

**SCORE FUSION USING HYBRID BACTERIAL
FORAGING OPTIMIZATION AND PARTICLE
SWARM OPTIMIZATION (BFO-PSO) FOR
HAND-BASED MULTIMODAL BIOMETRICS**

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HAND-BASED MULTIMODAL BIOMETRICS**

by

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LIST OF ABBREVIATIONS

SI	Swarm Intelligence
EC	Evolutionary Computing
PSO	Particle Swarm Optimization
BFO	Bacterial Foraging Optimization
FA	Firefly Algorithm
HBF-PSO	Hybrid Bacterial Foraging – Particle Swarm Optimization
HIBS	Hybrid Improved Bacterial Swarm
FP	Fingerprint
PP	Palm print
FIKP	Finger Inner Knuckle Print
FAR	False Acceptance Rate
FRR	False Rejection Rate
GAR	Genuine Acceptance Rate
ROC	Regional Operating Characteristic
ROI	Region of Interest
DET	Detection Error Trade-off
EER	Equal Error Rate
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
DB	Database
Sf	Fused Score

LIST OF SYMBOLS

Δ	Delta
μ	Mean
Σ	Summation
Θ	Position of bacterium
\emptyset	Velocity of bacterium
α	Randomization variable
Rand	Random number generator
t	Threshold
C(i)	Step size of BFO
<i>pbest</i>	Local optimum value
<i>gbest</i>	Global optimum value
N_{ed}	Number of Elimination dispersal iterations
N_{rep}	Number of Reproduction iterations
N_c	Number of Chemotaxis iterations
N_s	Number of swim iterations
C1,C2	Acceleration constants
w	Weight
S1,S2,S3	Scores of FP,PP and FIKP

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**PENGGABUNGAN PENILAIAN MENGGUNAKAN PENGOPTIMUMAN
PENCARIAN BAKTERIA HIBRID DAN PENGOPTIMUMAN PARTIKEL
BERKELOMPOK (BFO-PSO) UNTUK BIOMETRIK MODAL BERGANDA
BERASASKAN TANGAN**

ABSTRAK

Algoritma kepintaran berkelompok memainkan peranan dalam meningkatkan ketepatan prestasi kepada tahap yang lebih tinggi dalam proses pengesahan biometrik pada masa kini. Kebanyakan penyelidikan berkait dengan algoritma kepintaran berkelompok ini secara khusus atas sebab keperluan untuk menggabungkan lebih daripada satu algoritma dalam melahirkan hasil yang lebih baik. Oleh itu, kajian ini memberi tumpuan kepada gabungan nilai-nilai modaliti biometrik berganda berasaskan tangan dan pemberat optimum menggunakan Pengoptimuman Pencarian Bakteria Kacukan – Pengoptimuman Partikel Berkelompok (HBF-PSO). Ketepatan modaliti geometri berasaskan tangan yang bersifat unimodal dan ditemui di permukaan tapak tangan yang dibahagikan kepada beberapa modaliti berganda sebagai kesan jari (FP), kesan telapak tangan (PP) dan jari bahagian dalam genggam (FIKP) secara berturutan. Penilaian berasaskan keperincian pengekstrakan ciri adalah dilakukan untuk mengambil nilai-nilai modaliti ini yang mana akan dijumlahkan secara penimbangan penilaian. Penggabungan algoritma BFO dan PSO adalah hasil kacukan berdasarkan pengurangan objektif untuk mengurangkan kadar kesalahan setara (EER) bagi sistem pengesahan biometrik berganda berasaskan tangan, seterusnya memberipeningkatan dari segi ketepatan yang sangat dikehendaki. Algoritma BF-PSO yang dicadangkan ini, iaitu yang terlibat dalam pengurangan kesalahan sistem biometrik berasaskan tangan digunakan untuk pengoptimum pemberat yang dikaitkan

dengan nilai-nilai modaliti berganda pada gabungan nilai tertimbang yang menghasilkan nilai EER yang telah dikurangkan. Tambahan lagi, algoritma HBF-PSO digunakan untuk mengurangkan kelemahan seperti penumpuan yang pramatang dan perlahan pada setiap algoritma kepintaran berkelompok, PSO dan BFO. Selepas gabungan penilaian, gabungan yang telah dinilai akan dibandingkan dengan keputusan ambang untuk mengesahkan identiti yang dikenalpasti sebagai tulen atau tidak. Ekperimen ini dijalankan menggunakan pangkalan data imej Bosphorus dari imej kiri dan kanan tangan dan hasil eksperimen ini menggunakan pendekatan yang dicadangkan telah mencapai hasil yang signifikan dari segi kadar ralat. Nilai EER untuk imej kiri dan kanan adalah masing-masing $4.90e-03\%$ dan $7.00e-03\%$ yang sangat hampir dengan sifar. Oleh itu, ketetapan sistem biometrik berganda berasaskan tangan terus dipertingkatkan dengan peningkatan setinggi 2.5237% dengan menggunakan algoritma HBF-PSO yang dicadangkan pada gabungan nilai-nilai tertimbang.

**SCORE FUSION USING HYBRID BACTERIAL FORAGING
OPTIMIZATION AND PARTICLE SWARM OPTIMIZATION (BFO-PSO)
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ABSTRACT

In recent times of biometric authentication, the influence of swarm intelligence algorithms role-played in enhancing the performance accuracy to a greater extent. Most researches related to Swarm Intelligence (SI) algorithms have done on the particular, due to the need to integrate more than one SI algorithm for better results. Therefore, this research is focused on the hand-based multimodal biometric score fusion which incorporates the scores of hand-based multimodalities and the optimal weights using Hybrid Bacterial Foraging - Particle Swarm Optimization (HBF-PSO) algorithm. The minutiae-based hand geometry modality is unimodal and found on the inner surface of the hand which is further segmented into multimodalities as Fingerprint (FP), Palm Print (PP), and Finger Inner Knuckle Print (FIKP) respectively. The minutiae-based score feature extraction is done to extract the scores of these modalities which take part in the weighted sum score fusion. The combination of BFO and PSO algorithms are hybridized based on the minimization objective to minimize the Equal Error Rates (EER) of the hand-based multi-biometric verification system in terms of accuracy enhancement are highly demanding. The proposed hybrid BF-PSO algorithm involved in the error minimization of the hand-based multibiometric system is used to optimize the weights associated with the scores of multi modalities at the weighted sum score fusion resulting in minimized EER values. Further, the HBF-PSO algorithm is used to mitigate the weaknesses like premature convergence and slow

convergence of the individual SI algorithms PSO and BFO respectively. After the score fusion, the fused score is compared with the decision threshold in order to verify the claimed identity as a genuine or an impostor. The experiment is carried out using the BOSPORUS database of left and right-hand images and the experimental results using the proposed approach have achieved significant results in terms of error rates. The EER values for the left-hand and right-hand images are $4.90e-03\%$ and $7.00e-03\%$ respectively which are very close to zero. Therefore, the accuracy of the hand-based multibiometric system is further enhanced to a greater extent of 2.5237% increase by using this proposed HBF-PSO algorithm at the weighted sum score fusion.

CHAPTER 1

INTRODUCTION

1.1 Biometric System

Biometric systems are the methods of verifying or recognizing the identity of a living person (S.-H. Lin & S. Kung, 1997) based on physiological or behavioral characteristics (J. Wayman et al., 2005). The physiological components classified as fingerprint, palmprint, face, iris, hand geometry and so on. The biological features can be classified as signature, voice, gait recognition and so on. Biometrics is always an ever-growing field of research since from its inception have been attracting extensive attention from both researchers and engineers for personal authentication due to the ever-growing demands on access control, public security, forensics, and e-banking.

A biometric verification system authenticates a person's identity by comparing the captured biometric characteristic with his previous biometric reference template pre-stored in the system. It conducts a one-to-one comparison to confirm whether the claim of identity by the individual is real (A. El-Sisi, 2011).

A biometric identification system recognizes an individual by searching the entire enrollment template database for a match. It conducts a one-to-many comparison to confirm whether the claim of identity by the individual is real by T. Djara et al. (2016). In an identification system, the system establishes a subject's identity without the subject

having to claim a status. The difference between verification and identification in a biometric system is shown below in Figure 1.1. Finally, the verification system is a 1:1 matching whereas; the identification system is a 1: N matching. Biometric systems can be majorly classified as unimodal biometrics and multimodal biometrics.



Figure 1. 1: Multimodal biometric Verification vs. Identification

1.1.1 Unimodal Biometrics

Unimodal biometrics has dealt with a single modality either physiological or behavioral characteristics for verifying the human identity. The ideal biometric feature has seven inequalities: universality, uniqueness, permanence, measurability, performance, acceptability and circumvention (Maltoni et al., 2009).

Even though the unimodal biometrics has several advantageous over commercial and government applications like border security, immigration, identity verification, attendance system; it is vulnerable to spoofing attacks when deploying them in real-world applications involving an extensive database. According to A. A. Ross et al. (2006), it is listed as noisy data, intra-class variations, inter-class similarities, non-universality, spoofing attacks.

- Noisy data: Susceptibility of biometric sensors to noise leads to inaccurate matching, as noisy data may result in false rejection.
- Intra-class variations: The biometric data would not be identical at the verification phase as same as template data generated at the enrolment phase. It is known as intra-class variation. Large intra-class variations increase the False Rejection Rate (FRR) of a biometric system.
- Inter-class similarities: Inter-class similarity refers to the overlap of feature spaces corresponding to multiple individuals. Substantial inter-class similarities increase the False Acceptance Rate of a biometric system.
- Non-universality: Some persons cannot provide the required standalone biometric due to illness and disabilities.
- Spoofing attacks: Unimodal biometrics is vulnerable to spoofing where the data can be imitated or forged.

1.1.2 Multimodal Biometric System

The multimodal biometric system utilizes more than one modality for the personal authentication of a human than unimodal. The multi-biometric system used in the recent

research due to its universality, vulnerability to spoof attacks, no inter-class similarities, no intra-class variations, and no noisy data which further enhances the authenticity of the system.

Among the all biometric technologies, the hand based biometrics, including fingerprint, palmprint, hand geometry or hand shape, finger knuckle print, finger inner knuckle print, hand vein, and finger vein is the most popular and have the most significant shares in biometrics market by A. Ross and A. Jain (2003). It is due to the advantage of these traits such as low-cost, low-resolution imaging and stable features. Further, there are still many challenges in improving the accuracy, robustness, efficiency, and user-friendliness of hand-based biometric systems in accordance with the state of the art techniques (M. A. O. Ahmed et al., 2018).

1.2 Swarm Intelligence Algorithm

Swarm Intelligence algorithm is based on the collective social behavior of organisms. Social behavior increases the ability of an individual to adapt. There is a relationship between adaptability and intelligence. Intelligence arises from the interactions among individuals. A population of interacting individuals that optimizes a function or goal by collectively adapting to the local or global environment is called Swarm intelligence by J. Kennedy et al. (2001). Typical swarm intelligence algorithms include Particle Swarm Optimization(PSO), Firefly Algorithm (FA), Bacterial Foraging Optimization (BFO), Artificial Bee Colony (ABC) and so on (J. Kennedy et al., 2001).

1.2.1 Hybrid Swarm Intelligence Algorithm

The hybridization can be done by combining any two or more SI algorithms or combining SI and EC algorithms and SI and other data structure. The need for a hybrid swarm intelligence algorithm over the existing classic SI algorithms is to minimize the error rates in the biometric applications in order to enhance the performance accuracy. Further, it reaches the optimum value within the least number of iterations along with the fewer error rates. Furthermore, it is used for feature selection algorithm for selecting the best feature set which increases the classification accuracy. In our proposed system, the hybrid SI algorithm(HBF-PSO) is used at the weighted sum score fusion of a hand-based multimodal biometric system to optimize the weights associated with the scores of FP, PP, and FIKP multimodalities to minimize the error rates in terms of accuracy enhancement.

1.3 Problem Statement

The purpose of this study is to enhance the performance accuracy of a hand-based multimodal biometric system in terms of minimizing the error rates using a Swarm Intelligence(SI) based fusion approach.

Swarm Intelligence is an emerging paradigm in bio-inspired computing for implementing adaptive systems which are an extension of evolutionary computing. While evolutionary algorithms based on a genetic adaptation of organisms, Swarm Intelligence algorithms based on the collective social behavior of organisms.

According to P. Kora and S. R. Kalva (2015), the SI algorithms suffered by a critical issue called slow convergence which reported in algorithms like Bacterial Foraging Optimization (BFO). It is due to the fixed step size in the tumbling stage of the bacterium in BFO. In BFO, the step size of the chemotaxis of each generation is the primary determining factor for accuracy as well as the convergence of the global best optimum. According to P. Kora et al. (2019), during the process of random walk, the BFO algorithm searches for the random direction, which increases delay. This delay leads to the slow convergence of the BFO algorithm. To overcome the delay in reaching the global optimum and also to boost up the performance of BFO, we need to fine-tune the BFO algorithm.

Similarly, the SI algorithms face another issue called the premature convergence reported in the algorithms like Particle Swarm Optimization (PSO) in C. Dalila et al. (2015) and Ant Colony Optimization(ACO) in (A. Kumar & A. Kumar, 2016). The underlying principle behind this problem is the fast rate of information flow between the particles which results in the creation of similar particles with a loss in diversity that increases the possibility of being trapped out in the local optima resulting in premature convergence (A. Kumar et al., 2010; K. K. Veeramachaneni et al., 2003).

According to A. Kumar and B. Wang (2015), a typical multimodal biometric verification system requires three parameters. They are namely the optimal weights to the biometric matches, a fusion rule for the integration of matching scores and the decision threshold for the final accept and reject the decision to discriminate the claimed identity

as a genuine or an impostor. These three fusion parameters determine the performance accuracy of the system. Fine-tuning of any of these parameters like optimal weights, decision threshold and score fusion using SI algorithms will lead to further enhancement in the performance accuracy of the system.

However, while fine-tuning the optimal weights using SI algorithms in the hand-based multibiometric system, it has been noted that the individual SI algorithms have its limitations like ending up in the local minimum (premature convergence) (C. Dalila et al., 2015; A. Kumar & B. Wang, 2015).

According to M. Hanmandlu et al. (2008), fusion strategies are an essential aspect of any multimodal biometric verification system. Further, this kind of hand-based biometric verification system has been implemented by various fusion approaches using deterministic based fusion, probabilistic based fusion and evolutionary-based fusion.

Evolutionary-based fusion is the recent promising state-of-the-art approach in the multimodal biometric verification than other fusions (A. Kumar & B. Wang, 2015; G. S. Walia et al., 2019). The main advantage of this fusion in the context of biometrics is an improvement in the overall matching accuracy.

Interestingly, the approach of a hybrid swarm intelligence algorithm has been proposed to mitigate the weaknesses of SI algorithms like premature convergence and slow convergence of PSO and BFO respectively. Further, the optimal weights associated with the scores of hand-based modalities have been optimized using this hybrid swarm

intelligence algorithm at the score fusion to attain minimized error rates which enhances the performance accuracy to further extent.

1.4 Motivations

The principal motivation behind this proposed research is to hybrid the BFO algorithm and the PSO algorithm to propose a hybrid Bacterial Foraging -Particle Swarm Optimization (HBF-PSO) algorithm in order to mitigate the slow convergence of BFO and premature convergence of PSO algorithms.

Applying this proposed hybrid algorithm (HBF-PSO) into the hand-based multimodal biometric verification system for the accuracy enhancement in terms of minimizing the error rates by optimizing the weights associated with the scores of multi modalities at the weighted sum score fusion.

1.5 Research Objectives

This research aims to enhance the performance accuracy of the hand-based multi-biometric verification system by minimizing the error rates using a novel hybrid swarm intelligence algorithm. Intrinsicly, emphasize is being given to proposing a hybrid swarm intelligence algorithm in order to mitigate the individual weaknesses of the SI algorithms and also to optimize the weights associated with the scores of the hand-based modalities at the weighted sum score fusion to minimize the Equal Error Rate.

- i. To propose a novel hybrid swarm intelligence algorithm(HBF-PSO) in order to mitigate the weaknesses like slow convergence of BFO and premature convergence of PSO of the individual SI algorithms.
- ii. To enhance the performance accuracy of the hand-based multibiometric system in terms of minimizing the error rates by optimizing the weights associated with the scores of hand-based multimodalities (FP, PP, FIKP) using the proposed novel hybrid swarm intelligence (HBF-PSO) algorithm at the weighted sum score fusion.

1.6 Research Contributions

The key contributions of this thesis are:

- i. In the proposed HBF-PSO algorithm, the inadequacies like the slow convergence of BFO and premature convergence of PSO have been mitigated. First, the slow convergence of BFO has been alleviated by introducing the different adaptive step sizes ranging between $[0,1]$ in the proposed HBF-PSO instead of a fixed step size ranging between $[-1,1]$ as in original BFO. The adaptive step size is introduced by the random walk procedure of the Firefly algorithm which helps to increase the convergence speed. So, the slow convergence of the BFO algorithm is mitigated. Further, the BFO algorithm is used for local searches only in the proposed HBF-PSO algorithm. Secondly, the PSO algorithm is used as a mutation operator in the HBF-PSO algorithm. So, the trapping out in the local optima (premature convergence) is being avoided as it is used for the global search only rather than local search in the proposed HBF-PSO algorithm.

- ii. The performance accuracy of the hand-based multibiometric system can be further enhanced by optimizing the weights at the weighted sum score fusion using the proposed Hybrid Bacterial Foraging -Particle Swarm Optimization algorithm (HBF-PSO). Weighted sum score fusion is done by incorporating the minutiae-based hand modalities scores of FP, PP, and FIKP and the weights associated with the scores. Weight optimization is done by using the proposed novel hybrid swarm intelligence algorithm (HBF-PSO) at the weighted sum score fusion resulting in minimized Equal Error Rates(EER). The error minimization which in turn enhances the accuracy of the hand-based multibiometric system.

1.7 Scope of the Research

This research is limited to the fusion of matching scores of hand-based modalities and the optimal weights. The hand-based patterns (FP, PP, and FIKP) involved in this research have been selected based on the minutiae feature representation in the inner hand geometry. The weights associated with the scores of these modalities are optimized by the influence of a hybrid swarm intelligence algorithm (HBF-PSO) at the weighted sum score fusion for enhancing the accuracy of the hand-based multibiometric system in terms of minimizing the error rates. Further, the choice of SI algorithms like BFO and PSO have been selected for hybridization based on the minimization objective. Adaptive step size is introduced by the Firefly algorithm in the BFO algorithm of the proposed HBF-PSO algorithm which is also based on the conceptual similarity between the BFO and FA algorithm. As concentrating on the inner hand surface and the selection of modalities

based on minutiae feature, the other hand-based patterns like hand veins and finger knuckle print are beyond the scope of the research.

1.8 Research Methodology

In this research, three different hand-based modalities fingerprint, finger inner knuckle print and palm print which are found on the inner surface of the hand are taken as input. First, the inner hand surface image which is taken from the Bosphorus database as hand geometry trait, and the image segmentation and Region of Interest (ROI) techniques are deployed to extract these modalities. After segmentation, the preprocessing and minutiae feature extraction is done for all these three modalities using Spectral Minutiae Recognition(SMR). Then, the feature extracted images are stored in a template database as a feature vector for matching.

After that, the matching scores of all these three modalities is generated by Euclidean distance matcher and deployed into tan-h score normalization, to check for the similarity measure in order to ensure that all the three scores are in the same range between 0 and 1.

At the score level fusion, the weighted sum rule classifier is used. The weighted sum score fusion is done by incorporating the optimal weights and the scores of these three modalities. The weights associated with the scores are being optimized by using the proposed HBF-PSO algorithm.

At last, the fused score is being compared with the decision threshold. If the score value is greater than the threshold, the claimed identity is accepted as a genuine user, otherwise an impostor.

The HBF-PSO algorithm is proposed to minimize the error rates (EER) of the hand-based multibiometric system in terms of enhancing the accuracy to further extent. In addition to that, the hybrid algorithm is used to mitigate the individual weaknesses of BFO and PSO algorithms like slow convergence and premature convergence respectively. In HBF-PSO, the BFO algorithm is used for local search which is accompanied by using the chemotactic operation of BFO as well as the PSO algorithm is used for the global search which acts as a mutation operator. In the classical BFO, the step size $C(i)$ of the tumbling stage of the bacterium is random search with fixed step size and it is a unidirectional random vector ranging between $[-1, 1]$. So, it delays further in attaining the local optimum. In the proposed HBF-PSO algorithm, the fixed step size is fine-tuned into varying step size using the random walk procedure of Firefly Algorithm (FA) ranging between $[0,1]$. The step size $C(i)$ is fine-tuned in the range from 0.01 to 0.5 in the increasing order to reach the optimum at the earliest convergence.

The Database used for the proposed research is the BOSPORUS hand image database. It consists of 642 persons left and right-hand images. The left and right-hand images belong to the same person in which each person has three poses of images from the left as well as right hands. So, a total of 3,852 samples have been used.

The performance evaluation of the biometric verification is done by plotting of ROC curve against GAR and FAR. The performance accuracy of the system is validated by having lesser EER. DET curves are a graphical plot of error rates similar to ROC curves which are plotted against FAR and FRR.

The benchmark functions have been selected based on the features like continuous, unimodal, multimodal, separable and inseparable in order to prove the effectiveness of the proposed hybrid BF-PSO algorithm over classical BFO and PSO algorithms. In addition to that, the weighted sum score objective function of the proposed system supports continuous, separable and multimodal features. So, the eight benchmark functions have been selected based on these features.

The performance of the hand-based multibiometric authentication system is being statistically analyzed by using Likelihood ratio hypothesis testing and implemented by using MATLAB 2014- 64 bit and IBM SPSS 21.0.

1.9 Organization of Thesis

This thesis has been organized as follows: In Chapter 2, the literature review of existing works related to feature extraction of hand-based modalities, score fusion techniques, and score normalization, review of SI algorithms and variants of BFO and PSO algorithms, hybrid BFO-PSO algorithm and its variants, related works using score fusion of hand-based multimodal biometric authentication system, the influence of hybrid

SI algorithm in the score fusion of multimodal biometric authentication system have been thoroughly discussed.

The research methodology includes the general framework, description of Bosphorus Database, evaluation procedures used in this study are given in Chapter 3. In Chapter 4, the weighted sum score fusion incorporates the weight optimization by using the proposed HBF-PSO algorithm and the minutiae-based score feature extraction of hand-based modalities are given. In Chapter 5, the results of score extraction which are minutiae-based, the proposed HBF-PSO algorithm used in the weight optimization at the weighted sum score fusion, the HBF-PSO algorithm is compared with the classical BFO and PSO algorithms using benchmark functions and the performance evaluation of hand-based multi-biometric verification system using Bosphorus database is done. The conclusion of the thesis and the future work suggested for further research are given in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter describes the image segmentation and feature extraction of hand-based modalities based on the state-of-the-art methodologies. It also focuses on an overview of various score normalization techniques, and taxonomy of score fusion techniques. Further, the multiple swarm intelligence algorithms comprehensively compared and reviewed based on the objectives, strengths, and limitations. Furthermore, the related works of score fusion for the hand-based multimodal biometric system and the influence of hybrid Swarm Intelligence algorithms in the score fusion of multimodal biometric authentication system reviewed in this Chapter.

2.2 Feature Extraction of Hand-based biometrics

The human hand has various measurable characteristics that are used for feature extraction in the multimodal biometric system fusion. From the hand-image, several biometric features have been extracted: fingerprint, palm print, hand geometry, finger vein, and finger knuckle print and inner knuckle print, dorsal vein, palm vein and so on. The hand-based modalities have been attracting extensive attention from the researchers due to its accuracy, ease of use, low cost, user-friendliness, and reliability. Our proposed research is based on the hand-based modalities which are minutiae-based and are found

on the inner hand surface. The modalities have been satisfied the above criterion is namely fingerprint, palm print and finger inner knuckle print. These modalities have found on the inner surface of the hand as hand geometry discussed below in Figure 2.1 in detail.

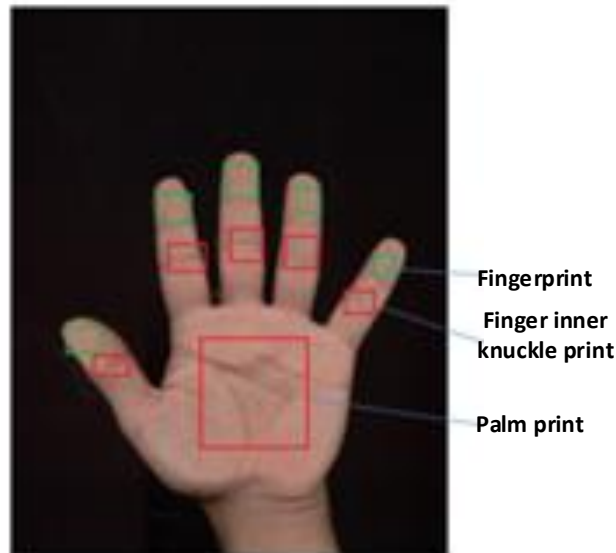


Figure 2.1: Inner hand of the Bosphorus image

2.2.1 Fingerprint

Fingerprint recognition is the promising modality known for its reliability, high security, and ease of use than other hand-based modalities. Fingerprint recognition classified as Correlation-based fingerprint matching, Minutiae based fingerprint matching, and Non-minutiae based fingerprint matching. Fingerprint recognition extensively described in work (D. Maltoni et al., 2009). Most fingerprint-based biometric systems follow the minutiae-based approaches due to high accuracy (A. Jain et al., 2001; A. J. Willis & L. Myers, 2001);(T.-Y. Jea & V. Govindaraju, 2005); (W. Chen & Y. Gao,

2007). It also supports the state of the art technology in fingerprint recognition (M. M. Ali et al., 2016; F. Chen et al., 2013; W. Lee et al., 2017; W. Zafar et al., 2014).

Minutiae are the combination of ridge ending and ridge bifurcation which is shown in Figure 2.2 (a),(b) and (c). It is found in the inner hand surface as palm print, fingerprint, and fingers inner knuckle print.

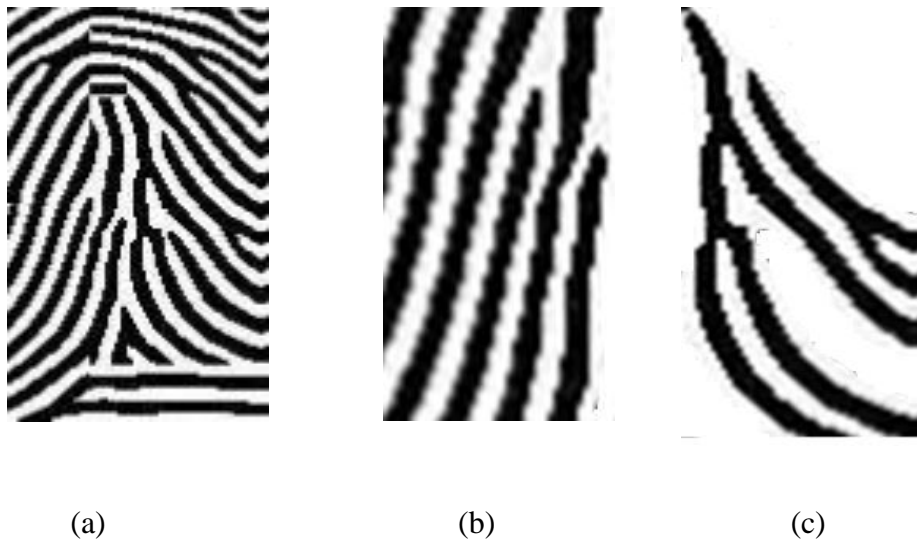


Figure 2.2: (a) Minutiae Feature Extraction (b) Ridge ending (c) Ridge bifurcation

First, the hand image captured from an image sensor in which the ROI of the fingerprint is further segmented from the hand image by image segmentation technique which is shown in Figure 2.3 (a) and (b). Later, the preprocessing method implemented on the ROI of the fingerprint by using image enhancement, binarization, and spur removal. Finally, minutiae feature extraction was done by detecting the number of ridge endings, and ridge bifurcations found in the fingerprint image, and then minutiae matching have done.

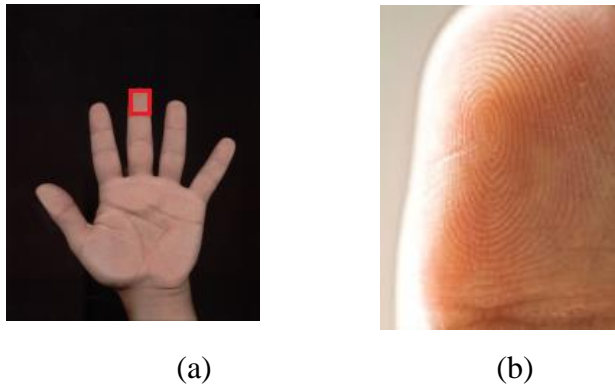


Figure 2.3: (a) Boundary extraction of Fingerprint (b) ROI of the Fingerprint image (Bosphorus DB)

2.2.2 Palm Print

The palm print is the kind of biometric indicator extracted from low-resolution images. Palm print features are composed of principal lines, wrinkles, and ridges which are shown in Figure 2.4 (a) and (b). Palm print feature extraction classified as i) texture-based approaches, ii) line-based approaches, and iii) appearance-based approaches (M. Saigaa et al., 2013). This modality can be easily used for authentication systems to provide an enhanced level of confidence in personal authentication. The minutiae-based matching approaches for palmprint recognition are more accurate than other techniques which are strongly proved experimentally (A. K. Jain & J. Feng, 2009; Y. Zheng et al., 2007). It also supports the state-of-the-art-technology for palmprint recognition (R. Cappelli et al., 2012; F. Chen et al., 2013; A. Muñoz-Briseño et al., 2015).



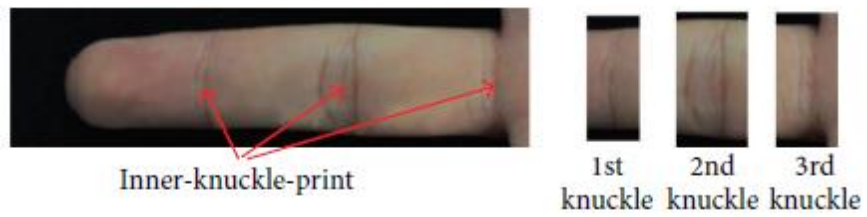
Figure 2. 4: (a) Boundary extraction of Palmprint (b) ROI of Palm print image (Bosphorus DB)

2.2.3 Finger Inner Knuckle Print

Finger inner knuckle print is considered as one of the unique novel biometric verifiers in the recent times of hand-biometric research. It is located on the inner surface of the hand which can be as a first knuckle, second knuckle, and third knuckle which is shown in Figure 2.5 (a). It was noted that the skin pattern of the finger inner knuckle print is highly rich in texture and also unique. So, the FIKP features can better exploit. Most of the researchers have concentrated in the hand biometrics with the maximum use of finger knuckle print except a little with finger inner knuckle print as it has newly arrived. So, there is no publicly available database for FIKP.

Further, the FIKP recognition will support the state-of-the-art-technology and only decidedly fewer researchers have done so far in FIKP than FKP (M. Liu et al., 2014; M.

Liu et al., 2013; X.-M. Xu et al., 2015). In our proposed research, a novel approach of minutiae-based inner knuckle print recognition is made which is motivated by (A. Kumar & B. Wang, 2015). The boundary extraction and ROI image of finger inner knuckle print are extracted from the hand image which is shown in Figure 2.5 (b) and (c).



(a)



(b)



(c)

Figure 2.5: (a) Finger Inner Knuckle Print images (Xu et al., 2015)

(b) Boundary extraction of FIKP (c) ROI of FIKP (Xu et al., 2015)

2.3 Score Normalization

Score normalization is used for checking the similarity measure from the output of the scores of individual modality. According to A. Jain et al. (2005), it also refers to changing the location and scale parameters of the match score distributions at the outputs of the individual matches. So that, the match scores of different modalities transformed into a standard domain (A. Ross & A. K. Jain, 2004) ranging like $[0,1]$, $[0,10]$, and $[0,100]$. The score normalization would not be needed if the outputs of the scores of different matches are homogeneous; if the scores are from different modalities, then the normalization has to be done. In our proposed research, the scores of FP,PP and FIKP have to be transformed into the common domain ranging $[0,1]$ using score normalization.

Table 2.1: Summary of Score Normalization techniques (A. Jain et al., 2005).

Normalization technique	Robustness	Efficiency
Min-Max	No	N/A
Decimal Scaling	No	N/A
z-score	No	High
Median and MAD	Yes	Moderate
Double sigmoid	Yes	High
Tanh-estimators	Yes	High
Bi-weight estimators	Yes	High

It is precisely understood from Table 2.1 that the normalization techniques namely double sigmoid, tanh estimators and bi-weight estimator resulting in high efficiency from the summary of normalization techniques. In our proposed research, the tanh score normalization technique is used to transform all the scores of hand-based modalities to a typical range $[0, 1]$.

2.4 Multibiometric Fusion

The multi-biometric fusion used in the multimodal biometric authentication system can be as pre-classification fusion and post-classification fusion. The image level and feature level fusions belong to pre-classification fusion whereas the post-classification fusion includes rank level fusion, decision level fusion, and score level fusion. In our proposed research, the user-specific score level fusion used for matching the scores of hand-based modalities. Figure 2.6 shows the taxonomy of fusions available in the multimodal biometric system and various levels of matching score fusion.

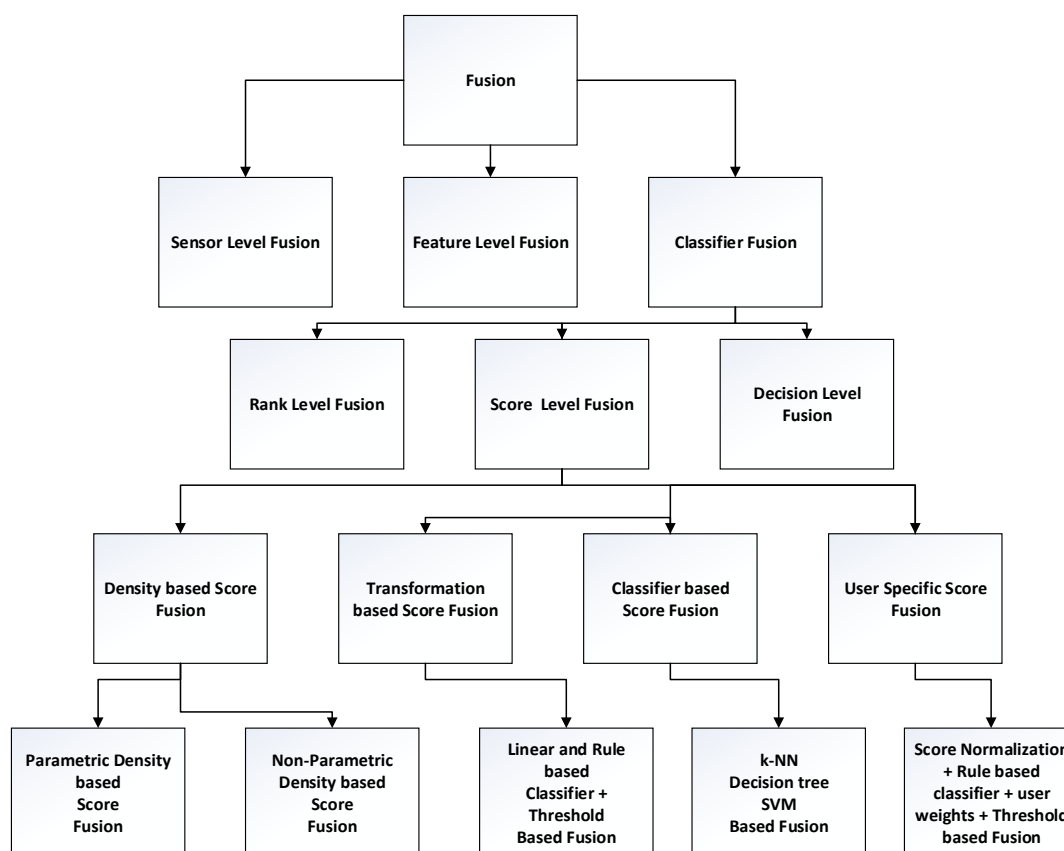


Figure 2. 6: Levels of score fusion techniques in multimodal biometrics

(A. A. Ross et al.,2006)

2.4.1 Score level fusion

Score level fusion is more successful and popular in multimodal biometrics fusion than image, feature, rank and decision level fusions due to its ease of fusion and effectiveness of fusion with multiple traits. The score level fusion can be further as density level score fusion, classifier-based score fusion, transformation-based score fusion and finally user-specific score fusion. The various classifiers used at each level of score fusion techniques are given below in Table 2.2.

Table 2.2: Summary of Classifiers used at various levels of Score fusion techniques
(A. Ross & A. K. Jain, 2004)

Score fusion techniques	Classifier	References
Classifier-based score fusion	Neural networks k-NN Decision trees SVM	(M. Dorigo & K. Socha, 2006; P. Kora & S. R. Kalva, 2015)
Transformation based score fusion	Linear combination classifiers – LDA, FDA Rule classifier –sum rule, min rule, max rule, median rule, product rule	(K. Shanmugasundaram et al., 2019; Y. Shi & R. C. Eberhart, 1999)
Density-based score fusion	Parametric classifier- Gaussian density function Non-parametric - k-NN density and parzen window	(K. Shanmugasundaram et al., 2017; K. Shanmugasundaram et al., 2015a; X.-S. Yang, 2010)
User-specific score fusion	Weighted sum rule classifier	(S. Artabaz et al., 2015; C. Dalila et al., 2015; X.-S. Yang, 2010)

In accordance with the state-of-the-art technique, user-specific score fusion can be considered for the proposed work which is inclusive of the normalized matching score, the weighted sum rule classifier, the user weights, and the decision threshold.

2.4.2 Score fusion for Hand-Based Multimodal Biometric System

In our proposed research the weighted sum score fusion is used with the hand-based modalities of fingerprint, palm print and finger inner knuckle print. The Minutiae feature extraction is done for all these three modalities in order to extract the scores using Euclidean distance matcher. The swarm intelligence approach(HBF-PSO) is used to optimize the weights associated with the scores of these three modalities at the weighted sum score fusion. By implementing this approach will result in minimized Equal Error Rates(EER) over other classifier methods relating to score fusion of hand-based modalities of the multimodal biometric system which is summarised in Table 2.3.

According to M. Hanmandlu et al. (2011), t-norms based transformation based fusion is better in performance than the classifiers like SVM, k-NN, decision tree, neural network, and LDA and KFA. In this transformation based fusion, the t-norms are used in the associated or combinatorial notation like $S = (s1.(s2.s3))$. so, the results won't be accurate as mentioned by the author. If the scores from different modalities are homogeneous, t-norms are a rational choice for merging the scores (Mourad, 2003). In our proposed research, we use three modalities of homogeneous patterns like a fingerprint, palmprint and finger inner knuckle print. So, this method can't provide good results over the modalities taken from the inner hand homogeneous image.