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Adaptiveness, Error Resilience and Robustness Validation of the Multimodal Hand Biometric Recognition System

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Abstract: The multimodal biometric system based on palm print (PP), finger geometry (FG) and dorsal palm vein (DPV) modality is proposed, specifically for high-security applications. This paper aims to prove that the proposed multimodal biometric system is an adaptive, error-resilient and robust system. A novel 'Optimum Weights Algorithm' makes the system adaptive and provides the best possible accuracy. An erroneous database of 100 users is collected to check an error resilience and robustness of the multimodal system. PP, FG and DPV feature extraction algorithms are used to extract feature vectors for all three modalities. Accuracy prediction is made by plotting the ROC curve for the multimodal system and estimating GAR_{min} from that ROC curve. It is observed that the accuracies of the FG and DPV modalities remain unaffected for the erroneous database; however, there is a small decrease in the accuracy for PP modality. The values of accuracies obtained for the PP modality with both the degradations, namely, chalk dust and fine dust are 97.50% and 98.55% respectively, with a very low FAR level of 0.0001. For the erroneous database, the proposed multimodal system provides an accuracy of 99.80%.

Keywords: False Acceptance Rate (FAR), Genuine Acceptance Rate (GAR), Optimal Weights Algorithm (OWA), Receiver Operating Characteristic (ROC), Area under the Curve of Receiver Operating Characteristic (AUC), Erroneous Database

1. INTRODUCTION

Biometrics is the activity measurement of people's distinctive physical or behavioural characteristics. The technology is principally extensively used for personal recognition and access management. The essential premise of identity verification is that each person can be accurately known by his or her intrinsic physical or behavioural traits [1] [2] [3]. Authentication by biometric verification is becoming more and more common for security purposes in companies, public security systems, examination control rooms, bank lockers and several high-security applications. In addition to security, the drive behind biometric verification has been a convenience, as there are no passwords to recollect or security tokens to hold. Hand-based biometrics identifies the users by distinctive characteristics in their hands, like fingerprints, palm prints, finger geometry, finger veins, and dorsal palm vein patterns [4] [5] [6] [7] [8] [9] [10] [11]. Hand-based features have specific benefits compared to systems using traits like the face or voice [12] [13] [14] [15] [16].

After doing a comprehensive literature survey of various hand-based Multimodal Biometric Systems (MMBS) [17] [18] [19] [20], three hand-based modalities namely Palm Print (PP), Finger Geometry (FG) and Dorsal Palm Vein (DPV) are specially selected in the proposed system to recognize the person [21] [22] [23] [24] [25] [26]. Biometric systems can be used primarily for two different kinds of applications, 'General Security Applications (GSAs)', and extremely High-Security Applications (HSAs). Examples of GSAs are, maintaining the 'Time and Attendance record' of the college students/faculty/staff/employees and mobile phone access control. In such GSAs, thresholds are adjusted such that the 'Equal error rate' (EER) is minimized. 'Equal Error Rate' is the point where 'False Acceptance Rate' (FAR) and 'False Rejection Rate' (FRR) are minimal and equal

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[27] [28] [29] [30]. For the HSAs, like Bank lockers, Airport security, and Jail security or in Military applications, typically FAR is kept purposefully very low so that, the biometric security system shall not give access to an unauthorized user at any cost [31] [32] [33] [34]. A low value of FAR may lead to a slightly higher value of FRR, but it is acceptable for high-security applications. In this work, a hand based multimodal biometric recognition system is proposed using a unique combination of PP, DPV and FG modalities, specifically for HSAs. In the proposed MMBS, the value of FAR is purposefully kept very much lower (FAR $\leq$ 0.0001) so that the system will be useful at high security applications. FAR equals 0.0001 means that the maximum of one amongst ten thousand imposters may be falsely accepted. Neyman Pearson initially proposed this method, so it is known as the NP technique [35] [36].

The paper is organized as follows: After a brief introduction, **Section 2** outlines the related work from our previously published technical papers. S**ection 3** defines a few essential terms. **Section 4** is devoted to erroneous image data acquisition, and **section 5** describes feature extraction and feature mapping process for an erroneous database. **Section 6** includes an analysis of recognition performance. **Section 7** is devoted to the discussions on results, followed by conclusions.

2. Related Work From Our Previously Published Scopus Indexed Journal Papers

In our previously published papers two essential aspects of the biometric systems have been considered [35] [36]. The first aspect is to increase the minimum value of Genuine Acceptance Rate (GAR_{min}) for unimodal systems, to boost their accuracies and the second aspect is to improve the overall accuracy of the multimodal system so that the system can be useful for high-security applications.

The first objective is achieved by proposing mathematical modelling of binary signal detection performance and derivation of system accuracy in terms of GAR_{min} for high-security applications (HSAs) [35][36]. The importance of the correlation between the overall detection performance and the area under the 'Genuine Acceptance Rate versus False Acceptance Rate' graph, commonly known as 'Receiver Operating Characteristic (ROC)' is emphasised here. Using the ROC curve, the relation between GAR_{min} and minimum recognition accuracy is proposed, mainly for HSAs. PP modality is used to check the theoretical concepts. This modality provides reasonably good recognition accuracy. For PP modality, various feature extraction techniques are used to increase the area under the curve of its ROC characteristics. In this research paper, in order to enhance the accuracy of the PP based recognition system, different techniques are implemented, such as use of Harris Corner Detector, different Discrete Wavelet Transform (DWT) coefficients and combinations of different DWT coefficients. The minimum value of GAR_{min} decides the detection performance of the system. Further to enhance the accuracy of the system, a novel iterative 'Optimum Weights Algorithm (OWA)' is suggested. The proposed palm print based unimodal system gives improved accuracy of 99.25% with a very low FAR level of 0.0001. This represents the fairly accurate and significantly user-friendly unimodal biometric system, suitable for high-security applications [35][36].

Here focus is given on improving the overall accuracy of the multimodal system so that the system will be useful for HSAs [36]. A MMBS is designed using a distinctive combination of the PP, FG and DPV modalities. DWT technique is used for features extraction for PP and DPV modalities. For FG modality, simple geometrical features are extracted. Accuracies of 98.775%, 98.45% and 97.60% are obtained for PP, FG and DPV modalities respectively. Further, the multimodal system is proposed along with a different basis for optimally choosing the weights using 'OWA'. The score level fusion is done using these optimized weights. The proposed MMBS provides an enhanced accuracy of 99.80% with a very low value of the FAR level, which is set equal to 0.0001 [36]. The accuracy obtained for MMBS increases further if we make use of combined 'approximate and horizontal coefficients' of PP in addition to DPV and FG modalities [36]. In this case, accuracy reaches almost 99.95%, with a very low value FAR, which is set equal to 0.0001. This system represents highly accurate, robust and significantly user-friendly MMBS, suitable for HSAs [35] [36].

The research work presented in this paper is the extension of the work presented in above two papers [35] [36]. This paper aims to prove that the multimodal biometric system which is designed and presented in our previously published paper [36] is an adaptive, error-resilient and robust system. To understand the precise meaning of the terms, 'Adaptive, Error resilient and Robust', their definitions are given as follows

3. Important Definitions

A. Adaptive

The system should be capable of adapting through an iterative sequence for getting the maximum possible accuracy.

B. Error resilient system

It is a system that can handle erroneous data and still should provide very good performance.

C. Robust System

The robustness is the property that characterizes how effective the system is while being tested on the new independent (but similar) dataset. The robust system can also fight against spoofing attacks.

An 'Optimum Weights Algorithm' (OWA) is presented to decide the weights of different modalities in our previous published journal papers [35] [36].

With every next step of the iteration (i), weights of the modalities get updated and the ROC curve shifts towards ideal value, which in turn increases the area under the ROC curve i.e. AUC value. Here AUC^{i} is directly linked to $AUC^{(i-1)}$, and an algorithm is designed such that as iteration number 'i' increases, AUC moves towards ideal value, i.e. '1' which in turn changes GAR_{min} which in turn improves the accuracy value for the multimodal biometric system. The overall accuracy goes on increasing with every next step of the iteration. The iteration process stops when accuracy reaches to 'Maximum Point'. Thus we are 'Optimizing Weights' which shows that our proposed 'OWA' is iterative to get the best possible accuracy. Hence 'OWA' provides the first part, i.e. 'Adaptive' nature [35] [36]. To consider the remaining two aspects, namely 'Error Resilience' and 'Robustness' of the proposed multimodal biometric system, an erroneous database is collected using the data acquisition system.

4. Erroneous Image Data Acquisition

(a) (b)

Figure 1 Sample images from an erroneous database (a) with chalk dust degradation (b) with fine dust degradation

The database of a single person for all three above mentioned modalities was not available. A specific Data Acquisition System (DAS) is designed and fabricated to acquire hand images for different modalities of the same person. An error free/ clean database of 150 persons is collected using this DAS. For each person, 10 images per modality are collected [35] [36].

To check error resilience and robustness properties of the multimodal system, an erroneous database of 100 users is collected in the second phase in a typical environment. We have taken 30 images per user. Out of those, ten images are clean or error-free images, ten images are collected with chalk dust, and ten images are obtained with fine dust. Figures 1(a) & 1(b) show samples from an erroneous database with hands dirtied with chalk dust (a) and then with hands dirtied with fine dust (b).

5. Features Extraction And Features Mapping For Erroneous Database

By applying PP, DPV and FG feature extraction techniques on these erroneous images, feature vectors are extracted for all three modalities. Features extraction is done in a similar way as discussed in paper [36] for PP, FG and DPV modalities, respectively. After feature extraction, mapping of these feature vectors is done likewise, as explained in [36] for PP, FG and DPV modalities respectively. Accuracy prediction is made by plotting the ROC curve and determining GAR_{min} from the relevant ROC curve. To calculate the minimum values of accuracy, the following equation (1) is used.

$$\%\ of\ Accuracy_{min} = \left[\frac{1}{2}(1 + GAR_{min})\right] \times 100\% \quad (1)$$

For better appreciation the detailed derivation of equation (1) and the flow chart for iterative algorithm OWA are included at Appendix A.

6. Results of PP, FG and DPV Modalities for Erroneous Database

Figure 2, Figure 3 and Figure 4 show the ROCs for acquired PP, FG and DPV modalities respectively for error-free and erroneous databases.

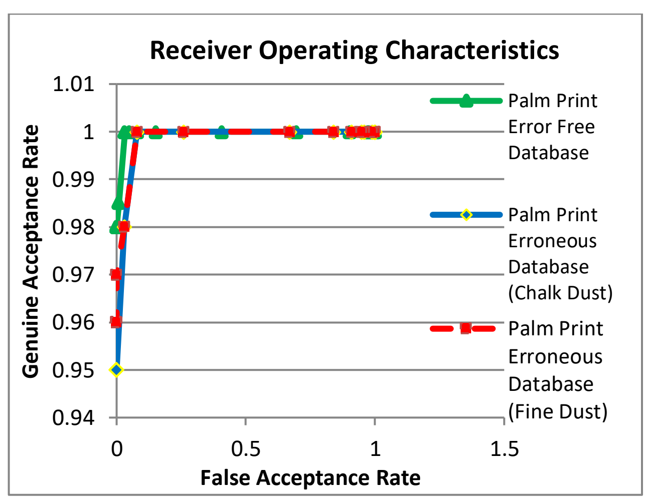


Figure 2 ROCs for PP error-free and erroneous databases

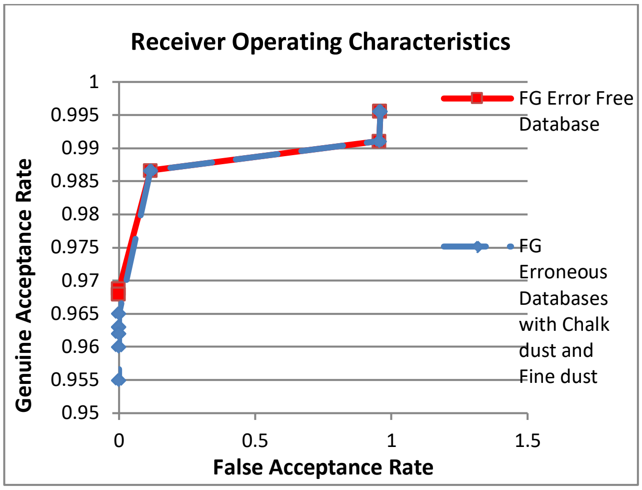


Figure 3 ROCs for FG error-free and erroneous databases

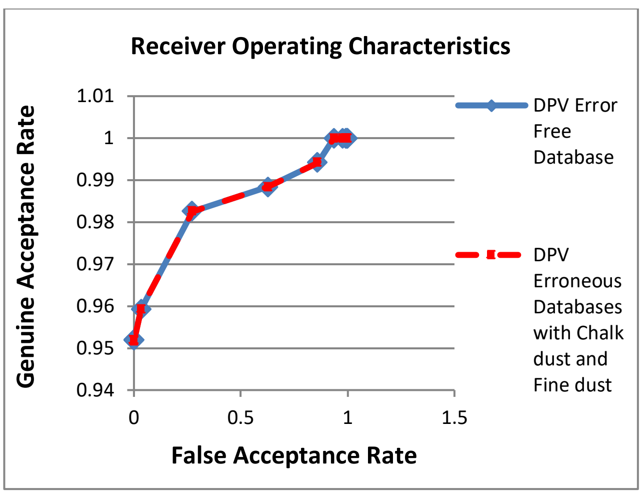


Figure 4 ROCs for DPV error-free and erroneous databases

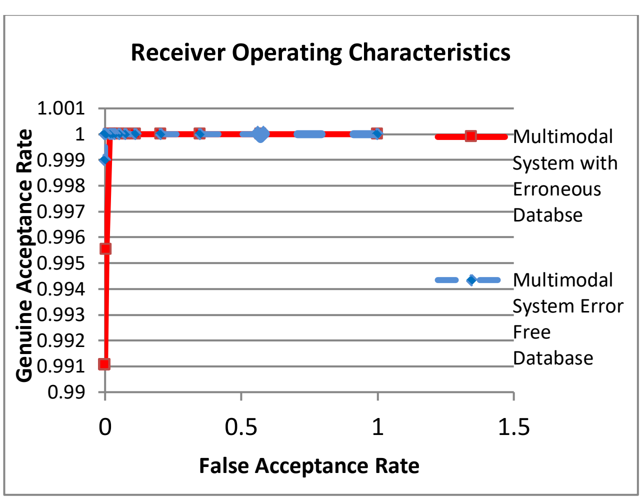


Figure 5 ROCs for Multimodal system with error-free and erroneous databases

Figure 5 shows the ROCs of the proposed multimodal system for error-free and erroneous databases.

Please refer to Table 1 given at the end of the paper. Table 1 shows a few samples of hand images from an erroneous database for all three modalities. This table also gives information regarding whether the person is properly identified as a 'genuine user or not' by the proposed unimodal systems and the proposed multimodal system. Most of the hand images from an erroneous database are properly recognized, but few hand images have failed to recognize correctly using the individual unimodal system. Table 1 shows that those failed images are properly recognized by the proposed multimodal system due to its high accuracy.

A. Comments:-

- **User 1**:- Recognized properly as a genuine user.
- **User 2**:- PP with chalk dust image has failed to recognize by PP based unimodal system, as prominent PP features are covered due to excess amount of chalk dust. Figure 6 shows ROI marked on the PP image of user 2 and Figure 7 shows the ROI extracted in which prominent PP features are covered with chalk dust.

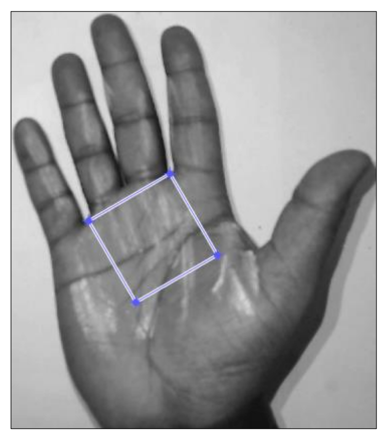


Figure 6 ROI marked on the PP image of user 2

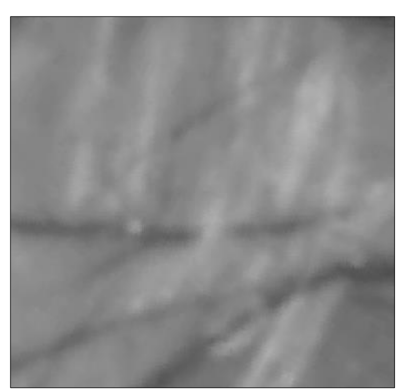


Figure 7 Extracted ROI of the PP image of user 2

- **User 3**:- Appropriately recognized as a genuine user.
- **User 4**:- Appropriately recognized as a genuine user.
- **User 5**:- Appropriately recognized as a genuine user.
- **User 6:-** PP with fine dust has failed to recognize by PP based unimodal system, as prominent PP features are covered due to fine dust. Figure 8 shows ROI marked on the PP image of user 6 and Figure 9 shows the ROI extracted in which prominent PP features are covered with fine dust.

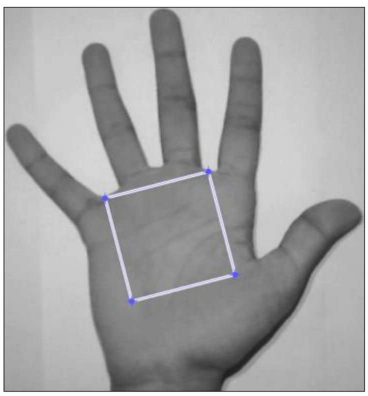


Figure 8 ROI marked on the PP image of user 6

Figure 9 Extracted ROI of the PP image of user 6

- **User 7**:- Recognized as genuine user.
- **User 8**:- DPV image is failed to recognize by DPV based unimodal system. It seems that the image is not appropriately captured (perhaps user 8 has not kept his hand properly in IR illuminated region), due to which the image appears blackish. Figure 10 shows ROI marked on the DPV image of user 8. Figure 11 shows the extracted ROI of DPV image in which the dorsal palm veins are not properly visible.

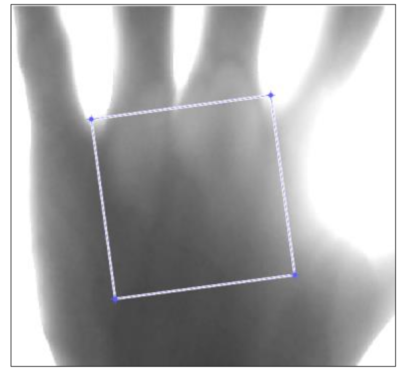


Figure 10 ROI marked on the DPV image of user 8

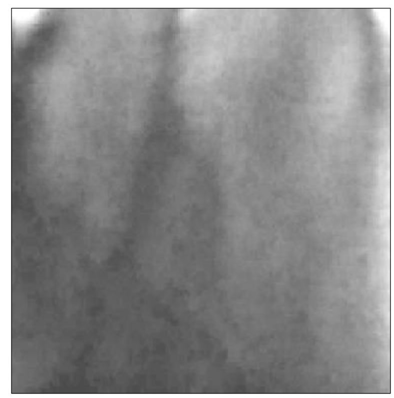


Figure 11 Extracted ROI of DPV image of user 8

The multimodal biometric system (MMBS) which is developed appropriately recognizes all of the above hand samples. This proves an advantage of using the MMBS over the unimodal biometric system (UMBS).

7. Results and Discussions

From Figures 2, 3, 4 and 5, GAR_{min} values are determined for each database and accuracies are calculated using equation no (1). Results are tabulated in Table 2. While deciding values of GAR_{min}, we have to expand the scale on FAR (i.e. 'X' axis) between 0.00 and 0.005 by approximately a hundred times and note down the point on GAR (i.e. 'Y' axis) at which the ROC characteristics just tangentially departs from the 'Y' axis, by a small amount. This value is known as 'GAR_{min}'.

Please refer to Table 2 given at the end of the paper. From Table 2, it is observed that the accuracy for the FG and DPV modalities are not getting much affected by this erroneous database, but there is a small amount of reduction in the accuracy for PP modality. Still, the values of accuracies (97.50% with chalk dust degradation and 98.55% with fine dust degradation) for the PP modality for erroneous databases are also reasonably good, keeping the view that FAR level is set equal to 0.0001. This is an expected result as when hands become dirty, it affects palm print area by the maximum extent,

and it does not affect much for finger geometry or dorsal palm vein images. Particularly for DPV, the IR signals pass through the hand. The IR energy gets absorbed by human blood and results in blackened areas on the image. The dust particles do not affect the IR signals at all, and the ROC remains almost unchanged and shows least or no effect as far as DPV imaging is concerned. (Similar to the application of IR light in the Infrared astronomy).
The proposed multimodal system provides a very good accuracy (99.95%) for an error-free database. For the erroneous database also, good value of accuracy (99.80%) is obtained using the proposed multimodal system. This clearly shows the benefits of using a multimodal system over the unimodal systems.

Table 3 shows a comparative study of performances reported by other researchers in the field of hand based multimodal biometric systems. The last row of this Table 3 shows results obtained for the proposed multimodal biometric systems. From Table 3 it is very much clear that our multimodal system provides better accuracy as compared to other systems developed by other researchers. Thus in the proposed multimodal biometric system; eventually, PP features show marginal accuracy degradation and the FG and DPV images provide requisite 'Error Resilience'. In addition to PP and FG modalities, a separate sensor is used to capture images of DPV modality. Forging is impossible for DPV patterns, as they lie below the skin [10] [11]. Furthermore, the scans rely on the blood flowing through living humans; hence, DPV scans are virtually impossible to counterfeit. Thus our system can fight against spoofing attacks; therefore, it ensures 'Robustness' in the system.

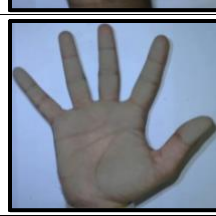
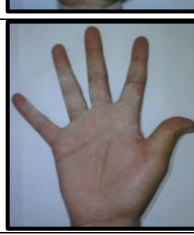
8. CONCLUSIONS AND FUTURE SCOPE

The above results show that for an erroneous database also, our system provides reasonably good accuracies. The system is thus capable of handling erroneous databases, which indicates that it is 'Error Resilient System'. Further, the DPV also provides the capability to resist the spoofing attacks possible and thus ensures required 'Robustness' of the MMBS. The MMBS is capable of 'adapting' through an iterative sequence for getting the maximum possible accuracy. All these results are computed at a very low value of FAR (FAR $\leq$ 0.0001); hence, the system is useful for higher security applications. This proves that the proposed MMBS constitutes an adaptive framework for error-resilient and robust multimodal hand biometric system for higher security applications.

Here 'OWA' is used for combining three different modalities. In future, the proposed optimization algorithm may be very effectively used for combining four or more modalities using the standard principle of mathematical induction, to boost the accuracy and increase the effectiveness of the multimodal systems. In this work, it is assumed that there is no other security screening of users and all users can have equal access to biometric system which manages the access control. It is therefore assumed that occurrence probabilities of genuine and imposter are same. In many practical situations, however, this may not hold true. In practice the priori occurrence probability of genuine user could be much higher than imposter. In this case the equation for estimation of minimum genuine acceptance rate (GAR_{min}) and system accuracy need to be modified appropriately. In this research work, DWT technique is used for feature extraction. In future, in a view to enhance the accuracy of MMBS further, other feature extraction technique like Curve let transform can be tried out. Curvelet transform is a higher dimensional generalization of the Wavelet transform designed to represent images at different scales and different angles. It actually overcomes the missing directional selectivity of wavelet transforms in images. Curvelets are designed to handle curves using only a small number of coefficients. Hence the Curvelet handles curve discontinuities well.

In the proposed system, the entire analysis is based on the assumption that image degradation may be modelled as 'additive Gaussian noise'. This holds true for general image degradations, including one due to fine dust degradation. However, this assumption may not be applicable to chalk dust erroneous image, particularly for palm print images. This is reflected in the relatively worse value of GAR_{min} for ROC for image degraded by chalk dust errors. For this case, different image degradation model based on 'Poisson Point Process' may be more appropriate. However, this analysis would involve separate mathematical treatment and can be taken up as a future extension possible for this research.

TABLE 1 USER IDENTIFICATION FROM AN ERRONEOUS DATABASE

Users	PP and FG Erroneous Images with		DPV Erroneous Images	Recognized as Genuine User				
	Chalk dust (CD)	*Fine Dust (FD)*		*PP with CD*	*PP with FD*	*FG*	*DPV*	*MMBS*
User 1				✓	✓	✓	✓	✓
User 2				×	✓	✓	✓	✓
User 3				✓	✓	✓	✓	✓
User 4				✓	✓	✓	✓	✓
User 5				✓	✓	✓	✓	✓
User 6				✓	×	✓	✓	✓

User 7				✓	✓	✓	✓	✓
User 8				✓	✓	✓	×	✓

TABLE 2 ACCURACY PREDICTIONS FOR DIFFERENT DATABASES

Sr. No.	**Modality**	**Error Free Database**		**Erroneous Database (Chalk Dust)**		**Erroneous Database (Fine Dust)**	
		$GAR_{min.}$	***Accuracy***	***$GAR_{min.}$***	***Accuracy***	***$GAR_{min.}$***	***Accuracy***
1	PP	0.985	99.25%	0.950	97.50%	0.971	98.55%
2	FG	0.969	98.45%	0.965	98.25%	0.965	98.25%
3	DPV	0.952	97.60%	0.951	97.55%	0.951	97.55%
4	Multimodal System using 'OWA.'	0.999	99.95%	0.996	99.80%	0.996	99.80%

TABLE 3 COMPARISON OF THE PERFORMANCE PARAMETERS OF DIFFERENT MULTIMODAL SYSTEMS

Sr. No.	**Author**	**Modalities Used**	**Technique Used**	**Performance Parameter Obtained**	
1	Goh Kahong Michael et al. (2012)	Hand Geometry, Palm Print, PKP, Finger Vein, Palm Vein	Score Level Fusion (Directional Coding)	Accuracy	98%
2	Miguel A. Ferrer et al. (2014)	Hand Palm, Hand Dorsum	Multimodal System SWIR hyperspectral	GAR	96.7%
				EER	0.05%
3	Rupali L. et al. (2014)	Face, Finger Print	Minutiae matching	Accuracy	97.5%
			Gabor filter techniques	FAR	1.3%
4	Aditya Nigam et al. (2015)	Palm Print, Knuckle Prints	Local Gradient SLG Method	GAR	99%
				FAR	0.1%
5	G. Prabhua et al. (2015)	Fingerprint, PP and HG	Minimal Search Time	Accuracy	98%
6	Muhammad Imran Ahmad et al. (2016)	Face, Palm Print	Multimodal System Non-stationary feature fusion	GAR	97%
7	Gopal et al. (2016)	Palm Print, Dorsal Hand Vein, Palm-Phalanges Print	Dubois Prade Score Level Fusion	Accuracy	99.60%
8	S. Khellat Kihel et al. (2016)	Finger-Knuckle- Print, Finger Vein, Finger Print	Feature Level Fusion	GAR	99.1%
			Decision Level Fusion	GAR	95.3%

9	Puneet Gupta et al. (2016)	Dorsal palm veins Dorsal Fingers	Score Level Fusion	GAR	99.34%
				EER	1.87%
10	E. Sujatha et.al. (2018)	Palm Print, Face, Iris, Signature	Feature Level Fusion using encoded DWT	Accuracy	98.50%
				FAR	1.0%
11	Pallavi Deshpande et al. (2019) Proposed MMBS	Palm Prints, Dorsal Palm Veins, Finger Geometry	Multimodal System using combined 'approximate plus horizontal' coefficients for erroneous database	GAR_{min}	0.996
				Accuracy	99.80%
				FAR	0.01%
			Multimodal System using combined 'approximate plus horizontal' coefficients for regular database	GAR_{min}	0.999
				Accuracy	99.95%
				FAR	0.01%

APPENDIX

ARCHITECTURE PROPOSED FOR THE SYSTEM

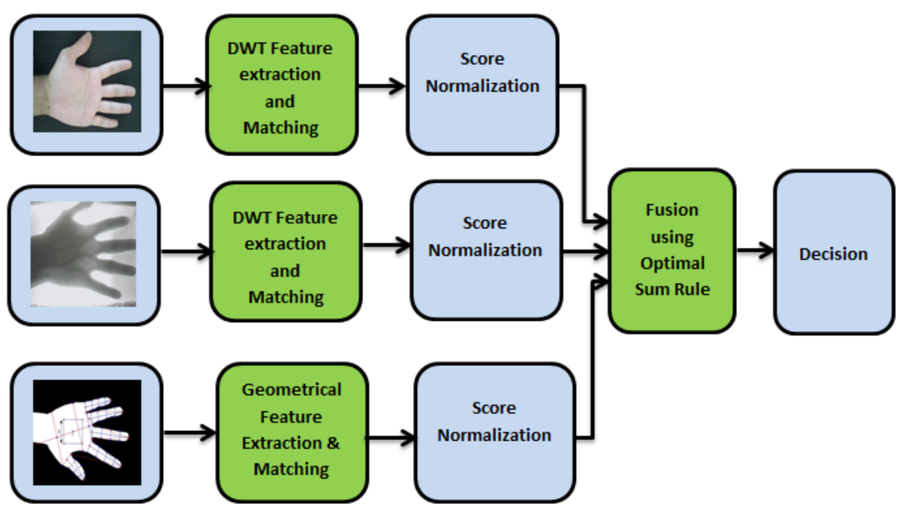


Fig.A Architecture of Proposed Multimodal Biometric System

Mathematical Background for Signal Detection

The simplest binary communication system is shown in Figure B. A typical simple case consists of a single observation of the received signal corrupted by additive noise. The input signal is assumed to be in the binary form with two distinct values 'm_o' and 'm_1', corresponding to two binary hypotheses, 'H_o' and 'H_1' respectively.

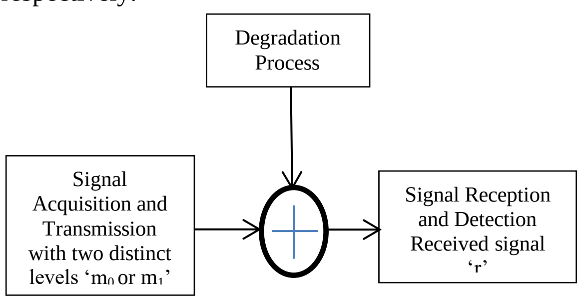


Fig. B The simplest binary communication system

The received signal 'r' can be expressed as,

$$r/H_i = m_i + \text{noise} \quad \text{(Where 'i'= 0 or 1)}$$

Here 'm_i' represents a binary signal and degradation process introduces 'noise' which is assumed to be additive, with zero mean, Gaussian distributed with variance 'σ^2'. The probability density function (PDF) for the observed signal can be expressed as,

$$P(r|H_i) \underline{\underline{\text{def}}} G(m_i, \sigma^2)$$

Here symbol '$\underline{\underline{\text{def}}}$'means equality in PDF and 'G' represents standard Gaussian distribution. For the simplest example considered, the Generalized Likelihood Ratio Test (GLRT) is derived as,

$$GLRT = \frac{P(r|H_1)}{P(r|H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \tag{2}$$

Here 'γ' represents decision threshold. For the simple case of single observation, the above equation leads to,

$$r \underset{H_0}{\overset{H_1}{\gtrless}} \gamma$$

$$\text{Here,} \quad \gamma = \frac{\sigma^2}{m_1}\ln(\eta) + {}^{m_1}\!/_{2}$$

Here for simplicity, signal value for H_0 is assumed to be zero (i.e. $m_0 = 0$) and 'η' represents ratio of occurrence of probabilities of two hypotheses H_0 and H_1. For equiprobable hypotheses, '$\eta = 1$' and decision threshold becomes '$\gamma = m_1/2$'.

The Genuine Acceptance Rate can now be expressed as,

$$GAR = \int_{\gamma}^{\infty} P(r|H1)dr \tag{3}$$

And False Acceptance Rate, can be expressed as,

$$FAR = \int_{\gamma}^{\infty} P(r|H0) \tag{4}$$

In biometric terms, 'GAR' and 'FAR' are known as 'True Positive' and 'False Positive' respectively. The ROC curve represents plot of 'GAR verses FAR' as value of decision threshold 'γ' is varied from very low value to very large value. As 'γ' threshold increases, both GAR and FAR get reduced. In this case, for High Security Applications, we follow test suggested by Neyman- Pearson (NP) [18] [28], in which decision threshold is decided by level of maximum FAR permissible in the application. In this GAR is maximised for the stipulated value of FAR. In high security applications, value of FAR ≤ 0.0001 (maximum of one amongst ten thousand samples may be falsely acceptable). Hence, we set our threshold based on equation no. (4), with FAR = 0.0001.

Analysis of Detection Performance

Typical ROC characteristics for the simplest case are shown in the Figure C, where typical signal values, $m_5 > m_4 > m_3 > m_2 > m_1$ are used and m_0 is assumed to be zero. The ideal characteristics would be GAR = 1 & FAR = 0 and the worst scenario, GAR = FAR which is diagonal solid line marked as 'Worst Performance' in Figure C. It is observed that as the signal value increases, the ROC curve shifts towards the ideal curve and the detection performance improves. Thus, the area under curve (AUC), ($0.5 \leq$ AUC, ≤ 1) of the ROC represents the quantitative measure of the detection performance of the system.

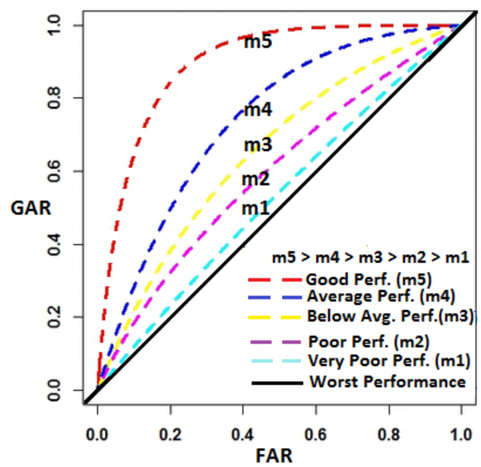


Fig. C ROC curves for different signal values

The Error in the binary system can be defined as,

$$E_r = [P_0 \times \text{(False Acceptance Rate)} + P_1 \times \text{(Genuine Rejection Rate)}]$$

Here GRR and FAR represent 'False Negative and False Positive' respectively for biometric system. P_0 and P_1 represent probabilities of hypotheses H_0 and H_1 respectively. Assuming two hypotheses to be equally likely i.e. $P_0 = P_1 = ½$, the error situation can be expressed as,

$$E_r = (FAR + GRR) /2$$

The detection accuracy can be expressed as, Accuracy = $(1-E_r)$. For the simple equiprobable binary hypotheses, the above equation leads to,

$$\text{Accuracy} = \left[1 - \left(\frac{\text{FAR} + (1-\text{GAR})}{2}\right)\right] \quad (5)$$

Further, for high security applications, where FAR is very small compared to GAR, above equation approximates to,

$$\%\ \text{Accuracy}_{\min} = \left(\frac{1}{2}\ (1 + \text{GAR}_{\min})\right) \times 100\% \quad (6)$$

It can be readily seen from the ROC that 'GARmin' is the value of GAR, at which the ROC curves depart from FAR = 0 (i.e. Y axis) tangentially. Further, as a value of AUC (0.5 < AUC < 1.0) increases, the value of GARmin also increases, which leads to accuracy enhancement. For the worst scenario, GARmin = 0. For ideal scenario, GARmin approaches to 1.0 and the best accuracy level then reaches up to 100%. One more commonly used test in binary recognition is Equal Error Rate (EER) method i.e. FAR = GRR. In this case for equiprobable hypotheses, the accuracy can be expressed as,

$$\%Accurcy = (1 - GRR) \times 100$$

$$\%Accurcy = (GAR) \times 100$$

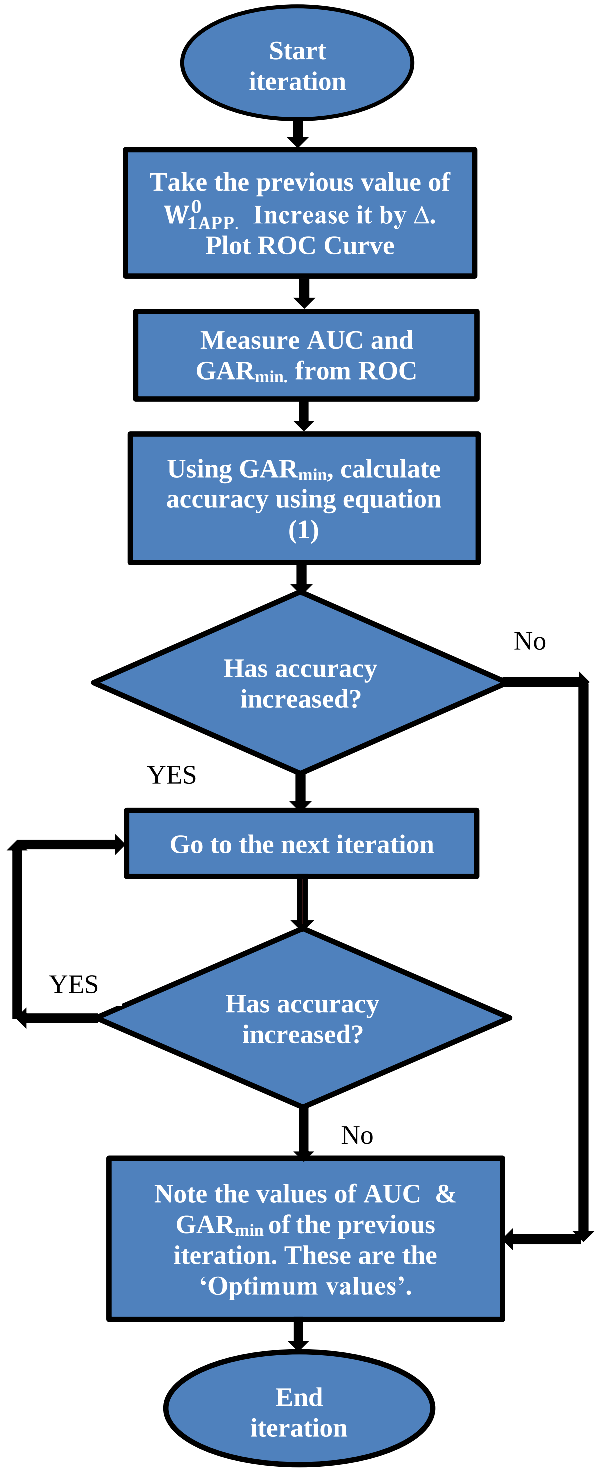
However, in this case GAR has to be determined at the EER point. As the focus of this paper, is on High Security Applications, we use only NP test explained above and evaluate the percentage accuracy using equation no. (6).

In this research work, we have used three different hand based modalities namely Palm Print, Dorsal Palm Vein and Finger Geometry. The database of a single person for all three above mentioned modalities is not available. A specific Data Acquisition System (DAS) is designed, developed and fabricated to acquire hand images for different modalities of the same person. Two different databases are collected using this DAS. Initially a database of 150 users is collected using this data acquisition system. For every user, ten images for each modality are captured. Discrete Wavelet Transform (DWT) technique is proposed to be used for extracting image features from the ROIs for palm print and dorsal palm vein modalities. The feature extraction for FG modality is greatly simplified and restricted to only geometric spatial domain direct measures. An erroneous database is collected using the data acquisition system to consider the remaining two aspects, namely 'Error Resilience' and 'Robustness' of the MMBS. An erroneous database of the single person for all three modalities, namely PP, FG and DPV is not available. An erroneous database of 100 users per modality is collected in a normal environment to check an 'Error Resilience and Robustness' of the proposed MMBS. In this case, we have taken 30 images per user. Out of those, ten images are clean images or error-free images, ten images are collected with chalk dust degradations, and ten images are obtained with fine dust degradations.

We have presented a novel 'Optimum Weights Algorithm' (OWA) to decide the weights of different coefficients or modalities [35] [36]. With every next number of iteration, weights of the modalities get updated and the ROC curve shifts towards ideal value, which in turn changes the value of the 'area under the ROC curve' (AUC). The overall accuracy goes on increasing with every next number of iteration. The iteration process stops when accuracy reaches to 'Maximum Point'. Thus we are 'Optimizing Weights' which shows that our proposed 'OWA' is iterative to get the best possible accuracy. Thus 'OWA' makes the system 'Adaptive' in nature [35] [36]. To explain this process, we have added flow chart below.

OPTIMUM WEIGHT ALGORITHM

Flow chart showing the sequence of the iteration process is as follows,



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