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Multimodal Biometric Authentication Parameters on Humanbody

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Abstract

An essential feature of Multimodal Authentication Systems of biometric parameters in human body is categorized into two major set. These two set of biometric factors are analyzed in many effective research work .Also, a first and most important issue is that different applications and services employ each its own authentication method and use different credentials. In majority of application, the authentication is base on the principle of checking "What the user Knows". Face and hand are two supersets which is used for authentication in our human body. Such like supersets are guaranteed by limiting in time complexity and space validity. Biometric system relies on person's behavioral and/or physiological characteristics as an alternative means of person authentication (traditional means being password, smart card, ID etc.). However, biometric system based solely on a single biometric may not always meet security requirements. Thus various number of biometric systems are emerging as a trend which helps in overcoming limitations of single biometric solutions, such as when a user does not have a quality sample to present to the system and reduces the ability of the system to be tricked fraudulently. A reliable and successful biometric system needs an effective fusion scheme to integrate the information presented by multiple matchers. In this research, we integrate results of different mono modal biometric matchers (face, ear ,iris,hand and foot) with the logistic regression approach of rank level fusion method. In this approach, not only the outcomes of the these mono-modal matchers are considered, but also their effectiveness, based on previous research, are also considered for final rank aggregation. Here we are going to prove that an encapsulating system can provide better performance for the day today customer needs.

Key Words- Multimodal Biometric system, Fusion, Logistic regression, Biometric identification , Biometric authentication .

1.Introduction:

An essential feature of new applications services employ each its own authentication method and use different credentials. In the majority of applications the authentication is based on the principle of checking "What the user Knows", the user simply use pins, usernames and password which are difficult to remember. If they are so simple that can be kept in mind.

It's a given that biometric technologies can be combined to provide enhanced security. This combined use of two or more biometric technologies in one application is called a multimodal biometric system. A multimodal system allows for an even greater level of assurance of a proper match in verification and identification systems. Multimodal systems help overcome limitations of single biometric solutions, such as when a user does not have a quality sample to present to the system and reduce the ability of the system to be tricked fraudulently [2].

Various biometric systems have been developed for governmental and commercial applications. Most of these systems can verify, 1-to-1 match or identify a person in a small database, 1-to-many match. Real time large-scale identification is still a challenging problem in terms of matching speed and accuracy. Of existing biometric technologies Iris Code developed 1993 and continuously improved by Daugman [1]–[3] is able to identify a person in an extremely large database in real time. In the last few years authentication has become of paramount which importance both on corporate internet and on the global web. The assess right of a person has been faced with two different approaches. Biometric identification and biometric authentication. Biometric identification and biometric authentication are differentiated as follows :biometric identification occurs when an individual provides a sample biometric which sometimes without any additional knowledge the system must compare that sample with every stored record to identify a match. This is known as a one-to-many match ,and executed without any corroborating data. By contract ,biometric authentication occurs when an individual present a biometric sample and some additional identifying data, such as a photograph or password, which then compared with the sample for that individual. biometric authentication provides some inherent advantages as compared to other non-biometric identifiers .since biometric correspond to a direct evidence of personal identity versus possession of secrets which can be potentially stolen .Moreover, most of the times the biometric enrollment is executed in-person an in controlled environments making it very reliable for future use. Both engines try to check the user's credentials before granting access to computer system. In some issues related to strong biometric authentication methods are still unsolved. In this paper we analyze the potentiality of multimodal authentication for the user based on two super set of parameters of human body .Face and hand has a set of biometric parameter which is used for authentication.

Biometric method is recognizing a person based on a physiological or behavioral characteristic. Biometric technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions. Examples of physiological characteristics include handor finger images, facial characteristics, ear shapes, iris or retina characteristics etc. Behavioral characteristics are traits that are learned or acquired. Signatures, voice, keystroke, gait pattern etc. are example of behavioral characteristics.

Multiple biometrics could also involve multiple instances of a single biometric, such as, two fingerprints, two hands or two eyes.A reliable and successful multibiometric system needs an effective fusion scheme to combine the information presented by multiple matchers. The goal of fusion is to determine the best set of experts in a given problem domain and devise an appropriate function that can optimally combine the decisions rendered by the individual experts [4]. Evidences in a multibiometric system can be integrated in several different levels, such as, sensor level, feature level, match score level, rank level and decision level. Among all of the above fusion approaches, fusion at the sensor, match score, feature and decision levels have been extensively studied in the literature. Fusion at the rank level, however, is a new and significantly understudied problem [5], which has a high potential for efficient consolidation of multiple matcher's outputs. Many multimodal biometric systems with various methods of fusion and strategies have been proposed over the last decade to achieve higher accuracy performance from the multibiometric systems. However according to our literature review, very few of these research concentrated on rank level fusion methods for combining multiple biometrics. Our aim in this paper is to combining different biometric matchers (iris, ear, face, hand and foot) using rank level fusion to increase the performance and reliability of a human authentication system.

2. Research motivation

From the last decade, several approaches have been proposed and developed for multimodal biometric authentication system. In 1998, a bimodal approach was proposed by L. Hong and A. K. Jain for a PCA-based face and a minutiae-based fingerprint identification system with a fusion method at the decision level [6]. In 2000, R. Frischholz and U. Dieckmann developed a commercial multimodal approach, BioID, for a model-based face classifier, a VQ-based voice classifier and an optical-flow-based lip movement classifier for verifying persons [7]. In 2003, J. Fierrez-Aguilar and J. Ortega-Garcia proposed a multimodal approach including a face verification system based on a global appearance representation scheme, a minutiae-based fingerprint verification system and an on-line signature verification system based on HMM modeling of temporal functions, with fusion methods, sum-rule and support vector machine (SVM) user-independent and user-dependent, at the score level [8].The LSB method is used in my paper[4] the security method usimg the biometric parameter fingerprint. In the same year, Wang and others proposed a multimodal approach for a PCA-based face verification system and a key local variation-based iris verification system, with fusion methods at the matching score level by using un-weighted and weighted sum rules.Aiming at the same issue, i.e., to reduce false acceptance and false rejection error rates, we fill the niche and develop a multibiometric system incorporating three unimodal experts for face, ear and iris. As, our main issue in this work is the fusion method, so, we use three established matching approaches for the three biometric traits. We can use neural network for face, eigenimage for ear and Hamming distance for iris. The multi monomodal matches are discussed below,

A. Hand-geometry-based systems

The human hand provides the source for a number of physiological biometric features; the most frequently use the fingerprint, the palm print, the geometry of the hand and the geometry of fingers[9].

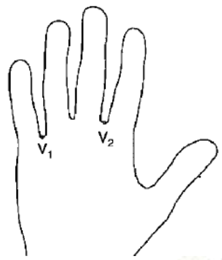

Fig 1

The Fig 1.Extracted contours of the hands showing the two reference points (V1 and V2).The two reference points are selected from the hand geometry,
(i) The valley between the little finger and the ring finger (point V1), and
(ii) The valley between the index finger and the middle

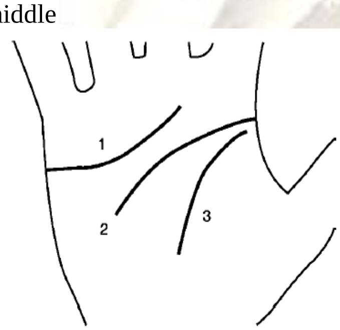

Fig 2.Principal lines of a palm 1. heart line; 2: head line; 3: life line

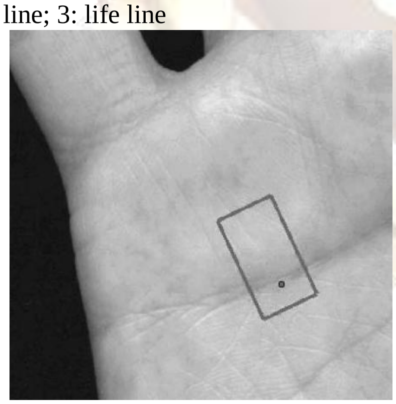

Fig. 3 segment of the heart line.

we were not able to obtain satisfactory results. finger (point V2).Point V1 is used to determine a subregion (120 × 60 pixels) of the palm where a segment of the heart line (Fig.2) can be detected.
Table 1: FAR(false acceptance rates) and FRR results for the proposed system . Since systems based on finger characteristics provide low

	F	H	P	F–H	H–P	F–P	F–H–P
FAR	0.00	15.30	3.80	0.00	1.22	0.00	0.00
FRR	1.20	13.00	1.40	1.15	1.10	0.30	0.20

Table -1
F: finger-geometry features;H:hand-eometry features; P:palm-print features.Data given in percentage

B. Fingerprint

In order to measure the sensor performance we have three different commercial minutia extractor for the feature extraction:
i) Neurotechnology, Veringer 6.0
ii) TST Biometrics, Basic SDK 2.1
iii) NIST, NIST2 SDK

All of the above mentioned SDKs includes functionality to extract a set of minutiae data from an individual .Finger print image and compute a comparison-score by comparing one set of minutiae data with another. The image processing of obtaining the templates can be found in the each SDK documentation report. In my paper[4] the data embed in the ridges that produce a better result than the other authentication systems.

Fig.3.Fingerprint image using optical sensor/Line sensor

C. Nails Factor

The nails on the finger should also be taken into consideration while studying about the hand. Ordinarily, these nails are at the tip of the fingers and help in protecting the fingers. The function of nails from the scientific point of view is to protect the tips of fingers so that the fingers do not get damaged or hurt by a blow from outside[10].The nail biometric can be use as secondary level of authentication factor.

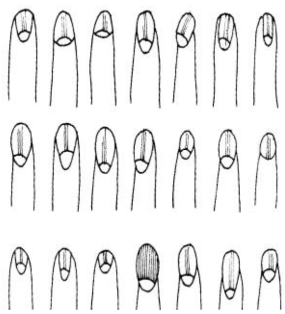

Fig 4.Different Types of Nails

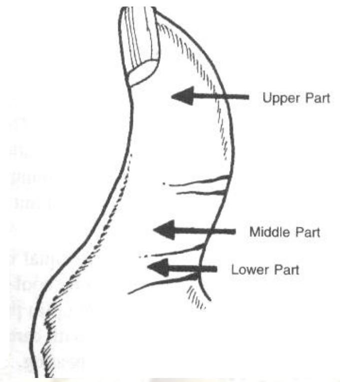

Fig 5.Thumb as of paramount importance
Main Parts of a Thumb

D. Face Matcher

For the face matcher, we use holistic approach (all parts of the face images are used for training and recognition purposes). One of the most widely used representations of the face region which uses this approach is Eagan face [11], which is based on principal component analysis. Another approach is using neural network which is used in this work.

Global features of a face are used in this system. But as all the images in the database (FERET) [12] that we use in this system are in the size of 256x384 pixels, a neural network with 98304 (256x384) input nodes would be very large and time consuming and would need large scale memory for training and recognition purpose. For this, we employ pixel minimization technique, which is a very effective way to improve the network performance.

Since we are working with gray scale image whose pixels values are in the range 0-255, input images are normalized in the range of value 0-1. Higher value in the input node of a neural network causes difficulties in convergence. Transfer functions or adaptive functions do not except higher range of value. So the pixel values of the original images are converted into normalized images by dividing all the pixel values by 255, since 255 is the highest value of gray label. Normalized function [12] can be described by following equation –

$$I_{norm} = I/255 \qquad \text{- - - -(1)}$$

After normalize the input images, the pixels in the images are then minimized.

E.Nose Matching

The following attributes of nose can be used for the authentication purpose which are Nose Highlight,Nose Selection,Nose Area and Nose Matching.In this Data Selection Module, the user has to select the data that is to be inputted (ie., input image) well as the user has to select the database images for the multiple nose region matching for face recognition system.Extract the Probe Image from Database Images

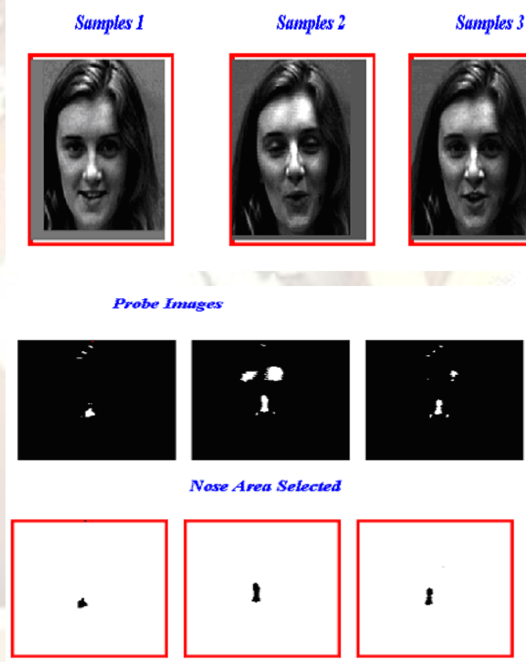

Fig 6. Nose

F.Ear matcher

We initialize the ear matching process by acquiring the training set, i.e. the images of ear. Then we computer eigen vectors and eigenvalues on the covariance matrix of those images [11]. The M highest eigenvectors are kept. Finally, the known images are projected onto the image space, and their weights are stored. This process is repeated as necessary.

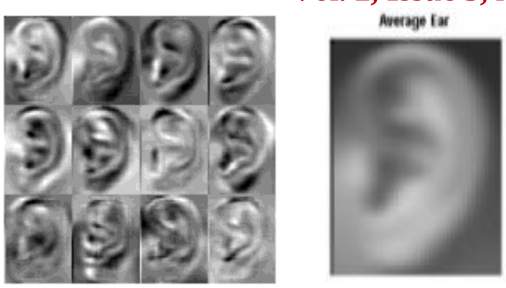

Fig. 7. Sample of average ear, and Eigenears

After defining the eigenspace, we project any test image into the eigenspace. An acceptance (the two images match) or rejection (the two images do not match) is determined by applying a threshold. Any comparison producing a distance below the threshold is a match [11]. The steps for recognition process can be summarized as follows:

1. When an unknown image is found, project it into eigenspace.

2. Measure the distance between the unknown image's position in eigenspace and all the known image's positions in eigenspace.

3. Select the image closest to the unknown image in the eigenspace as the match.

G.Iris Matcher

The iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye. Formation of the unique patterns of the iris is random and not related to any genetic factors [13].

The iris recognition system is composed of a number of sub-systems, such as, segmentation locating the iris region in an eye image, normalization creating a dimensionally consistent representation of the iris region, feature encoding creating a template containing only the most discriminating features of the iris and matching final recognition of the test iris with the template.

The iris region can be approximated by two circles, one for the sclera boundary and another, interior to the first, for the pupil boundary. The eyelids and eyelashes normally occlude the upper and lower parts of the iris region. Also, specula reflections can occur within the iris region corrupting the iris pattern.

Fig 8. a) Eye image, b) Edge map of eye c) Edge map with only horizontal gradients d) Edge map with only vertical gradients

In order to make the circle detection process more efficient and accurate, the Hough transform for the sclera boundary is performed first, then the Hough transform for the pupil boundary is performed within the iris region, instead of the whole eye region, since the pupil is always within the iris region. After that, eyelids are isolated by first fitting a line to the upper and lower eyelid using the linear Hough transform. This was eliminated using threshold, since reflection areas are characterized by high pixel values close to 255.

After segmentation, normalization is done to transform the iris region so that it has fixed dimensions in order to allow comparisons. The dimensional inconsistencies between eye images are mainly due to the stretching of the iris caused by pupil dilation from varying

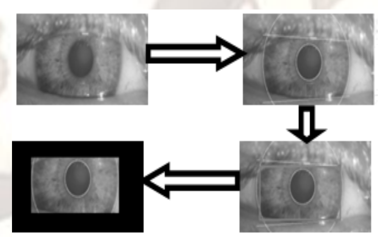

Fig. 9. Stages of segmentation with eye image

levels of illumination. Other sources of inconsistency include, varying imaging distance, rotation of the camera, head tilt, and rotation of the eye within the eye socket. The normalization process produces iris regions, which have the same constant dimensions, so that two photographs of the same iris under different conditions can have characteristic features at the same spatial location. Also the pupil region is not always concentric within the iris region, and is usually slightly nasal. This must be taken into account if trying to normalize the 'doughnut' shaped iris region to have constant radius.

We use the homogenous rubber sheet model [14], which remaps each point within the iris region to a pair of polar coordinates (r, Θ), where r is on the interval $[0, 1]$ and Θ is an angle $[0, 2\pi]$.

H. Footprint Recognition

Footprint identification is the measurement of footprint features for recognizing the identity of a user[15]. Footprint is universal, easy to capture and does not change much across time. Footprint biometric system does not require specialized acquisition devices. Footprint image of a left leg is captured for hundred people in different angles. No special lighting is used in this setup. The foot image is positioned and cropped according to the key points. Sequential modified Haar transform is applied to the resized footprint image to obtain Modified Haar Energy (MHE) feature. The sequential modified Haar wavelet can map integer-valued signals onto integer-valued signals abandoning the property of perfect construction. The MHE feature is compared with the feature vectors stored in database using Euclidean istance. The accuracy of the MHE feature and Haar nergy feature under different ecomposition levels and combinations are compared. This method 92.375% percent accuracy can be achieved using HE feature. The heel portion of the leg is cropped as it is havingmore intensity at this portion. This cropping is doneusing built-in function. The heel portion is dividedinto blocks using Sequential Modified HaarTransform. Minimum MHE is selected from all thecalculated MHEs.

Fig 10.

S.no.	Transform Types	Recognition Accuracy (%)
1	**DCT**	**83.64 142**
2	**FT**	**87.43 128**
3	**SHT** [Sequential Haar energy]	**92.375 118**

Table 2

3.Result and Analysis

The main goal of our research is to improve the recognition performance of a biometric system by incorporating multiple biometric traits.The key to successful multibiometric systems is in an effective fusion scheme, which is necessary to combine the information presented by multiple domain experts. Fusion can be employed in different levels of a multimodal biometric system. In this work, we provide fusion at the rank level for consolidating the rank information produced by the three separate monomodal matchers. There are many ways for rank consolidation – such as, majority rule, positional methods, utilitarian methods, multi-stage methods etc. In this work, we use the positional method, which considers the relative position of the element in the ranked list. Plurality voting, Borda count, logistic regression etc. are the examples of positional method.Plurality voting approaches considers only the elements which are at the top of the ranked list. This approach creates the final list with the element at the top which appears at the top of the base lists for the highest time [16].

For iris, they use the CASIA Iris Image Database (ver 1.0) from the Chinese Academy of Science [17]. This version of CASIA database includes 756 black and white iris images from 108 eyes (hence 108 classes). For each eye, 7 images are captured in two sessions, where three samples are collected in the first session and four in the second session.

To build our virtual multimodal database, we randomly choose 600 iris images from 300 subjects of CASIA database.600 ear and 600 face images are also chosen from USTB and FERET database respectively. Then 300 iris images are used for training and 300 for testing purposes. The same technique is applied for ear and face databases to collect 300 training samples for ear and 300 training samples for face. Then each sample of these 600 iris images is randomly combined with one sample of 600 ear images and one sample of 600 face images. Thus we obtained a virtual multimodal database containing 300 training and 300 testing multimodal samples.

We choose *0.2*, *0.5* and *0.3* as the weights for iris, ear and face respectively. The more the weight, the less the recognition rate of the system. This means, ear matcher gives us less accurate results than face or iris matchers. These weights are chosen by consequently executing and examining the system with the CASIA, USTB and FERET databases (for iris, ear and face respectively).we choosen the LSB method for the finger print and MHE feature os used for foot print.Usually, performance of a biometric system is expressed by ROC (Receiver Operating Characteristics) curves which is a ratio of false acceptance rate (FAR - the probability of an impostor being accepted as a genuine individual) and genuine acceptance rate (GAR - which is defined as 1 – FRR). FRR is the false rejection rate - the probability of a genuine individual being rejected as an impostor [2].

Significant performance gain can be achieved with the combination of rank information of different monomodal experts. The best performance we have received from this system is using the logistic regression method with an equal error rate (EER - a point in the graph plotted with FRR against FAR at various threshold, where FAR and FRR are the same) of 1.2%.

4.Concluions

Recently, more investigations have been carried out in the domain of multibiometrics. Investigation of good combination of multiple biometric traits and various fusion methods to get the optimal identification results are at the focus of current research.

In this paper, we present a multimodal biometric system using face, ear, iris,,hand and foot and biometrics incorporating various rank level fusion methods. Among the three positional methods of rank fusion approach used here, the logistic regression method appears as the best in terms of recognition performance.The Sequential Modified Haar Transform for the footprint bring the better result.Eventhough,By Considering the LSB on ridges of fingerprint is bring more accuracy result than the other methods

As these considerations have significant influence on the effectiveness of various recognition approaches, using a true multimodal Database in real-time environment and incorporating dual or tri-level fusion approaches are promising future directions of research in this domain.Eventhough the hand biometric parameters are easy to detect than the face biometric parameters. The above study state that the hand parameters are more accuracy than the other human body biometric parameters parameters.

Reference:

[1] J. G. Daugman, "High confidence visual recognition of persons " , vol. 15, no. 11, pp. 1148–1161,Nov. 1993

[2] J. Daugman, "Probing the uniqueness and randomnessof IrisCode: Re sultsfrom 200 billion irispair comparisons *Proc. IEEE*, vol. 94, 2006

[3] J. Daugman, "New methods in iris recognition *IEEE Trans. Syst Man, Cybern. B, Cybern* vol. 37, no. 5, pp. 1167–1175, May 2007.

[4] G.Suganthi and N.Suresh Singh "Ridge Enhanced steganography based on LSB and ArnoldTransformation",ISSN:2231-301X, ijetca,oct2011.

[5] J. Bhatnagar, A. Kumar, and N. Saggar, A novel approachto improve biometric recognition using rank level fusion, Proc. of IEEE Conf. on Computer Vision and Pattern Recognition, Minneapolis, USA, pp. 1-6, 2007.

[6] L. Hong, and A K. Jain, Integrating faces and fingerprints for personal identification, IEEE Trans. on PAMI, vol. 20, no. 12, pp. 1295–1307, 1998.

[7] R. Frischholz, and U. Dieckmann, BioID: A multimodal biometric identification system, IEEE Computer, vol. 33, no. 2, pp. 64-68, 2000.

[8] J. Fierrez-Aguilar et al., A comparative evaluation of fusion strategies for multimodal biometric verification, Proc. of the 4th Int. Con. J. Kittler, and M. Nixon, Eds., pp. 830–837, 2003.

[9] S. Ribaric , D. Ribaric Multimodal biometric user-identification system for network-based applications IEE Proc.-Vis. Image Signal Process., Vol. 150, No. 6, December 2003

[10] Dr.Narayanan Dutt,"Practical palmistry" p58-61.

[11] M. Turk, and A. Pentland, Eigenfaces for recognition,Journal of Cognitive Science, pp. 71-86, 1991.

[12]R. C. Gonzalez, and P. Wintz, Digital Image Processing,2nd Ed., Pearson Education Pvt. Ltd, 002.

[13]R. Wildes, Iris recognition: An emerging biometric technology, Proc. Of IEEE, Vol. 85, No. 9, pp. 1348-1363,1997.

[14]J. G. Daugman, How iris recognition works', IEEE Trans. On Circuits and Systems for Video Technology , Vol. 14, No. 1, pp. 21-30, 2004.

[15] V. D. Ambeth Kumar M. amakrishnan IJCSI International Journal of Computer Science Issues, Vol. 7, Issue 3, No 5, May 2010 ISSN 1694-0784,0814 Footprint Recognition using Modified Sequential Haar Energy Transform (MSHET)

[16] C. Dwork, R. Kumar, M. Naor, and D. Sivakumar, Rank aggregation methods for the web, Proc. Of 10th Int. WWW Conf., Hong Kong, China, pp. 613–622, 2001.

[17] CASIA: CASIA iris image database. www.sinobiometrics.com