analysis)*

Patil et al. (2011) [55] has focused on image fusion algorithm using hierarchical PCA. This paper also describes that the image fusion is a process of integrating two or more images of the same scene to get the more informative image. In this paper, the author proposed an image fusion algorithm by combining pyramid and PCA techniques and carryout the quality analysis of proposed fusion algorithm without reference image which can be used for feature extraction, dimension reduction and image fusion.

D. *DWT(Discrete wavelet transform)*

S. Daneshvar et al. (2011) [56] proposed an algorithm that integrates the advantages of both IHS and RIM fusion methods to improve the functional and spatial information content. Visual and statistical analyses show that the proposed algorithm significantly improves the fusion quality in terms of entropy, mutual information, discrepancy, and average gradient compared to the fusion methods including IHS, Brovey, discrete wavelet transform (DWT), a-trous wavelet and RIM. Image fusion has become a widely used tool for increasing the interpretation quality of images in medical applications. The acquired data might exhibit either good functional characteristic (such as PET) or high spatial resolution (such as MRI). The MRI image shows the brain tissue anatomy and contains no functional information. The PET image indicates the brain function and has a low spatial resolution. Hence, the image fusion task is carried out to enhance the spatial resolution of the functional images by combining them with a high resolution anatomic image. A perfect fusion process preserves the original functional characteristics and adds spatial characteristics to the image with no spatial distortion. The intensity-hue-saturation (IHS) algorithm and the retina-inspired model (RIM) fusion technique preserves more spatial feature and more functional information content respectively.

E. *Combine of DWT, PCA*

Phen-Lan Lin et al. (2011) [57] proposed two fusion methods, IHS&LG+ and IHS&LG++, based on IHS and log-Gabor wavelet for fusing PET and MRI images by choosing suitable decomposition scale and orientation for different regions of images in the first method, and refining the fused intensity of the first method to further reducecolor distortion and enforce the anatomical structure in the second method. This methods use the hue angle of each pixel in PET image to divide both PET and MRI images into regions of high and low activity. The fused intensity of each region is obtained by inverse log-Gabor transforming of high frequency coefficients of MRI intensity and low frequency coefficients of PET intensity-component. The experiments are performed on three sets of normal axial, normal coronal, and Alzheimer's disease which demonstrate that all three images fused by IHS&LG+ are with less color distortion and about the same structural information as the images fused by IHS&RIM, and all three images fused

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by IHS&LG++ are with both color and anatomical structural information closest to PET and MRI images both visually and quantitatively.

F. *Combination of Pixel & Energy Fusion rule*

Prakash et al. (2012) [58] explained that the image fusion is basically a process where multiple images are combined to form a discrete resulting fused image. This fused image is more active as compared to its original input images. The fusion technique in medical images is useful for ingenious disease diagnosis purpose. This paper illustrated different multi-modality medical image fusion techniques and their results are assessed with various quantitative metrics. CT and MRI-T2 are taken as input and then the fusion techniques are applied to the input images such as Mamdani type minimum sum mean of maximum (MINSUM-MOM) and Redundancy Discrete Wavelet Transform(RDWT) and the resultant fused image is analyzed with quantitative metrics such as Overall Cross Entropy (OCE), Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio(SNR), Structural Similarity Index(SSIM), Mutual Information(MI).In this paper the authors proved that Mamdani type MIN-SUM-MOM is more productive than RDWT.

G. *IHS fusion(Intensity Hue Saturation)*

MaruturiHaribabu et al. (2012) [59] proposed a new approach for PET- MRI image fusion by using the wavelet and spatial frequency method. In the proposed method the influence of image imbalance is eliminated and blurred the phenomenon of fusing image, improved the clarity and provided more reference information for doctors. The result shows that the performance of the proposed method is superior to the traditional algorithm based on PCA in terms of good visual & quantitative analysis fusion results.

H. *RIM(Retina Inspired model)*

Desale et al. (2013) [60], explained the Formulation, Process Flow Diagrams and algorithms of PCA (Principal Component Analysis), DCT (Discrete Cosine Transform) and DWT based image fusion technique. The PCA & DCT are conventional fusion techniques with many drawbacks, whereas DWT based techniques are better as they provides better results for image fusion. In this paper, the authors proposed two algorithms based on DWT called pixel averaging & maximum pixel replacement approach and their results are compared accordingly.

I. *Combination of IHS & RIM*

PhenLan Lin et al.(2014) [61], proposed a new method based on PET and MR brain image fusion based on wavelet transform for low and high activity brain image regions respectively. The proposed method can generate very good fusion result by adjusting the anatomical structural information in the gray matter (GM) area, and then patching the spectral information in the white matter (WM) area after the wavelet decomposition and gray-level fusion. A novel adjustment for the pixel intensity in the non-white matter area of high-activity region in the graylevel fused image will bring more anatomical structural information into the final color fused image. Spectral information patching in the white matter area of highactivity region will preserve more color information from PET image for the white-matter area. The fusion results are compared based on the performance metrics – spectral discrepancy (SD) and average gradient (AG).

Table 1. Comparison of Various Fusion Techniques

Sl. No:	Fusion Technique/Algorithm	Domain	Advantages	Disadvantages
1.	Simple Average	Spatial	Simplest method of image fusion.	Does not give guarantee to have clear objects from the set of images.
2.	Simple Maximum	Spatial	Highly focused image output obtained from the input image as compared to average method.	Affected by blurring effect which directly affect on the contrast of the image.
3.	PCA(Principal Component Analysis)	Spatial	Transforms number of correlated variable into number of uncorrelated variable.	Produces spectral degradation.
4.	DWT(Discrete wavelet transform)	Transform	Minimize the spectral distortion. Also provides better signal to noise ratio than pixel based approach.	Final fused image have a less spatial resolution.

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5.	Combine of DWT, PCA	Transform	Multi level fusion provides improved result and also the output image contains both high spatial resolution with high quality spectral content.	Complex in fusion algorithm.
6.	Combination of Pixel & Energy Fusion rule	Transform	Preserves boundary information and structural details without introducing any other inconsistencies to the image.	Complexity is more.
7.	IHS fusion(Intensity Hue Saturation)	Transform	Produces fused and enhanced spectral image. Also produces high spatial intensity images.	Spectral distortion is considerable.
8.	RIM(Retina Inspired model)	Transform	Preserves more spectral information than other conventional fusion methods.	Introduces spatial distortion into the resulting image.
9.	Combination of IHS & RIM	Transform	Produces a smooth combination of spectral and spatial features and also generates high resolution color image.	Some anatomical structural information in the gray matter (GM) area of the high-activity region is lost.

VI. PROPOSED WORK

The different stages of our multimodal biometric system are being shown in figure (2); these stages are executed as follow:

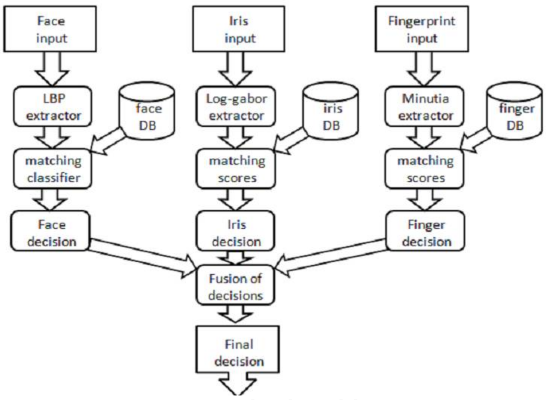

Fig.2. Proposed multimodal stages

Acquisition Images: In this stage fingerprint, iris and face image are captured by appropriate sensor for each trait then the three images are saved to be the input in next step.
Feature Extraction: This is the second stage where three feature extraction algorithms are presented to extract and formthe feature template. Minutia-based algorithm are applied to extract feature from finger image, Daugman algorithm with 1D log-Gabor filter for iris template extraction and Local Binary Pattern (LBP) to extract feature from face image.
Matching scores: Each extracted template is matched with the corresponding templates in the database. An alignment-based match algorithm is used as fingerprint matcher who determines the similarity between fingerprint templates, Hamming distance HD is applied for iris matching stage to give the dissimilarity between iris images and Chi square forface matching process which introduces the dissimilarity between face images.
Decision: Each subsystem will produce two decision values low or high based on predefined threshold.
Fusion: In this stage the resulting decisions from the previous stage are fused by Fuzzy logic and weighted fuzzy logic, and then unary decision will be out to determine the matching degree between client and individuals in database.

VII. CONCLUSION

This paper explains the different related works based onfusion techniques used for multimodal medical images.The various fusion techniques, their advantages anddisadvantages are discussed. The comparative analysis ofimage fusion techniques allows in selecting the best fusionmethod and therefore one can obtain better visualization ofthe fused image

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