Performance evaluation of multi-instance fusion for fingerprint templates at feature level

Divyashree[1], Dr. Chander Kant[2]
1: Asst Prof, Dept. of computer science, UIET, M.D. University, Rohtak, India.
2: Professor, Dept. of computer science & Applications, K.U. Kurukshetra, India.

Abstract:

Biometrics security is by all accounts logical techniques for utilizing an individual's remarkable physiological or social attributes for programmed recognizable proof and check. These attributes could be either physiological or conduct qualities for example unique mark, voice, face, and palm print, signature, stride and so on Notwithstanding, the unique mark acknowledgment for distinguishing proof viewed as more dependable and simple to secure. Notwithstanding of many works done, the issue of exactness actually endures which maybe can be ascribed to the changing quality of the procurement gadgets. At some point finger impression acknowledgment framework can be effortlessly caricature with the utilization of phony unique mark of the real client however by fusing multi-biometric or multimodal biometric, the framework works on the ability of conventional biometric framework. Further a multimodal biometric framework cause issue of more space, intricacy and reaction time needed for putting away and getting to highlight sets acquired from various sensors. A plan has been proposed in this paper to resolve these issues by melding various occasions of a quality for raising the biometric framework execution. Results show that the multi-occasion approach beats better as contrasted and single example or then again multimodal biometric. The effect on biometric execution using feature level blend under different mix rules have been displayed in this paper.

K-words: Biometric Trait, Fingerprint, Fusion, Multiple Instances, Multi-biometric, Voice, Face, Multimodal, Multi-event.

Introduction

Biometric framework is considered [1] as a strong innovation to give higher security utilizing natural qualities that could be either physiological (hand calculation, finger impression, iris, retina, face, and palm print) or conduct characteristics (signature, keystroke elements, step design). Illustration of such physiological and conduct characteristics utilized in biometric framework are displayed in Fig-

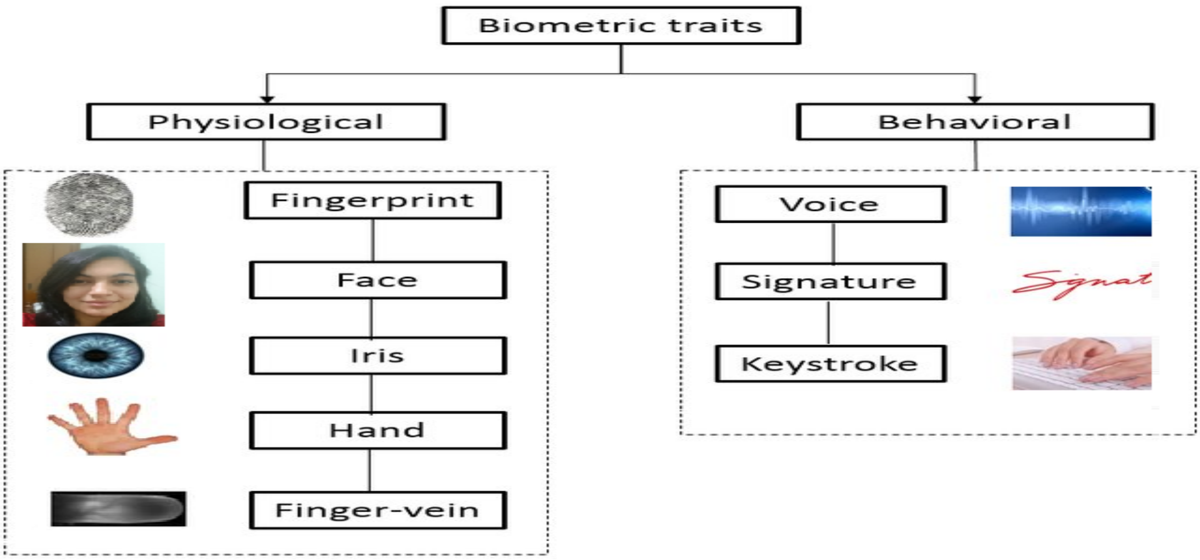


Fig1: Examples of physiological and behavioral traits.

Conventional framework gives validation utilizing single characteristic and is known as unibiometric framework. As unibiometric framework utilizes data about single biometric attribute it has a few disadvantages like boisterous information, bury and intra class variety, non-comprehensiveness, inadmissible blunder rates and satire assaults. To conquer a portion of the impediments of conventional unibiometric framework a multi-biometric framework is planned as displayed in fig 2 underneath. A multi-biometric framework can be arranged into one of the accompanying:

1) Multiple Sensors: Multiple sensors are utilized to catch a solitary biometric methodology.
2) Multiple Algorithms: In this a solitary biometric information can be handled by utilizing diverse element extraction calculation for making distinctive data content.
3) Multiple Instances: Multiple occasions of a solitary biometric quality can be utilized.
4) Multiple Samples: In this number of times same sensor can be utilized for procuring the equivalent biometric methodology and occasion.

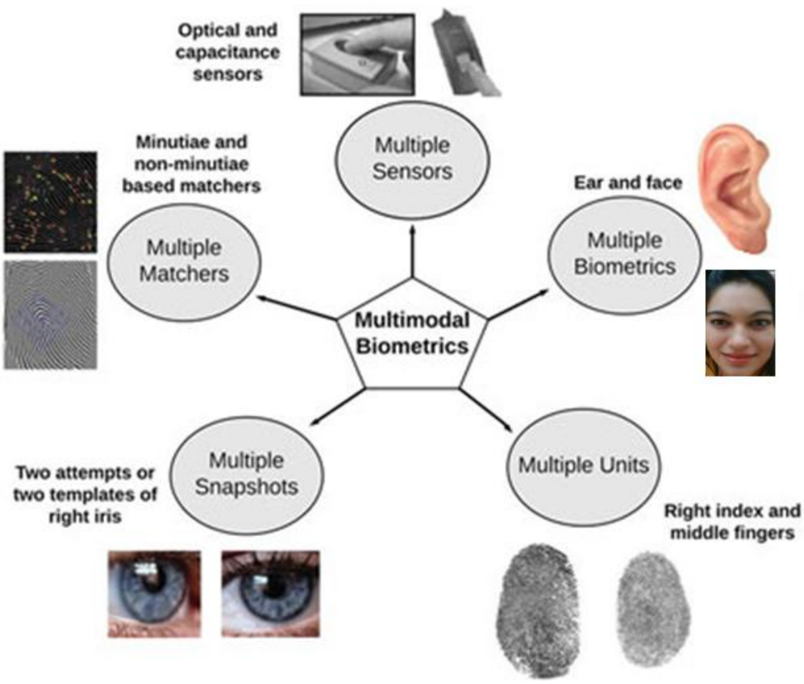


Fig 2. Example of multi-biometric system

A multi-biometric framework is proficient to lessen at least one of the accompanying inadequacies: I) False Acceptance Rate (FAR) ii) False Reject Rate (FRR) iii) Failure to Enroll Rate (FTE) iv) Susceptibility to Artifacts and Mimics Problem of all-inclusiveness and so on However multi-biometric frameworks are more dependable as contrasted and uni-biometric framework yet having a few disadvantages for example expanding generally cost by devouring memory space, expanding process time consequently postponing the last reaction. In a multimodal framework we meld at least two characteristics at various levels as examined in after area.

Biometric Fusion Strategies Plan.

Mix of biometric systems is a striking response for additional foster approval execution of biometric structures. Researchers have shown that multi-biometrics, i.e., mix of various biometric affirmations, further develops the affirmation execution [13]. In biometric structures; mix can be performing at different levels; Sensor Level, Feature Level, Score Level, and Decision Level Fusion as shown in Fig 3 underneath.

Sensor Level Fusion includes the association of evidence presented by different wellsprings of rough data before they are presented to feature extraction. Sensor level mix can benefit multi-test structures which get various sneak peaks of the comparable biometric.

Component Level Fusion in incorporate level mix, the capacities starting from different biometric estimations are cemented into a lone rundown of abilities by the utilization of legitimate component normalization, change, and lessening plans. The fundamental benefit of part level mix is the area of related incorporate qualities made by different biometric computations and, meanwhile, perceiving a remarkable course of action of arrangements that can additionally foster affirmation exactness [3]-[14]. The square framework of Score Level Fusion is shown in Figure-3

Score Level Fusion, the match scores yield by various biometric matchers are combined to make another match score (a scalar).

Decision Level Fusion, blend is finished at the hypothetical or decision level when simply extreme ends are free, this is the vitally open mix framework (for instance Furthermore, OR, Majority Voting, Weighted Majority Voting, Bayesian Decision Fusion). The second level of information mix is remembering level blend and results for most extreme level of information as broke down various frameworks.

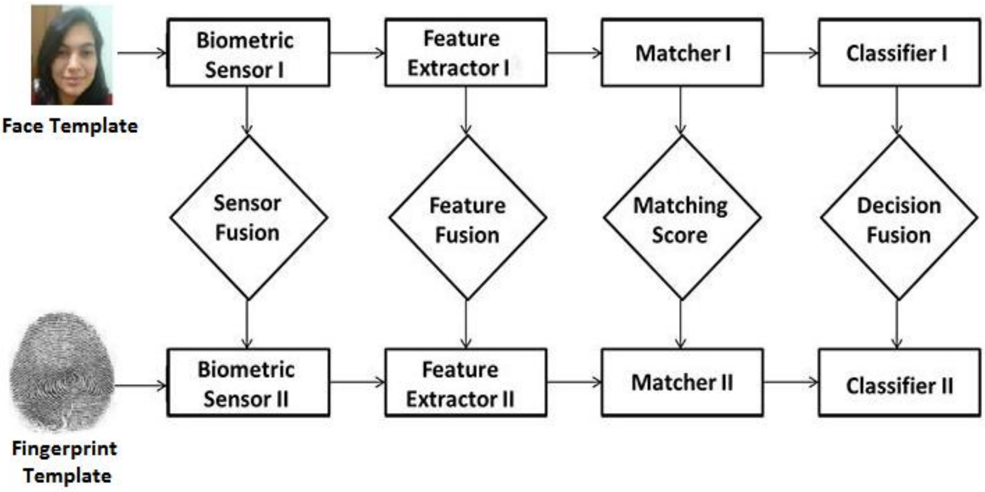


Fig 3. Different Level of fusion in multimodal biometric system

As examined in past area, multimodal biometric framework required more space for putting away element vectors got from various methodology obtained from highlight vectors of various sensors. While less extra room is needed to store include vectors caught from single sort sensor. The absolute number of element vectors beginning from same element extraction calculation can be decreased by just taking the averaging or gauges [19]. This paper presents a methodology for joining the comparable data given by sensor over various occurrences of a biometric methodology (for example unique mark). The general exhibition of the framework is dissected by incorporating various occurrences of a unique mark.

Related Work

Lin Zhang et al. [4] proposed an incredible affirmation plot by eliminating and assembling area and overall components of biometric pictures. The preliminary outcomes coordinated on exceptional imprint informational index show that the proposed close by overall information blend plan could generally additionally foster the affirmation precision got by either neighborhood or overall information are lead to promising execution of a FKP-based individual affirmation structure. The makers' preliminary outcomes coordinated on FKP data base exhibit that the proposed plan could achieve much better execution to the extent EER and the decidability list than the other top tier competitors.

T.C. Faltemier et al. [6] proposed a multi-model selection for face affirmation as a way of chipping away at the introduction of 3D face affirmation. The makers show that using various pictures to enroll a person in a display can deal with the overall show of a biometric structure. The makers showed that while using various pictures to enroll an individual, investigating from different explanations further creates execution over looking at simply a comparative enunciation.

Tobias Schiedam, et al. [8] proposed a mix of two instances of the comparable semantic, where semantics are elective composed by hand substance like numbers or sentences, in any case typically used imprint. To merge two instances of one semantic, a biometric approval is finished on both by Biometric Hash computation up to planning with score estimation. The blend is finished by the blend of the organizing with scores of two events of one physically composed semantic. The makers showed that while using three semantics and mix procedures, upgrades can be found conversely, with the best individual results.

Adams Wai-Kin et al. [7] have presented a part level coding plan for chipping away at the introduction of PalmCodes mix which applies four Gabor channels to the preprocessed palmprint pictures to figure four PalmCodes. Karthik Nandakumar et al. [10] have focused on the effect of different score normalization methodologies in a multimodal biometric structure. Min-max, z-score, and tanh normalization methodology followed by a direct measure of scores blend system achieves a higher GAR than the wide scope of different normalization and mix methodologies. The objective of our work is to design a biometric system with preferable accomplishment rate over give check to an individual to that a structure is arranged. The underlying advance of our arrangement is feature extraction for instance points of interest centers from biometric picture.

Unique mark extraction

This part portrays exhaustively the qualities of fingerprints and how they are removed for individual ID. Comprehensively elements of a unique mark picture can be assembled into two: worldwide and nearby. The worldwide unique finger impression highlights incorporate delta and center focuses otherwise called solitary focuses, just as the edge direction and separating. It is important to upgrade the finger impression acknowledgment as the nature of finger impression pictures can debased because of the presence of cuts and wounds and causes edge discontinuities. A portion of the means identified with unique finger impression upgrade are displayed in fig 4-Below.

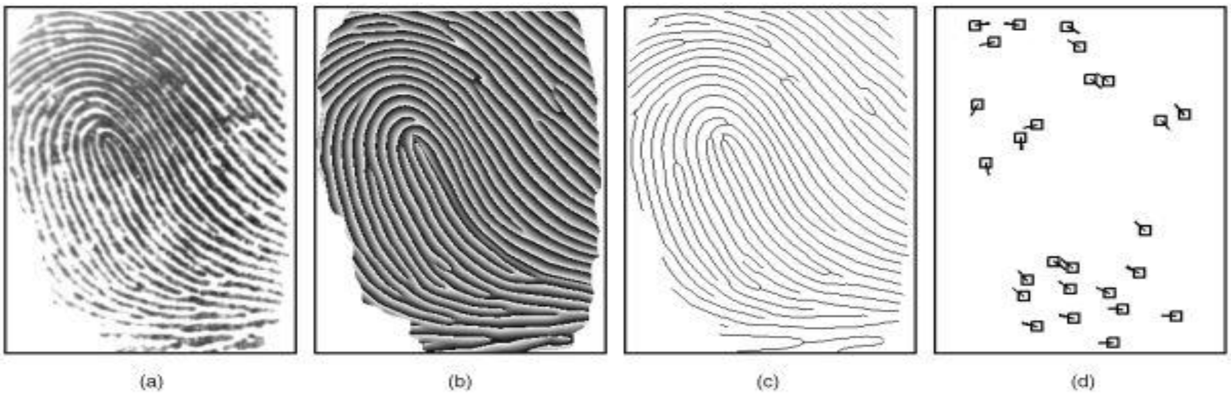


Fig 4. Feature extraction from fingerprint.

From unique finger impression, the details focuses are extricated for example attributes on a finger impression that exist either as an edge finishing or a bifurcation. In a word, the edge finishing is the end point of edges on the finger impression while an edge bifurcation is a point on the finger impression where one edge parts into two unique edges. Further a consecutive way to deal with binarization is simple and successful for extraction of provisions according to the perspective of plan and handling. As a general rule, the accompanying three stages comprise of a successive binarization system: binarization, diminishing, and particulars extraction [16].

Binarization. The first grayscale picture is changed over into a parallel picture which presents the picture as a 2D dim level power work f(x, y) with values going from 0 to $L-1$, where L means all singular dark levels. Allow n to signify the absolute number of pixels in a picture and ni be the quantity of pixels with dim level I, and the likelihood that dim level I might happen is characterized as

$$p_i= n_{i\ /}\ n$$

The fingerprint image gray-level is averaged with

$$\mu_T = \sum_{i=0}^{L-1} i p_i$$

After averaging, the fingerprint image pixels are classified into two distinct groups: C_1 ={0, 1, . . . , t } and C_2={t + 1, t + 2, . . . , L−1} with t as the threshold value.

Feature level fusion

As currently talked about combination could be at various levels for example sensor level combination, include level combination, match score combination and choice level combination. Component level combination [17][18] is one which can be accomplished by incorporating the capabilities got from various sources and element determination is performed on the got resultant vector.

If there should be an occurrence of element level combination standardization [8] is ruined acquiring the standardized score and afterward expanding every one of the accessible standardized scores. Another procedure [9] was suggested that arrangements in normalizing the element vectors first and afterward NN classifier is utilized to choose a competitor class having least distance as the class having a place with the testing test. For multimodal biometric framework the proposed [10] troupe calculation was utilized for highlight level combination. This combination calculation figures the standardized capabilities which were extricated exclusively from two characteristics of client and component determination is done on the link vector.

Picture improvement procedures [11] are utilized to preprocess the catch pictures. Curvelet Transform, Gabor Filter and Principal Component Analysis are utilized to separate the element. Euclidean Distance is utilized to meld the element vectors which are coordinated later on. Component extraction [12] is done dependent on the high goal unique mark pictures. A new smoothing calculation is utilized for proficiently discovery of components of fingerprints. Not set in stone with the assistance of eight unique veils and a paired picture of edges is ready from the grayscale finger impression picture.

Proposed Scheme

The proposed plot coordinates the different cases of fingerprints for getting quicker reaction time and high unwavering quality by including highlight level combination at enlistment stage and validation stage and circuit them at include level thereafter. The enlistment stage basically incorporates catch of different occurrences of fingerprints while selecting with the framework for first time. After that list of capabilities of each occurrence is extricated independently by applying highlight extraction. At the point when capabilities of each occurrence get accessible, the standardization (min-max) method is applied to each independently and afterward combination process (straightforward total principle) is applied to acquire combination score thus. This combination score is then put away in the retrievable information base which can be utilized for confirmation (check/recognizable proof) purposes.

During the confirmation stage a very comparable way goes through with catch of numerous occasion of fingerprints utilizing sensor. Element extraction is applied to crude information which is accessible from sensor and list of capabilities is gotten comparing to each unique finger impression case. After that standardization (min-max) strategy is applied to the singular list of capabilities that outcome in standardized score followed by combination process by straightforward aggregate guideline lastly the combination score is gotten. Finally, the got combination score is contrasted and the current information base and correspondingly registers the match score. In the event that the subsequent match score is equivalent to or over the edge esteem the client is acknowledged as real if not framework will dismiss it and imprint the client as phony client.

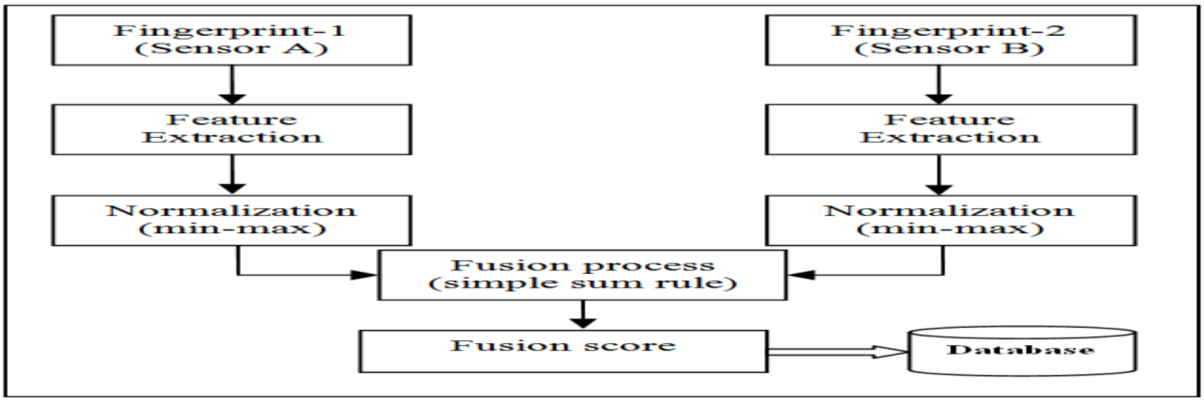


Fig 2: Enrollment process for multiple instances

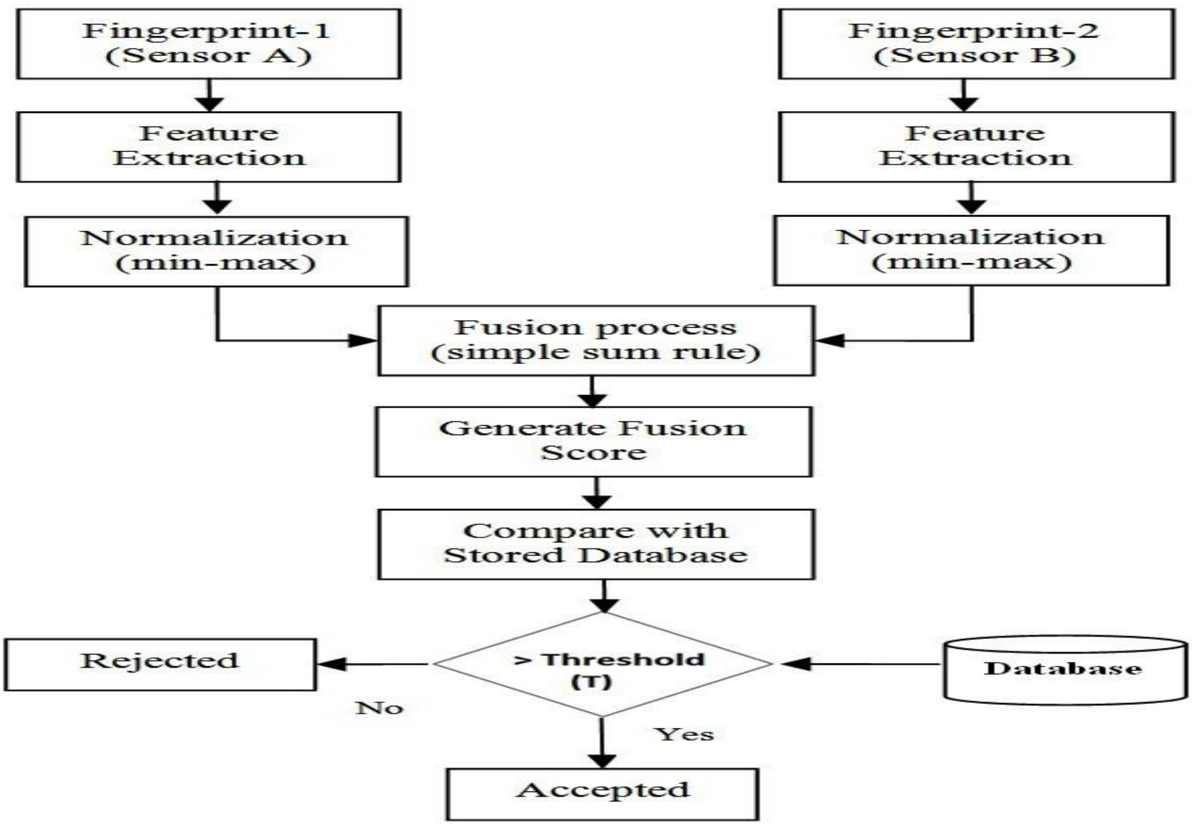


Fig 3: Authentication process for multiple instances

Proposed Algorithm

Algorithm for multi-instances of fingerprint is as follows:

Capture fingerprint-1 from Sensor

Capture fingerprint-2 from Sensor

Extract feature set for fingerprint-1

Extract feature set for fingerprint-2

Separately apply normalization (min-max) on fingerprint x and fingerprint y

Apply feature level fusion process (simple sum rule) on Normalized Scores

Generate the fusion score

Compare the obtained fusion score with the existing database

If (|score > Threshold|)

User is Accepted |else| Rejected

End

In step5, the normalization is required for incorporate sets acquired from the two fingerprints. Different normalizations strategies are open for score normalization process as shown in Table1 under, the most un-complex normalization system is the Min–max normalization. The min–max normalization is generally suitable for the circumstance where the cutoff points (most noteworthy and least potential gains) of the scores made by a matcher are known.

Table 1. Commonly used normalization techniques

Normalization Technique	**Robustness**	**Efficiency**
Min–max	No	N/A
Decimal scaling	No	N/A
z-score	No	High
Median and MAD	Yes	Moderate

For this situation, we can undoubtedly move the base and most extreme scores to 0 and1, separately. In any case, regardless of whether the coordinating with scores are not limited, we can appraise the base and most extreme qualities for a bunch of coordinating with scores and afterward apply the min–max standardization. Given a bunch of coordinating with scores {sk}, k =1, 2,...,n, the standardized scores are given by

S'k = (Sk-min)/(max-min)

At the point when the min and max esteems are assessed from the given arrangement of coordinating with scores, this technique isn't strong (i.e., the strategy is exceptionally delicate to anomalies in the information utilized for assessment). The min-max standardization holds the first dissemination of scores aside from a scaling factor and changes every one of the scores into a typical reach [0,1]. The most usually utilized score standardization method is the z-score that is determined utilizing the math mean and standard deviation of the given information. This plan can be anticipated to perform well provided that earlier information about the normal score and the score variety of the matcher is accessible.

For this situation, we can undoubtedly change the base and greatest scores to 0 and 1 individually. Let sij mean the ith match score yield by the jth matcher, I = 1,2,..., N; j = 1, 2 , . . . , (R is the quantity of matchers and N is the quantity of match scores accessible in the preparation set). The min-max standardized score n sij for the grade sij is given by

$$ns_j^t = \frac{s_j^t - min_{i=1}^N s_j^i}{max_{i=1}^N s_j^i - min_{i=1}^N s_j^i}$$

The most regularly utilized score standardization strategy is the z-score standardization that utilizes the math mean and standard deviation of the preparation information. This plan can be anticipated to perform well if the normal and the difference of the score dispersions of the matchers are accessible. In the event that we don't have the foggiest idea about the upsides of these two boundaries, we really wanted to gauge them dependent on the given preparing set. The z-score standardized score is given by

$$ns_j^t = \frac{s_j^t - \mu_j}{\sigma_j}$$

Where μj is the number juggling mean and σj is the standard deviation for the jth matcher. Notwithstanding, both mean and standard deviation are delicate to anomalies and consequently, this technique isn't vigorous.

For combination process basic aggregate principle strategy is utilized. This technique utilizes direct changes for adding the score.

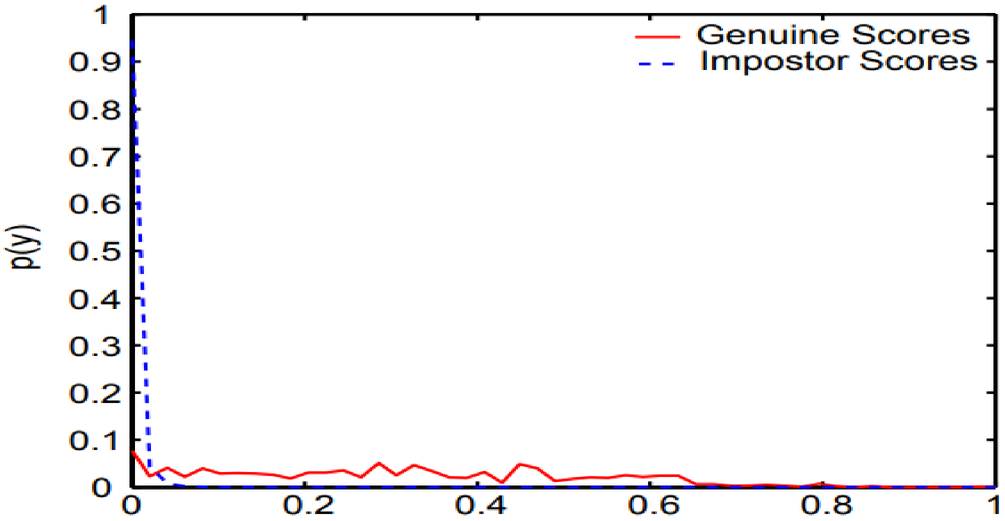
Then, at that point,

X= (a1 x1 - b1) +… . + (a xn - bn)

Where simulated intelligence and bi are the weight and one-sided values which can be input according to the need of client.

The standardized scores are given by

S'k = (sk-μ)/β
where μ is the number juggling mean and β is the standard deviation of the given information. Notwithstanding, both mean and standard deviation is delicate to anomalies and, consequently, this technique isn't vigorous. Z-score standardization doesn't ensure a typical mathematical reach for the standardized scores of the various matchers



Min-max Normalized Fingerprint Score (y)

Fig. 3. Distribution of genuine and impostor scores after min–max normalization for fingerprint;

Table-2: the presentation of two examples at Feature level with various standardization strategies.

FAR (%)	GAR (%) With Z-Score Normalization					
	RI+RM	RI+LI	RI+LM	LI+LM	RM+LM	RM+LI
0.01	68.22	56.67	65.56	58.00	70.67	63.78
0.10	76.22	71.33	76.89	71.33	78.67	73.56
1.00	86.22	80.89	87.33	83.78	89.33	85.33
	GAR (%) With Tanh Normalization					
0.01	68.22	58.23	65.78	64.67	70.67	64.00
0.10	76.22	70.88	76.89	71.33	78.67	73.56
1.00	88.22	80.89	87.33	83.78	89.33	85.33
	GAR (%) With Median Absolute Normalization					
0.01	57.56	52	58.00	55.35	52.64	51.33
0.10	69.78	65.78	69.56	67.33	66.23	65.23
1.00	81.33	78.22	82.00	81.56	83.34	82.67
	GAR (%) With Min-Max Normalization					
0.01	58.00	51.87	52.22	48.23	63.78	53.33
0.10	69.11	62.89	66.00	65.33	74.00	67.33
1.00	82.44	79.11	82.22	82.67	80.00	77.89

From Table-2 it will in general be seen that the mix of two events finger has a basic further foster score over the single model with Z-score and tanh-assessors, yet has relatively little advancement with Min-Max and Median and MAD. Figure-4 under shows the ROC twist for the show mix of two cases at Feature level with different normalization techniques.

Fig-4: The ROC curve Feature Level Fusion combination of two instances with different Normalization rules using Min-Max.

From the above outcomes clearly the proposed approach worked on the Overall presentation of the framework by lessening FAR (bogus acknowledgment rate) and FRR (bogus oddball rate). Clearly less extra room is needed as the different cases are taken of same methodology.

Comparison and effectiveness viewpoints

Considering the quantity of choices and accommodation of finger examining can change in various combination situations, we need to assess the combination proficiency notwithstanding the adequacy we saw from the testing results. To look at the combination effectiveness of various combination situations in a more exact manner than the overall assessment given in proposed conspire that presents a method for confirmation utilizing the idea of multi-examples. The plan plays out the element extraction level combination with multi-examples of fingerprints and ends up being more solid. The presentation models displayed in table 3 underneath is additionally determined w.r.t. effectiveness per show, the proficiency per show is characterized as the exhibition attainable under similar measure of finger introductions (seasons of testing), which considers the accommodation to the subjects.

Since the work required is practically something similar under similar measure of finger introductions, the presentation is more tantamount. This effectiveness basis matters principally on the multi-calculation combination since it needs just one finger show. The combination execution focuses that are nearest to the exhibition target (FRR $\leq$ 1%, FAR = 0.1%) under various combination situations, in which the focuses with a similar measure of finger show (set apart in a similar shading) are equivalent among one another. Then again, if two situations have similar measure of finger introductions, almost certainly, the situation which combines more calculations accomplishes a better.

Table 3: Performance of separate features (minutiae and DWT)

Dataset	Minutiae only (%)	DWT only (%)
DB1_B (TouchView II optical sensor)	50	95
DB2_B (FX2000 optical sensor)	70	80
DB3_B (100 SC capacitive sensor)	40	95
DB4_B (SFinGe v2.51 synthetic FP generator)	65	40

Conclusion & Future Scope

This paper looks at the impact of multi-occasion strategies on the presentation as contrasted and multimodal biometric framework. We have shown that the standardization of scores procured with multi-cases further develops the acknowledgment execution of a multimodal biometric framework that utilizes the various fingerprints for client verification. The proposed approach gives a more successful and dependable technique for multibiometric validation utilizing various occasions and gives secure confirmation. The proposed conspire beats the defects and limits of conventional uni-biometric framework just as existence issue related with multimodal biometric framework. This plan decreases the FAR (bogus acknowledgment rate) and FRR (False oddball rate). The utilization of multibiometric approach works on the general presentation of the framework. In future, this methodology can be executed essentially to give high security utilizing multibiometric framework.

References

[1] B. Ulery, A. Hicklin, C. Watson, W. Fellner and P., "Hellinan Studies of Biometric Fusion," 2006.
[2] C. Kant, "A Multimodal Approach to Improve the Performance of Biometric System," BIJIT-BVICAM's International Journal of Information Technology, 2015.
[3] S. S. Patil, G. S. Chandel and R. Gupta, "Fingerprint Image Enhancement Techniques and Performance Evaluation of the SDG and FFT Fingerprint Enhancement Techniques," International Journal of Computer Technology and Electronics Engineering(IJCTEE), pp. 184-190, 2012.
[4] Lin Zhang, Lei Zhang, David Zhang, and Hailong Zhu “Ensemble of local and global information for finger–knuckle-print recognition”. Elseveir / Pattern Recognition 44 (2011) 1990–1998.
[4] R. Kaur, P. Sandhu and A. Kamra, "A Novel Method for Fingerprint Feature Extraction," in IEEE Conference 2010 on Networking and Information Technology, 2010.
[5] P. Verma, Y. Bahendwar, A. Sahu, M. Dubey and P. Verma, "Feature Extraction Algorithm of Fingerprint Recognition," International Journal of Advanced Research in Computer Science and Software Engineering, 2012.
[6] S. A. Sudir and R. T. Yuwono, "Adapatable Fingerprint Minutiae Based Algorithm Based on Crossing Number Method for Hardware Implementation using FGPA Devices," International Journal of Computer Science, Engineering and Information Technology (IJCSEIT), 2012.
[7] A. R. a. R. Govindarajan, "Feature Level Fusion using Hand and Face Biometrics," in Proceeding of SPIE Conference on Biometric Technology for Human Identification.
[8] A. J. Jacob, N. T. Bhuvan and S. M. Thaampi, "Feature Level Fusion using Multiple Fingerprint," International Journal on Computer Applications,Special Issue on Computational Science-New Dimensions & Perspectives, pp. 13-18, 2011.
[9] Y. -F. Yao, X.-Y. Jing and H.-. S. Wong, "Face and Palmprint Feature Level Fusion for Single Sample Biometrics Recognition," Journal on Neuro Computing, pp. 1582-1586, 2007.
[10] Zhuang De-Wen, Zhou De-Long: “Face recognition based on Log-Gabor filter binary transformation”.Control Conference (CCC), 2010 29th Chinese. 2792 – 2795,2010.
[11] T.C. Faltemier, K.W. Bowyer, and P.J. Flynn “Using multi-instance enrollment to improve performance of 3D face recognition”. Elseveir / Computer Vision and Image Understanding 112 (2008) 114–125.
[12] Adams Wai-Kin Kong and David Zhang “Feature-level Fusion for Effective Palmprint Authentication” ICBA_2004.
[8] Tobias Scheidat, Claus Vielhauer, Jana Dittmann “Single-Semantic Multi-Instance Fusion of Handwriting Based Biometric Authentication Systems” IEEE ICIP 2007.
[13] Karthik Nandakumar, Anil K. Jain, and Arun A. Ross “Score Normalization in Multimodal Biometric Systems” Elsevier patteren Recognition 2005.
[14] Arun Ross and Rohin Govindarajanb, “Feature Level Fusion Using Hand and Face Biometrics”, SPIE Conference on Biometric Technology for Human Identification II, Volume, 5779, pp.196-204(Orlando, USA) March 2005.
[15] S. Bhardwaj, "An Algorithm for Feature Level Fusion in Multimodal Biometric System," International Journal of Advanced Research in Computer Engineering & Technology(IJARCET), 2014.

[16] M. Vatsa, R. Singh, A. Noore, S.K. Singh "Belief Function Theory based Biometric Match Score Fusion: Case Studies in Multi-instance and Multi-unit Iris Verification" Seventh International Conference on Advances in Pattern Recognition 2009.
[17] Massimo Tistarelli • Stan Z. Li • Rama Chellappa "Handbook of Remote Biometrics for Surveillance and Security" Springer
[18] Riad I. Hammoud and Besma R. Abidi "Face Biometrics for Personal Identification Multi-Sensory Multi-Modal systems".
[19] S. Inamdar and Y. Dandawate, "Fusion Based Multimodal Biometric Cryptosystem," in 2015 International Conference on Industrial Instrumentation and Control(ICIC), 2015.