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Comparative Analysis of Chameleon Swarm Optimization and Weighted Sum Fusion Techniques in Bi-Modal Recognition System

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Abstract

Bi-modal biometric systems integrate modalities such as palm-vein and face by fusion techniques to enhance biometric based security systems. Several techniques (especially evolutionary algorithms/swarm intelligence) have been developed and improvised as fusion techniques to reduce false positive rate and increase accuracies of biometric based recognition systems. However, these new techniques have not been adequately analyzed and compared with the conventional techniques like Weighted Sum rule. This study evaluates the performance of Chameleon Swarm Optimization (swarm intelligence algorithm) and Weighted Sum Rule as feature level fusion technique in a bi-modal recognition system. One thousand faces and palm-veins samples were collected from a university environment. The acquired images were pre-processed to remove noisy areas and Local Binary Pattern was employed to extract features. The two outputs from face and palm-vein features were fused by the selected techniques. The fused features were subjected to classification by Support Vector Machine and the performance of these techniques was evaluated and compared. The results of the evaluation at an threshold of 0.85 showed that the Chameleon Swarm Optimization achieved a false positive rate (FPR) of 5.00% and accuracy of 95.67% and at a recognition time of 169.01µs while the Weighted Sum Rule achieved a FPR of 10.00%, and an accuracy of 92.33% at a recognition time of 116.35µs.

Keywords: *Chameleon Swarm Optimization, Support Vector Machine, Bi-modal biometric systems, Weighted Sum Rule, Fusion.*

I. INTRODUCTION

Biometric refers to the identification (or verification) of an individual (or a claimed identity) by using certain physiological or behavioural traits associated with the person. Physiological traits include fingerprint, iris, retina, palm, face and so on, while behavioural traits include gait, voice, signature and keystroke. Biometric recognition systems have become increasingly vital in modern security solutions, with palm-vein and face recognition emerging as two prominent modalities Biometric systems can be unimodal or multimodal. A unimodal system uses a single biometric trait while multimodal systems use more than one biometric trait. Unimodal systems may encounter problems as a result of missing information (for example, occlusion), poor data quality. Multi-biometric systems can overcome some of the limitations of a uni-biometric system by combining information obtained from more than one trait, biometric sensor, algorithm or sample in order to establish the identity of an individual [3, 8,14].

Palm-vein recognition is favored for its high security due to the internal, unique vascular patterns of an individual‘s palm, which are difficult to replicate. Face recognition, on the other hand, is widely adopted for its non-invasive nature and ease of use in both surveillance and authentication applications. Combining these two modalities into a bi-modal system enhances recognition accuracy by leveraging the strengths of both traits. [20]. Information used in multi-biometric systems can be gotten from multiple representations or multiple algorithms for the same biometric trait, multiple samples of the same biometric trait (e.g., two impressions of a person‘s right index finger), and multiple biometric traits [9, 11].

Artificial Intelligence (AI) is the study of intelligent behavior and how to make machines do things at which humans are doing better. Natural computing is a field in AI that investigates models and computational techniques inspired by nature and, dually, attempts to understand the world around us in terms of information processing. Swarm intelligence techniques (which is an advance optimization) inspired by the behavior of groups of organisms is one of the first strands of research in natural computing. Examples of swam intelligence include Moth Flame Optimization [27], Grey Wolf Optimization [22], Grasshopper Optimization Algorithm [17], Artificial Bee Colony [23], Chameleon Swarm Optimization [6] etc.

Biometric fusion is the use of multiple types of biometric data, or method of processing, to improve the performance of biometric systems. Systems that consolidate evidence from multiple sources of biometric information in order to reliably determine the identity of an individual are known as multibiometric systems [10]. An example is as shown in Figure 1 showing Example of Multimodal System that uses fingerprint, voice and palm recognition for identification [19].

Fig 1 Example of Multimodal System [19]

The fusion of biometric modalities in a bi-modal recognition system typically occurs at different levels viz: *Sensor Level* (the biometric traits taken from different sensors are combined to form a composite biometric trait and process); *Feature Level* (the fusion of feature vectors gathered from various feature sources like from a single biometric using different sensors, from different entities but from a single biometric, from several biometric traits).

Fusion techniques are categorised into two (2) main types. These are fixed rules (rule-based) and trained rules (learning-based). The fixed rules are also known as the nonparametric rules while the trained rules are called the parametric rules [29]. Trained rules require sample outputs from the individual modalities for training. In other words, they use development data to calculate some required parameters. These parameters are then used to appropriately fuse the score data in the test phase. Examples of the trained rules are Fisher Linear Discriminant, Quadratic Discriminant Analysis, Weighted Sum rule and Weighted Product rule. In fixed rules, the contribution of each modality is fixed a priori. Examples of fixed rules are AND rule,. OR rule [12]), Maximum rule [26], Minimum rule [26] and Majority voting [2], Product Rule [1].

Weighted Sum Rule Fusion (WSF) is one of the most commonly used fusion techniques in biometric recognition systems. It assigns weights to each modality based on its reliability and importance, thereby creating a weighted sum of both the palm-vein and face recognition data at the fusion level. This method ensures that the more reliable biometric trait contributes more to the final decision, increasing the system's overall accuracy. Despite its widespread use, WSF is not without limitations, particularly when dealing with high-dimensional data [18].

The Chameleon Swarm Optimization (CSO) is a relatively new metaheuristic algorithm inspired by the hunting and defensive behavior of chameleons. Metaheuristic algorithms like CSO are highly effective for optimization problems due to their flexibility in finding optimal solutions in complex search spaces. In biometric systems, CSO can be utilized to optimize the fusion process by selecting the best features from both palm-vein and face recognition data. The adaptability and convergence rate of CSO make it a suitable candidate for enhancing recognition performance [24].

However, conventional methods, such as Weighted Sum Algorithm, are widely used for bi-modal fusion due to their simplicity, but they often struggle with high-dimensional data and fail to adapt to different environments. And swarm intelligence techniques like Chameleon Swarm Optimization (CSO) offer dynamic feature selection capabilities but has not been employed in bimodal fusion problems. However, there is a need to compare its efficacy with conventional methods, such as Weighted Sum Rule in bi-modal recognition systems [4].

- *Face:*

This is one of the most widely used biometrics. It is applicable in so many areas ranging from security cameras in airports and government offices, to daily usage for cell phone authentication (such as in Face Identification in iPhones). The major challenges for facial recognition are the face‘s susceptibility to change over time as a result of aging or external factors, such as scars, or medical conditions. It is also sensitive to illumination variances and poses which occur in unstructured environments [28].

- *Palm-Vein Authentication:*

This is a type of vascular pattern authentication technology. Vascular pattern authentication involves vein pattern authentication using the vein patterns of the palm, back of the hand or fingers, and retina recognition using the vascular patterns at the back of the eye as personal identification. The vascular pattern used refers to the image of vessels in the body. Everyone has vessels, vascular pattern authentication can therefore be applied to almost all individual. Vascular patterns cannot be stolen by photographing, tracing, or recording them. This means that forgery would be extremely difficult under ordinary conditions [16]. Each individual has a unique palm-vein pattern; even identical twins do not have same vein patterns. Furthermore, vein patterns do not change within a human‘s lifetime except in the case of injury or disease [5].

II. RELATED WORKS

In 2013, the researchers in [13] proposed a novel approach combining fingerprint and iris features using a weighted sum rule optimization technique enhanced by Particle Swarm Optimization (PSO). Their method addressed the challenge of optimal weight determination in multimodal biometric systems by implementing an adaptive weight assignment mechanism. The experimental results demonstrated an improvement in recognition accuracy by 4.2% compared to traditional weighted sum approaches, achieving an overall accuracy of 98.7% on their custom dataset of 1000 subjects. The authors in [30] developed an innovative feature-level fusion framework incorporating deep learning and genetic algorithms for face and face biometric traits. Their methodology focused on addressing the dimensionality curse in feature-level fusion by implementing a novel feature selection mechanism based on evolutionary computation. The system achieved a remarkable 99.1% accuracy rate when tested on the public Chinese Academy of Sciences Institute of Automation (CASIA) database, demonstrating superior performance compared to existing methods. In 2021, the authors in [21] introduced a hybrid optimization technique combining Ant Colony Optimization (ACO) and artificial neural networks for fusing fingerprint and face biometric features. Their research specifically targeted the of feature selection and weight optimization in multimodal biometric systems operating in unconstrained environments. The experimental evaluation showed an impressive Equal Error Rate (EER) of 0.13% on their proprietary dataset of 2500 subjects. The system demonstrated robust performance under various environmental conditions and noise levels.

Also, the authors in [7] presented a novel approach utilizing Differential Evolution (DE) algorithm for optimizing feature-level fusion of iris and finger vein patterns. The work addressed the critical issue of feature compatibility and normalization in heterogeneous biometric fusion systems. Testing on the University of Tehran IRIS (UTIRIS) database and Shandong University Homologous Multi-Modal Traits (SDUMLA-HMT) databases yielded a recognition rate of 98.9% with significantly reduced false acceptance rates. In 2022, the researchers in [15] developed a comprehensive framework employing Quantum-inspired Genetic Algorithm (QGA) for optimizing the fusion of palm-vein and fingerprint features. The research focused on minimizing the feature vector dimensionality while maintaining discriminative power in the fused representation. The system achieved an impressive 99.3% accuracy rate on a large-scale database of 5000 subjects. The researchers conducted extensive comparative analysis against conventional fusion techniques.

III. MATERIALS AND METHOD

In applying the Chameleon Swarm Optimization and Weighted Sum Rule Search for palm-vein and face-based bimodal biometric system, the following steps were involved; acquisition of dataset, the pre-processing of the acquired images, feature extraction stage, feature fusion stage and classification stage.

➢ *Image Acquisition*

Palm-vein pattern is not easily seen in visible light and thus cannot be captured by ordinary camera. Therefore, near infrared CCD sensitive camera and digital camera was used to capture 250 individuals‘ palm-veins and faces respectively.

➢ *Palm-Vein and Face Pre-processing*

Data pre-processing plays an important role in any biometric system. In this work, location of the Region of Interest from the images acquired which include image cropping, image alignment, colour enhancement and normalizing the images which include image segmentation and histogram equalization.

➢ *Feature Extraction using Local Binary Pattern*

At this stage, the most important information of the palm-vein and face images for classification purpose were extracted using Local Binary Pattern (LBP). LBP technique was used to extract the features of palm-vein and face images. The LBP technique was used because it is characterized by both global and local feature representations calculated by dividing the image into blocks and computing the texture histogram for each one. The steps for the LBP algorithm were as depicted in Algorithm 1.

Algorithm 1. Local Binary Pattern (LBP)Algorithm

Step 1: Set g_c which corresponds to the gray value of the center pixel

Step 2: Set g_p as the gray values of the "n" neighbour pixels

Step 3: Set

$$M = \{1, \quad if\ g_c \geq 0 \quad 0, \quad if\ g_c < 0\}$$

Step 4: Compute LBP features as described thus;

$$LBP_{p,r}(x_c, y_c) = \sum_{p=0}^{n-1} M(g_p - g_c) * 2^P$$

Where x_c and y_c represent the horizontal and vertical component of the image; Mg_p and Mg_c are neighborhood patterns, P represent the bit binary number resulting in 2^P distinct values for the LBP code.

Step 5: Output selected LBP features

- *Feature Fusion Stage*

This stage involves the application of Weighted Sum Rule and Chameleon Swarm Optimization for fusion of extracted features from palm-vein and face modalities.

- *Weighted Sum Rule*

At this stage, the feature level fusion was performed by weight average of the two traits. The weights for face and palm-vein images were defined by two arrays W_{pp} and W_{pv} respectively,

$$\text{Where } 0 \leq W_{face}, W_{pv} \leq 1 \text{ and}$$

$$W_{face}(x,y) + W_{pv}(x,y) = 1,$$

The result were fused, and their feature represented as:

$$I(x,y) = W_{face}(x,y)\, I_{face}(x,y) + W_{pv}(x,y)\, I_{pv}(x,y) \quad (1)$$

- *Chameleon Swarm Optimization*

he chameleon swarm algorithm (CSA) [6] is a swarm intelligence optimization algorithm proposed by Malik in 2021. It was inspired by the effective hunting behavior of chameleons in deserts and forests. Chameleons are a unique and highly specialized evolutionary branch with a wide range of species and are known for their ability to change colour to blend in with their surroundings. The proposed Chameleon Swarm Optimization (CSO) approach for palm-vein and face fusion leverages the algorithm's unique adaptive hunting strategy and visual pursuit characteristics to dynamically optimize the fusion weights assigned to extracted features from both biometric modalities. The CSO algorithm was iterated through possible weight combinations by simulating the chameleon's behavior of pursuing prey, where the optimal weight configuration represents the target prey position, the current weight assignments represent chameleon positions, and the fitness function evaluates recognition accuracy based on the weighted combination of palm-vein vascular patterns and facial features.

The CSO algorithm continuously monitors the quality of features from both modalities and adjusts weights accordingly. Quality metrics including image clarity, feature distinctiveness, and noise levels are computed for each modality. When quality degradation was detected in either modality, the algorithm triggers weight redistribution through the visual pursuit behavior. The weight adaptation process considered both immediate quality metrics and historical performance data to ensure stable and reliable fusion. The algorithm maintains minimum weight thresholds for each modality to prevent complete exclusion of either biometric trait, ensuring system robustness as expressed in Algorithm 2.

Algorithm 2. Pseudocode of CSO

Input: Normalized Extracted Features of Concatenated Palm-vein and Face
1: $P_p \leftarrow 0.1$ (the position update probability)
2: $\boldsymbol{r_1, r_2, r_3, r^i}$,are random numbers between 0 and 1
3: µ and ꞁ are the upper and lower bounds of the search area
4: d $\leftarrow$ dimension of the problem
5: $\boldsymbol{y_t^i}$ is the center of the current position of fused feature i at iteration t
6: $\boldsymbol{yr_t^i}$ is the rotating centered coordinates of fused feature i at iteration t which can be defined $\boldsymbol{yr_t^i = m\ x\ yc_t^i}$
7: Randomly initialize the position of a swarm of $\boldsymbol{y^i = l, + r\ x\ (\mu_j - l_j)}$
8: Initialize the velocity of dropping fused features' tongues
9: Evaluate the position of the fused features
10: while *(t < T)* do
11: Define the parameter, µ $\boldsymbol{\mu = \gamma^{e\,(-\alpha t/T)^{\beta}}}$
12: Define the inertia weight ω $\boldsymbol{\omega = (1 - t/T)^{\rho\sqrt{(t/T)})}}$
13: Define the acceleration rate $a\boldsymbol{a = 2590\ x\ (1 - e^{-\log(t)})}$
14: for i 1 to *n* do
15: for j = 1 to d do
16: $\boldsymbol{if\ r^i\ \geq P_p}$then
17: $\boldsymbol{y_{t+1}^{ij} = y_t^{ij} + p_1(P_t^{ij} - G_t^i)r_1 + p_2(G_t^{ij} - y_t^{ij}r_2}$
18: else
19: $\boldsymbol{y_{t+1}^{ij} = y_t^{ij} = \mu\left((\mu^j - p)r_3 + p_b\right) sgn\,(rand - 0.5)}$
20: end if
21: end for
22: end for
23: for i = 1 to *n* do
24: $\boldsymbol{y_{t+1}^i = \ yr_t^i + y_t^i\ \ -}$
25: end for
26: for i to *n* do
27: for j = 1 to *d* do
28: $\boldsymbol{y_{t+1}^{ij} = \omega v_t^{ij} + c_1(G_t^j - y_t^{ij})r_1 + c_2(p_t^{ij} - y_t^{ij})r_2}$
29: $\boldsymbol{y_{t+1}^{ij} = y_t^{ij} + ((v_t^{ij})^2 - (v_{t+1}^{ij})^2)/(2a)}$
30: end for
31: end for
32: Adjust the fused features' positions according to *u* and *l*
33: Evaluate the new positions of the fused features
34: Update the position of the fused features
35: t = t + 1
36: end while
Output: Selected Fused Features from Concatenated Palm-vein and Face

- *Classification using SVM*

At this stage, the extracted features were optimally classified using SVM. The two systems were trained and tested each with 1000 images (500 palm-veins and 500 face images), two images per person from each modality (face and palm-vein). Given a training set of feature extracted data $T = \{(x_1 y_1), (x_2 y_2), \ldots, (x_i y_i)\}$ by PCA, $x \in \mathfrak{R}^n$is the sample feature extracted data while $y \in \{0,\ 1\}$ is the corresponding tag of the label. The extracted feature will be introduced into the Support Vector Machine (SVM) for classification.

The decision function of SVM will be expressed as

$$f(x) = sign\sum_{i=1}^{l} s\alpha_i y_i Kcso(x_i, x) + b \qquad (2)$$

The function $Kcso(\boldsymbol{x_i}, \boldsymbol{x_j})$ is a kernel function defined as

$$Kcso(x_i, x_j) \equiv \Phi^T(x_i)\ \Phi(x_j) \qquad (3)$$

Where$s\alpha_i \geq 0$, are Lagrange multipliers, $i = 1, 2, \ldots, l$, b is an offset scalar, sign of $f(x)$ gives the membership class of x and y_i in the input selected features. Equation 3.4, which was employed in this work, provides the kernel for the radial basis function (RBF):

$$Kpoa(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \qquad (4)$$

Whereσ is a constant that defines the kernel width. $\sigma$is likewise the penalty or regularization parameter, and it controls the trade-off between the size of the margin and the slack variable penalty. Setting these parameters in an attempt to find a better "approximating function" called selection procedure. The selected parameters are fed into the kernel and SVM will be applied to selected feature data sets.

➢ *Performance Metrics*

The performances of the applications of CSO and weighted sum rule were carried out with the following metrics viz; Accuracy, Sensitivity, Specificity and false positive rate, Precision and computation/recognition time using the following expressions [8, 9, 12]

$$\text{False Positive Rate} = \frac{FP}{FP+TP} \qquad (5)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \qquad (6)$$

$$\text{Specificity} = \frac{TN}{FP+TN} \qquad (7)$$

$$\text{Overall Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (8)$$

Where, TP- True Positive, TN - True Negative, FP - False Positive, FN - False Negative

IV. RESULTS AND DISCUSSION

An interactive Graphic User Interface, shown in figure 2, application was developed with a real time database consisting of both face and palm-vein dataset. The MATLAB R2023a was used for implementation on a computer system with a very good specification. A dataset of 1000 palm-veins and face images samples, divided into 70% (700 images) for training and 30% (300 images) for testing, ensured robust evaluation using random sub-sampling cross-validation. Performance metrics such as false positive rate (FPR), sensitivity, specificity, precision, accuracy, and computation/recognition time provided a comprehensive assessment of the two fusion methods. The fusion of palm-vein and face biometrics was evaluated, with thresholds set at 0.24, 0.35, 0.50, and 0.85. .

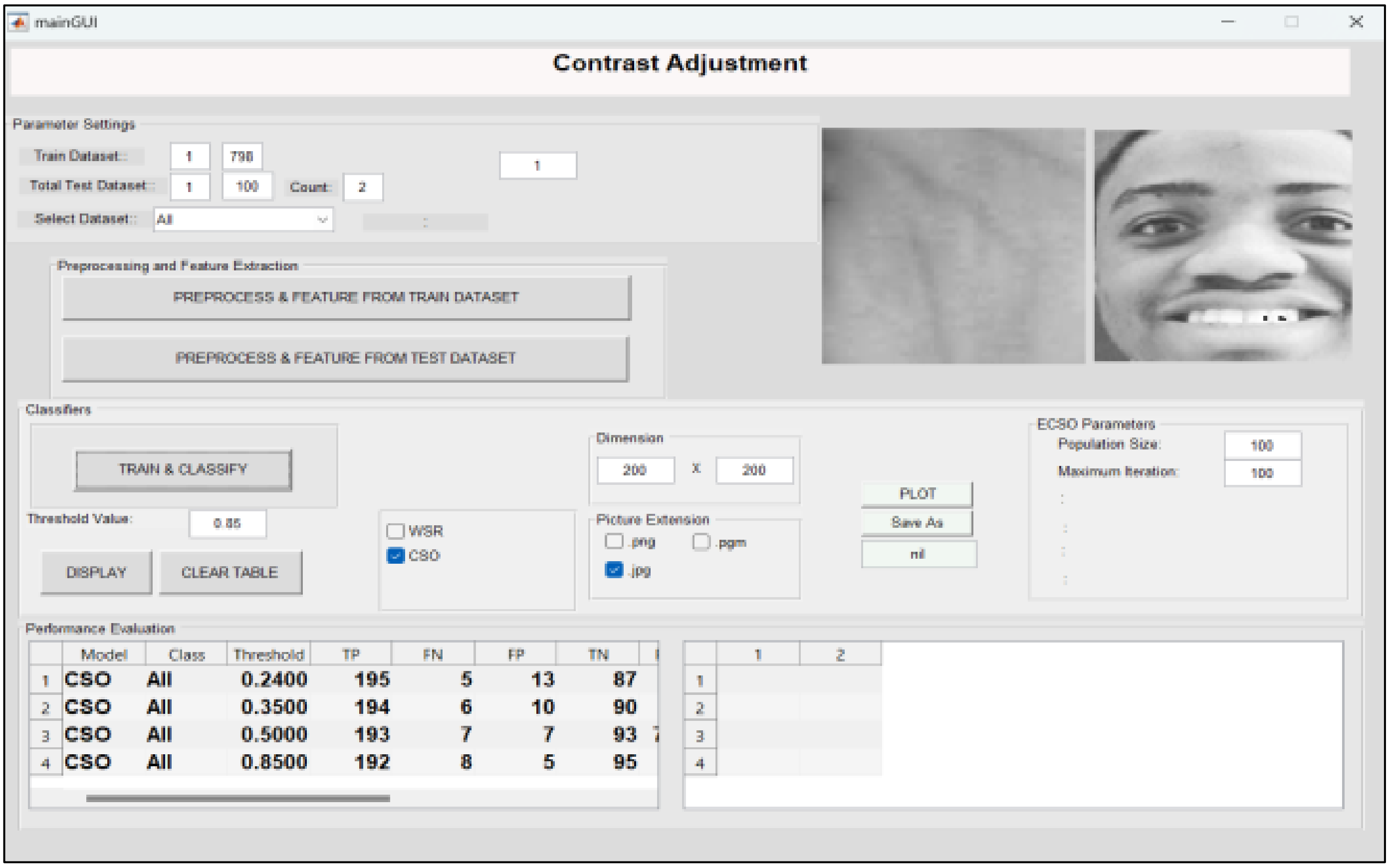

Fig 2 Graphical User Interface of WSR and CSO techniques

The application of the CSO at the feature fusion level for fusing palm-vein and face biometrics yielded promising results. At a threshold of 0.24, the system gave false positive rate (FPR) of 13.00%, specificity of 87.00%, sensitivity of 97.50%, precision of 93.75%, and accuracy of 94.00%, with a recognition time of 163.5µs. At the threshold of 0.35, the system produced FPR of 10.00%, specificity of 90.00%, sensitivity of 97.00%, and precision of 95.10%. accuracy at 94.67%, with a recognition time of 164.2µs. At the threshold to 0.5, the WSR gave FPR of 7.00%, specificity rose to 93.00%, sensitivity slightly decreased to 96.50%, precision is 96.50%, accuracy of 95.33%, and computation/ recognition time of 164.9µs, At the threshold of 0.85, the system demonstrated the best trade-off between performance and robustness. With TP of 192, FN of 8, FP of 5, and TN of 95, the metrics showed an FPR of 5.00%, specificity of 95.00%, sensitivity of 96.00%, and precision of 97.46%. Accuracy was the highest at 95.67%, with a recognition time of 165.3µs.

Table 1 Result of fusion of Palmvein and Face using CSO

Threshold	FPR **(%)**	SPEC **(%)**	SEN **(%)**	PREC **(%)**	ACC **(%)**	**Time (µs)**
0.24	13.00	87.00	97.50	93.75	94.00	163.5
0.35	10.00	90.00	97.00	95.10	94.67	164.2
0.5	7.00	93.00	96.50	96.50	95.33	165.1
0.85	5.00	95.00	96.00	97.46	95.67	165.3

The application of WSR as a feature fusion technique for combining palm-vein and face biometrics demonstrated notable performance variations across different thresholds. At a threshold of 0.24, the WSR fusion produced FPR of 17.00%, specificity of 83.00%, sensitivity of 95.00%, and precision of 91.79%, accuracy of 91.00%, with a recognition time of 118µs. At threshold of 0.35, the results showed FPR of 15.00%, specificity of 85.00%, sensitivity of 94.50%, precision of 92.7%, accuracy of 91.33%, and recognition time of 118.9µs. At threshold of 0.5, the results showed FPR of 13.00%, specificity of 87.00%, sensitivity of 94.00%, precision of 93.5%, accuracy of 91.67%, and recognition time of 119.4µs.

While at the highest threshold of 0.85, the WSR algorithm exhibited an FPR of 10.00% and specificity of 90.00%. Sensitivity of 93.50%, but precision peaked at 94.92%, and accuracy improved further to 92.33% and recognition time was 120.3µs.

Table 2 Result of Fusion of Palmvein and Face using WSR

Threshold	**FPR (%)**	**SPEC (%)**	**SEN (%)**	**PREC (%)**	**ACC (%)**	**Time (µs)**
0.24	17.00	83.00	95.00	91.79	91.00	118.2
0.35	15.00	85.00	94.50	92.65	91.33	118.9
0.50	13.00	87.00	94.00	93.53	91.67	119.1
0.85	10.00	90.00	93.50	94.92	92.33	119.3

The results of Chameleon Swarm Optimization (CSO) and Weighted Sum Rule (WSR) as feature fusion techniques for palm-vein and face biometrics above showed the superiority of CSO over WSR. Firstly, Figure 3 illustrates that CSO consistently achieves a lower FPR across varying thresholds compared to WSR, This indicates that CSO is more effective at minimizing false acceptances. In terms of specificity, as depicted in Figure 4, CSO outperforms WSR across all thresholds. In figure 4, CSO achieves high specificity values over WSR showing its robustness in accurately identifying true negatives over WSR. Also, in term of Sensitivity, as shown in figure 5, CSO outperforms WSR across all thresholds reflecting its potentials in identifying true positives over WSR. Also, figure 6 and 7 shows the that CSO outperformed WSR across all thresholds which highlight that advanced optimization algorithms significantly reduce false positives. However, despite its superior performance, CSO requires a longer recognition time compared to WSR (as shown in figure 8) because of its high computational complexity.

V. CONCLUSION

The comparative analysis of Chameleon Swarm Optimization (CSO) and Weighted Sum Rule (WSR) as feature fusion techniques for palm-vein and face biometrics revealed clear distinctions in their strengths and applicability. CSO consistently outperformed WSR in critical performance metrics, including low false positive rate (FPR), high sensitivity, high specificity, high precision, and high accuracy. Which means that CSO demonstrates its effectiveness in minimizing errors and maximizing recognition reliability. Its superior sensitivity and precision further underline its ability to identify true matches while avoiding false positives. These results position CSO as the optimal choice for security-critical applications where accuracy and robustness are paramount, although it comes with the trade-off of longer recognition times, at the highest threshold. However, the fusion of biometric traits provides improved resilience against spoofing, making it harder for unauthorized individuals to deceive the system using masks or fake credentials. Research is ongoing to develop more efficient fusion algorithms and privacy-preserving techniques for biometric data. As bi-modal systems continue to evolve, they offer great promise for future applications in areas like banking, healthcare, and border security.

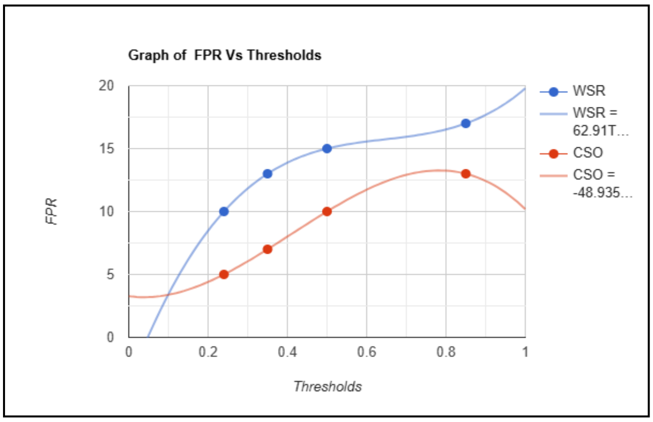

Fig 3 Graph of FPR Vs Threshold of WSR and CSO Techniques

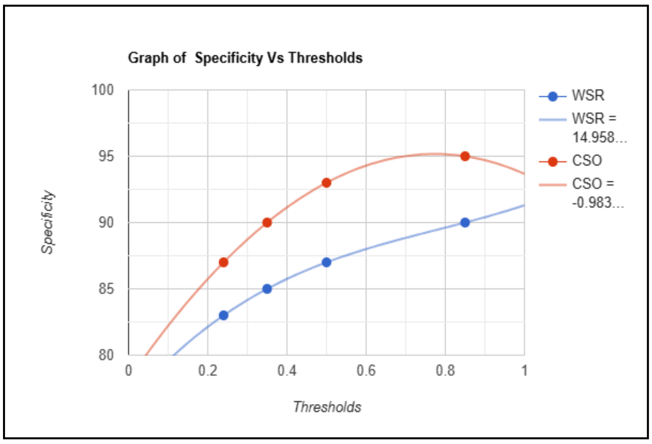

Fig 4 Graph of Specificity Vs Thresholds of WSR and CSO Techniques

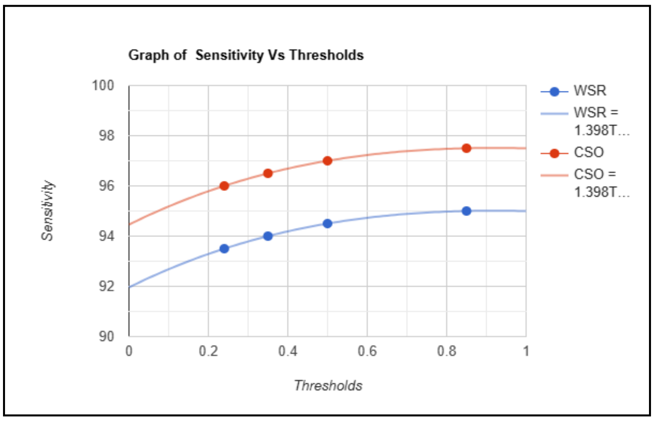

Fig 5 Graph of Sensitivity Vs Thresholds of WSR and CSO Techniques

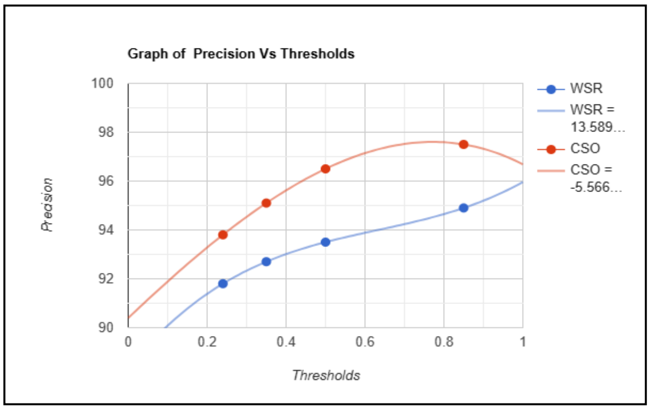

Fig 6 Graph of Precision Vs Thresholds of WSR and CSO Techniques

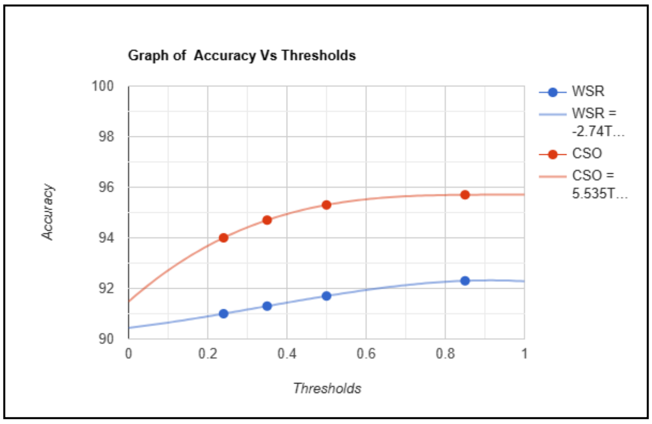

Fig 7 Graph of Accuracy Vs Thresholds of WSR and CSO Techniques

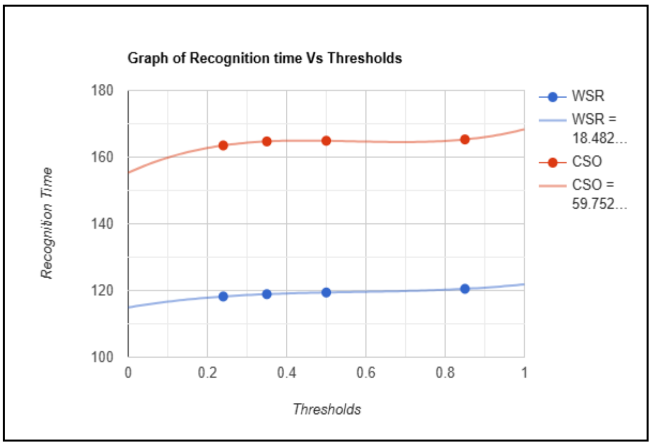

Fig 8 Graph of Recognition Time Vs Thresholds of WSR and CSO Techniques

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