Latent Fingerprint Recognition using Hybrid Ant Colony Optimization and Cuckoo Search

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Abstract: *Latent fingerprints are adapted as prominent evidence for the identification of crime suspects from ages. The unavailability of complete minutiae information, poor quality of impressions, and overlapping of multi-impressions make the latent fingerprint recognition process a challenging task. Although the contributions in the field are efficient for determining the match, there is a requirement to ameliorate the existing techniques as false identification can put the benign behind bars. This research work has amalgamated the Cuckoo Search (CS) algorithm with Ant Colony Optimization (ACO) for the recognition of latent fingerprints. It reduces the demerits of the individual cuckoo search algorithm, such as the probability of falling into local optima, the inefficient creation of nests at the boundary due to random walk and Levy flight attributes. The positive feedback mechanism of ant colony optimization makes it easy to combine with other techniques, reducing the risk of local failure and evaluating the global best solution. Prior to the evaluation of the proposed amalgamated technique on the latent fingerprint dataset of NIST SD-27, it is tested with the benchmark functions for different shapes and physical attributes. The benchmark testing and latent fingerprint evaluation result in the betterment of the amalgamated technique over the individual cuckoo search algorithm. The state-of-the-art comparison indicates that the amalgamation technique outperformed the other fingerprint matching techniques.*

Keywords: *Latent fingerprint, cuckoo search, ant colony optimization, swarm intelligence, biometric system, fingerprint recognition, latent fingerprint recognition, levy flight.*

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1. Introduction

Fingerprint recognition is one of the most widely accepted biometric systems among iris scanning, face recognition, palm print recognition, and fingerprint matching due to the distinctive attributes of fingerprint recognition such as uniqueness, permanence, reliability, and individuality [17]. A fingerprint consists of features such as dots, pores, ridge orientation, minutiae, singular points, incident ridges, etc., The minutiae are the bifurcation points and ridge endings [9]. Among the three categories of fingerprints (plain, rolled, and latent), latent fingerprints are the partial impressions that can be captured from the crime sites left accidentally by criminals [11]. The criminal entities are identified by matching the latent impressions with the plain or rolled fingerprints available in the criminal database accessible to enforcement agencies.

Comparing to complete (plain or rolled) fingerprint matching, the researchers have to face more challenges working on latent fingerprint matching. The challenging issues include the poor quality of finger impressions, broken ridge information, overlapping multiple impressions, and missing minutiae features.

The present work focuses on the latent fingerprint recognition system. The process incorporates the modules of pre-processing for initial enhancement, feature extraction to extract the minutiae information of latent fingerprints, and minutiae matching to find the match of latent fingerprints with complete fingerprints. Here, the matching of the latent fingerprint is performed using the proposed Amalgamation of Cuckoo Search and Ant Colony Optimization (ACSACO) technique. The major contributions of the paper are as follows:

- ACSACO for latent fingerprint recognition.
- Testing of the ACSACO technique on standard benchmark functions along with a comparison to individual CS algorithm.
- Applicability of the proposed ACSACO technique on the latent fingerprint dataset of NIST SD-27.
- Evaluation of the proposed ACSACO technique by comparison with state-of-the-art techniques.

The organization of the remaining paper is as follows: Section 2 briefs the work related to latent fingerprint recognition techniques. Section 3 defines the problem statement of the work. Section 4 presents the proposed ACSACO techniques. Section 5 illustrates the computational analysis of the proposed ACSACO by testing it on the standard benchmark functions. Section 6 describes the process of latent fingerprint recognition using the proposed ACSACO technique. Section 7 elaborates the experimentation results and comparison with state-of-the-art techniques. Section 8 ends the paper with the conclusion and future possibilities.

2. Related Work

The authors have made numerous contributions to latent fingerprint matching. Some of the quality contributions relevant to work are discussed here. The findings from the discussed research studies are summarized in Table 1.

Deshpande *et al*. [4] proposed the scale and rotation invariant minutiae approach for the matching of fingerprints. The algorithm of Latent Minutiae Similarity (LMS) was proposed to resolve the geometric constraints and Clustered Latent Minutiae Pattern (CLMP) for the geometric arrangements around the minutiae patterns. The experimentation on the FVC 2004 and NIST SD27 indicates the significant improvement of latent fingerprint matching in comparison with existing techniques. Venkatesh *et al*. [20] presented a neuro-fuzzy inference system based on fuzzy logic for fingerprint recognition from overlapped latent fingerprints. The technique of k-fold cross-validation was adapted for the classification evaluation. Cao and Jain [1] adapted the convolutional neural network for the ridge orientation estimation along with the minutiae matching technique for recognition, which has attained a higher recognition score than the descriptor-based Hough transform method proposed by Paulino *et al*. [16]. Further, Manickam *et al*. [15] used the Euclidean distance approach for fingerprint matching based on extracted features with Scale Invariant Feature Transformation. The authors have also conducted the enhancement of fingerprints using the type-2 fuzzy set prior to the fingerprint minutia extraction and matching. Furthermore, the authors (Manickam *et al*. [14]) conducted the research by considering the manually marketed regions of interest to improve the performance significantly. Gu *et al*. [7] selected the method without incorporating the minutia information for fingerprint matching. The authors have conducted the matching by aligning the dense patches of fingerprints and spatial transformation of fingerprint pairs. Xu *et al*. [21] presented the genetic algorithm-based fingerprint matching technique. The approach was efficient for self-learning the region of interest using the dictionary of fingerprints. Furthermore, Jindal and Singla [10] used the swarm optimization based cuckoo search algorithm for the recognition of latent fingerprints with experimentation on the NIST SD-27 dataset. The authors have evaluated the significant performance of the Cuckoo Search (CS) algorithm.

Table 1. Findings from the literature review on latent fingerprints recognition techniques.

Authors	Dataset	Technique	Findings
Deshpande *et al*. [4]	FVC 2004 and NIST SD27	Clustered Latent Minutiae Pattern and Latent Minutiae Similarity	• The authors indicated the attainment of efficient matching accuracy for the complete and latent fingerprints. • The work can be further improved with the addition of extended minutiae features.
Venkatesh *et al*. [20]	NIST SD27, FVC2006 DB1-A and B	Neuro-Fuzzy Inference System	• The authors recognized the fingerprints for the latent and overlapping finger impressions but they need to work for the overlapping fingerprints for better recognition accuracy.
Cao and Jain [1]	NIST SD27 and WVU latent database	Convolution neural network	• Convolution neural network (ConvNet) requires more training latent fingerprint data as only 3 ConvNets out of 14 were selected at feature selection stage.
Paulino *et al*. [16]	NIST SD27 and WVU latent database	Descriptor-based Hough Transform	• The manually marked minutiae of latent fingerprint images are matched with automatically marked minutiae of rolled fingerprint images.
Manickam et al. [15]	FVC-2004 and IIIT Latent fingerprint dataset	Euclidean Distance based Matching	• The fusion of the singular point features with the minutiae features was suggested by the authors for further improvement of results.
Manickam *et al*. [14]	FVC-2004 and IIIT Latent fingerprint dataset	Scale Invariant Feature Transformation (SIFT) and Euclidean Distance based Matching	• The authors mainly focused to match the fingerprints from the manually marked minutiae. • The extension on work on publically available large datasets was suggested by authors.
Gu *et al*. [7]	MOLF and NIST SD27	Alignment method and coarse-to-fine registration scheme	• The authors pointed out the limitations of time consuming process for local patch alignment, matching and more related skin distortions, etc.
Xu *et al*. [21]	NIST SD27	Genetic Algorithm	• The computations of the work could be reduced by considering simple fitness function.
Jindal and Singla [10]	NIST SD27	Cuckoo Search algorithm	• The authors attained the effective results for the recognition but the work could be improved for the enhancement and matching of fingerprints.

3. Problem Statement

Among the discussed techniques, it can be observed that the major work is related to the standard minutiae-based matcher techniques, which are limited to specific experimentations that can be improved with optimization techniques to attain higher recognition accuracy. The present work incorporates the optimization based amalgamation of Ant Colony Optimization (ACO) and CS algorithm based technique for latent fingerprint recognition. It is the extension of work discussed by Jindal and Singla [10]. The cuckoo search optimization algorithm was proposed by carefully perusing the behavioral characteristics of different species of cuckoo birds [22]. The propensity of cuckoo birds in terms of selecting a host bird's nest and timing of laying eggs is remarkable. But the individual cuckoo search algorithm lacks due to disadvantages such as

1) The initialization of cuckoo search with the random number of the nest can repeat the location and lead to the possibility of local falling.
2) The fixed step size and probability to determine the nest is considered to be bounded, which interrupts the system's performance at later iterations.
3) Moreover, the attribute of the cuckoo search algorithm to determine the nest location with a random walk and Levy flight remains within the boundaries, which makes it inefficient.

The standard attributes of the cuckoo search algorithm can't be directly improvised with minor modifications. These drawbacks can be surpassed by its amalgamation with ant colony optimization, which is efficient in determining the global solution to the problems. ACO mimics the characteristics of social species ants, being able to perform tasks in both local and global knowledge-sharing contexts [5]. The social insects, especially the ants, work in colonies in spite of behaving individually and describe a well-structured social behavioral organization. The way social species ants are organized makes them able to do complex tasks quickly and efficiently in the best way possible. The reason for the selection of the swarm intelligence technique is its successful applicability in different fields [3, 8, 12, 13, 18]. The swarm intelligence based cuckoo search and ant colony optimization are adapted for latent fingerprint recognition.

4. Proposed ACSACO Technique

The proposed ACSACO technique is an amalgamation of the swarm intelligence techniques of CS and ACO, which is termed the ACSACO technique. This amalgamation concept overcomes the demerits of individual CS by adding the merits of the ACO algorithm. In the case of individual CS, the CS algorithm lacks due to local falling, bounded attributes, and missing global exploration. These drawbacks can be surpassed by adding the merits of ACO, which is efficient to handle the global best solution. The overall local process involves the procedure to locate the possible match solution at the location having higher pheromone concentration, along with the best match solution evaluated by cuckoo agents as the best match. In the proposed ACSACO technique, the local best solution is evaluated by the initialization of ant agents to find the match as per the pheromone concentration along with the evaluation of the best host solution by cuckoo agents. The best local solution is stored, and the overall global best is provided as per the procedure of ant colony optimization. The algorithm of the proposed ACSACO technique is depicted in Algorithm (1).

Algorithm 1: Proposed ACSACO Algorithm

Initialize the parameters of CS and ACO algorithms:
Generate initial population of n cuckoo birds and m ant agents, host nests (x_i) where $i = (1,2,3,\ldots.,n)$, (β) as heuristic coefficient for ants, (σ) as local pheromone coefficient, and (q_0) as greediness factor of ants, MaxGen as the maximum number of iterations, p_a as the probability of worst nest, Objective function $f(x)$, where $x = (x_1, x_2, x_3, \ldots\ldots x_n)^t$.
$P_{best} \leftarrow HeuristicSolution(ProblemSize)$
$Pbest_{cost} \leftarrow Cost\ (S_{heuristic})$
$Pheromone_{initial} \leftarrow \frac{1.0}{ProblemSize * Pbest}$
$Pheromone \leftarrow InitializePheromone(Pheromone_{init})$
While (termination criteria) or (t1 <= MaxGen) do
- *cuckoo x_i is randomly selected and moved by levy flight*
- *solution obtained is new solution (x_{new})*
- *evaluate fitness value of solution $F_{(x_{new})}$*
- *nest x_j is randomly selected with fitness value $F_{(x_j)}$*

If $F_{(x_j)} < F_{(x_{new})}$ then
replace randomly selected nest x_j with new solution x_{new}
end if
- *compare the worst nest with new nests to find the solution*
- *rank the obtained solutions and find the optimal solution Opt_{cuckoo}*

end while
While (termination criteria) or (t2 <= MaxGen) do
For (i = 1 to m)
$S_i \leftarrow ConstructSolution\ (Pheromone, ProblemSize, \beta, q_0)$
$S_{i_{cost}} \leftarrow Cost\ (S_i)$
If $(S_{i_{cost}} \leq Pbest_{cost})$
$Pbest_{cost} \leftarrow S_{i_{cost}}$
$P_{best} \leftarrow S_i$
end if
Update Pheromone (Pheromone, S_i, $S_{i_{cost}}$, σ)
Obtain local optimal solution Opt_{ant}
end while
GlobalBestSol (Opt_{cuckoo}, Opt_{ant})
End

The proposed ACSACO technique is tested with the standard benchmark functions before employing the application of latent fingerprint recognition.

5. Computational Analysis of Proposed ACSACO Technique

Prior to applying the proposed ACSACO technique for latent fingerprint recognition, it is essential to evaluate it with the standard benchmark functions. The list of benchmark functions is heavily based on the shape and physical attributes. This research work enables the benchmark functions for which the results of the CS algorithm are determined by the inventor of the CS algorithm (Yang and Deb [22]). The selected list of benchmark functions includes Griewank, De Jong, Easom, Michalewicz, Schwefel, Rosenbrock, Rastrigin, and Ackley.

The Griewank function [2, 19] is a continuous uni-modal function that pertains to multiple local minima and illustrates the convergence of optimization technique. The formulation of the Griewank function is expressed in Equation (1) for the hyper-cubic input$x_i \in [-600,600]$.

$$f(x) = \sum_{i=1}^{d} \frac{x_i^2}{4000} - \prod_{i=1}^{d} cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \tag{1}$$

Where, i=*1, 2, ..., d* and the function possess the unique global minima [2, 19].

The De Jong [2, 19] depicts the sphere function for the *d* dimensions as formulated in Equation (2).

$$f(x) = \sum_{i=1}^{d} x_i^2 \tag{2}$$

Where, $x_i \in [-5.12, 5.12]$

The Easom function [2, 19] is a non-scalable function that depicts the sharp tip, and the formulation of the Easom function is presented in Equation (3).

$$f(x) = -cos(x_1)\,cos(x_2)\,exp(-(x_1-\pi)^2 - (x_2-\pi)^2) \tag{3}$$

Where, $x_i \in [-100, 100]$

The Michalewicz function [2, 19] also posses multiple local minima. It is a multimodal function, considered for the estimation of valleys and ridges. The formulation of this function is depicted in Equation (4).

$$f(x) = -\sum_{i=1}^{d} sin(x_i)\,sin\left[\frac{ix_i^2}{\pi}\right]^{2m} \tag{4}$$

Where, $x_i \in [0, \pi]$ and *i = 1,2, ..., d.*

The Schwefel function [2, 19] is a non-convex multimodal function with multiple local minima, as defined by Equation (5).

$$f(x) = \sum_{i=1}^{d} [-x_i \sin(\sqrt{|x_i|})] \tag{5}$$

Where, $x_i \in [-500, 500]$

The Rosenbrock function [2, 19] describes the valley structure with narrow global minima for search space. The formulation of the Rosenbrock function is illustrated in Equation (6).

$$f(x) = \sum_{i=1}^{d-1} \left[100\left(x_i^2 - x_{i+1}\right)^2 + (1-x_i)^2\right] \tag{6}$$

Where, x_i can be evaluated for the input range of -5 to 10 but stays within the limits $[-2.0482, 2.048]$

The Rastrigin function [2, 19] is a convex continuous function with distributed local minima. It can be evaluated with Equation (7).

$$f(x) = 10d + \sum_{i=1}^{d} [x_i^2 - 10\,cos(2\pi x_i)] \tag{7}$$

Where, $x_i \in [-5.12, 5.12]$

The Ackley function [2, 19] is a multimodal function with unique global minima and numerous local minima. The value of the Ackley function can be calculated using Equation (8).

$$f(x) = a exp\left(b\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - exp\left(\frac{1}{d}\sum_{i=1}^{d} cos(cx_i)\right) + a + \mathrm{e} \tag{8}$$

Where, $x_i \in [-32.768, 32.768]$, *i = 1,2, ..., d, a*=20, *b*=(-0.2), *c*= 2π, and *d* is the dimension.

The implementation of these benchmark functions is performed with MATLAB software. The proposed technique is tested a number of times for the benchmark functions to the extent that the function variation lesser than the predefined tolerance of 10^{-5}. The function values are determined in the pattern of mean ± standard deviation. As per Yang and Deb [22], the benchmark functions of De Jong, Michalewicz, Schwefel, Rosenbrock, and Ackley are tested with the value of *d* as 256, 16, 128, 16, and 128 respectively. Moreover, the Stubert function is tested with 18 minima value. The evaluated values and comparison of the proposed ACSACO technique with the individual CS algorithm is described in Table 2.

Table 2. Benchmark Testing and comparison of the proposed ACSACO technique and individual CS algorithm.

Function	CS	Proposed ACSACO
Griewank	10912 ± 4050	10087 ± 3512
De Jong	4971 ± 754	4622 ± 927
Easom	6751 ± 1902	5649 ± 1731
Michalewicz	3221 ± 519	2712 ± 504
Schwefel	8829 ± 625	7190 ± 589
Rosenbrock	5923 ± 1937	6124 ± 1843
Rastrigin	10354 ± 3755	9405 ± 3651
Ackley	4936 ± 903	4828 ± 792

The benchmark testing results illustrated in Table 2 indicates the higher performance of the proposed ACSACO technique as compared to the individual CS algorithm, except for the Rosenbrock function, for which the mean value is a bit lower than the CS algorithm. Comprehensively, it can be analyzed that the proposed ACSACO technique is more significant than the CS algorithm and makes it efficient to employ for the application of latent fingerprint recognition.

6. Latent Fingerprint Recognition using Proposed ACSACO Technique

The process of latent fingerprint recognition is composed of three modules: pre-processing, feature extraction, and fingerprint matching. The proposed ACSACO technique is employed for the final matching module. The module-wise description is illustrated here.

6.1. Pre-Processing

The pre-processing module is essential to refine the image from the background noise and to enhance finger impressions. The pre-processing covers the sub-modules of segmentation, normalization, enhancement, and Binarisation.

The segmentation process selects the fingerprint as the region of interest by removing the other background scenarios from the image. Here, segmentation is conducted based on the variance of each block of the image, obtained by dividing it into 16×16 pixel-sized blocks. The variance is calculated using Equation (9).

$$v(x) = \frac{1}{n^2} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (I(i,j) - M(x))^2 \tag{9}$$

Where, *M(x)* illustrates the mean value of the grey level block *x*. The value higher than the threshold indicates the consideration of the block as the region of interest.

The segmented image is required to normalize to standardize the variations of grey levels. The normalization is performed using Equation (10).

$$N(i,j) = \begin{cases} M_0 + \sqrt{\frac{v_0(I(i,j)-M)^2}{v}}, & if\ I(i,j) > M \\ M_0 - \sqrt{\frac{v_0(I(i,j)-M)^2}{v}}, & if\ I(i,j) \le M \end{cases} \tag{10}$$

Where, the expected values of mean and variance are M_0 and v_0 respectively. These actual values are M and v respectively.

Further, the images are enhanced using the Gabor filter and minutiae dictionary approach. The fingerprint enhancement begins with the gradient value evaluation, which is determined using the Sobel operator. Further, the orientation field is estimated and refined using the minutiae dictionary constructed with the complete fingerprint information and prior knowledge. The orientation is smoothened with the Gaussian function and preceded with the pixel quality enhancement with the Gabor filter as described in Equation (11).

$$G(x,y) = exp\left\{-\frac{1}{2}\left[\frac{x_\theta^2}{\sigma_x^2} + \frac{y_\theta^2}{\sigma_y^2}\right]\right\} cos(2\pi f x_0) \tag{11}$$

In this Equation (11), the symbols f and θ refer to frequency and orientation field respectively. The notations σ_x and σ_y depict the standard deviation of the Gaussian function with respect to x and y respectively. The values of x_0 and y_0 are calculated using Equations (12) and (13) respectively.

$$x_0 = x\,cos\,\theta + y\,sin\,\theta \tag{12}$$

$$y_0 = y\,cos\,\theta - x\,sin\,\theta \tag{13}$$

The enhanced image is Binarised to convert the grey level image into a binary form. The local adaptive Binarisation transforms the grey level image into binary image, where value 1 is assigned to the pixel blocks having a grey scale mean value higher than the threshold. On the other hand, the blocks with lesser than the threshold are allocated the value 0.

6.2. Feature Extraction

The performance of the fingerprint matching technique also depends on the extracted feature set. The efficient features make the matching technique significant and vice-versa. This research work extracts the minutia features for the matching of latent fingerprints with complete fingerprints. As the latent fingerprints do not possess the overall pattern structure of the complete fingerprints, therefore minutia features are adapted as an approach to match the latent fingerprints with complete. There are two types of minutia features:

a) Ridge bifurcation.
b) Ridge ending.

The evaluation of the minutiae point as normal, bifurcation or ending pixel depends on the cross number value which is evaluated in Equation (14).

$$CN = \frac{1}{2}\sum_{i=1}^{8} |P(i) - P(i+1)|, P(9) = P(1) \tag{14}$$

Where, the symbol P describes the centre pixel. The combination of the central pixel with neighboring pixels in the 3×3 matrix for the CN number 1 defines the minutiae type. This identification of minutiae type is illustrated in Figure 1.

0	0	1	0	0	0	1	0	0	0	1
0	1	0	1	0	1	0	0	0	1	0
1	0	0	1	1	0	1	0	0	0	0

a) Normal pixel. b) Ridge bifurcation. c) Ridge ending.

Figure 1. Identification of pixels in the 3x3 matrix.

The extracted minutia features of the latent fingerprints are required to process for the removal of spurious minutia as the extraction process can also include the false minutia. The instances of these minutia features are ladder, island, lake, spur, etc.

6.3. Latent Fingerprint Matching

The matching of the latent fingerprint with the complete fingerprints is the minutiae matching process. The minutiae of the latent fingerprint are matched with the minutiae of the plain or rolled fingerprints and a determination of 75% or higher similarity score value is considered an accurate match of the latent fingerprints. The minutia similarity can't be considered as 100% as latent fingerprints own lesser minutiae features. The similarity is evaluated by incorporating the structural and orientation similarity. It is described in Equation (15).

$$S_{i,d} = OS_{id} \,.\, SS_{id} \tag{15}$$

Where, the symbols i and d indicate the input image and database match images respectively. The notations OS_{id} and SS_{id} illustrate the orientation similarity and structural similarity respectively. The process of minutiae matching using the proposed ACSACO technique is step-wise discussed as follows. The workflow of the latent fingerprint matching process using the proposed technique is depicted in Figure 2.

1. Initialize the parameters of the cuckoo search and ant colony optimization. Here, *itr* defines the maximum number of iterations, α illustrates the pheromone exponential weight, β indicates the heuristic exponential weight, τ_0 is the initial pheromone value, τ_{ij} is the pheromone matrix, and *f(x)* illustrates the objective function. At the initial stage, the values of α =0.8, β = 0.2, T_0 = 0, and *itr*=100 are assumed.
2. Consider the image pixels of a latent image as the hybrid agents and the pixels of the complete original image as a solution set.
3. The local search is performed by considering the ant and the cuckoo agents to find the best match.
4. In the local search process, the ant agents use the property to find the local solution as per the pheromone concentration higher than the threshold, and cuckoo agents find the match by using the property of CS to determine the match as the best host nest solution. The solution is evaluated using Equation (16).

$$x_i^{t+1} = x_i^t + \alpha \oplus Lévy\,(\lambda) \quad (16)$$

Where, α refer to the step size with value *O(1)*, the notation $\oplus$ depicts the entry wise multiplication. The value of λ lies in the interval (1, 3].

5. After the determination of the local best solution, the global solution is obtained by evaluating the solution found by cuckoo agents and ant agents. The procedure of global solution determination is processed by the ACO algorithm. The pheromone concentration is evaluated for the global trail as depicted in Equation (17).

$$\tau_{ij}(itr) = [1-\rho].\tau_{ij}(itr-1) + \rho.\Delta\tau_{ij}(itr) \quad (17)$$

Where, $\tau_{ij}(itr-1)$ describes the pheromone concentration at the previous iteration, ρ describes the evaporation rate, and the change in pheromone concentration is evaluated with Equation (18).

$$\Delta\tau_{ij}(itr) = \sum_{k=0}^{m} \begin{cases} 1/f_k & if\ l_{ij}\ selected\ by\ ant\ k \\ 0 & otherwise \end{cases} \quad (18)$$

Where, *m* is any iteration in the total iterations *itr* and value of l_{ij} adapted by ants as the best fitness value.

6. The global solution obtained after the completion of iterations is stored and the best solution determines for the best minutiae match. The global solution is the match of latent and rolled fingerprints.
7. If the features of the latent fingerprint matched with the rolled complete image, then the pixel will be considered as the match.
8. Repeat the step of matching for all the pixels till the maximum iterations reached.

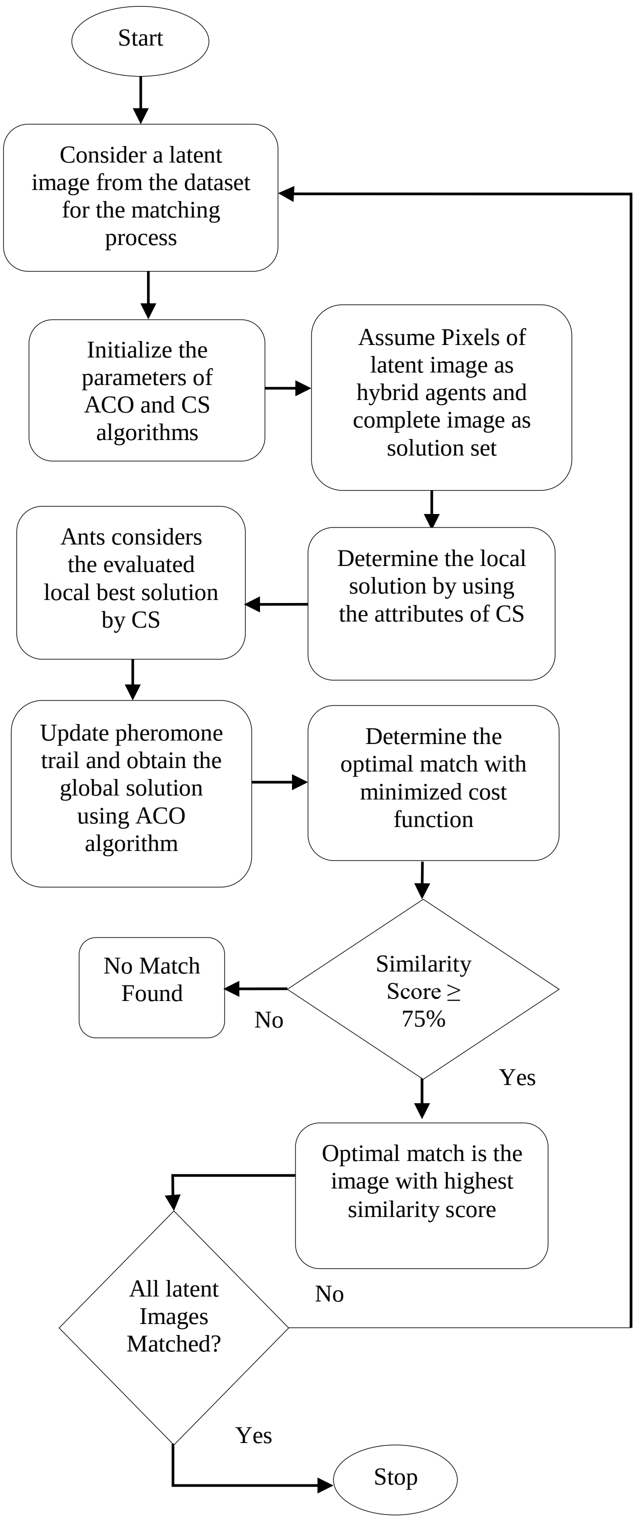

Figure 2. Workflow of the proposed ACSACO technique for latent fingerprint matching.

7. Results and Discussion

The robustness of the proposed ACSACO technique is tested for the NIST SD-27 dataset, which is a latent fingerprint dataset with the distribution of images on the basis of the quality of fingerprints [6]. This distribution of fingerprints encompasses 88 images of good quality, 85 images of bad quality, and 85 images of poor quality fingerprints. The dataset consists of latent fingerprints and their respective ten-print rolled images as well. Some of the latent fingerprint images of the NIST SD-27 dataset are illustrated in Figure 3.

Figure 3. NIST SD-27 dataset images.

The performance of the proposed techniques is determined in terms of identification rate, recall, precision, and f-measure. These measures depend on the similarity score determined by matching the minutia of latent and rolled fingerprints. The minutiae are matched using the proposed ACSACO technique along with caring the location and orientation of the fingerprints. Similarity scores calculated by the proposed ACSACO technique along with the comparison to individual CS for the same are illustrated in Figure 4.

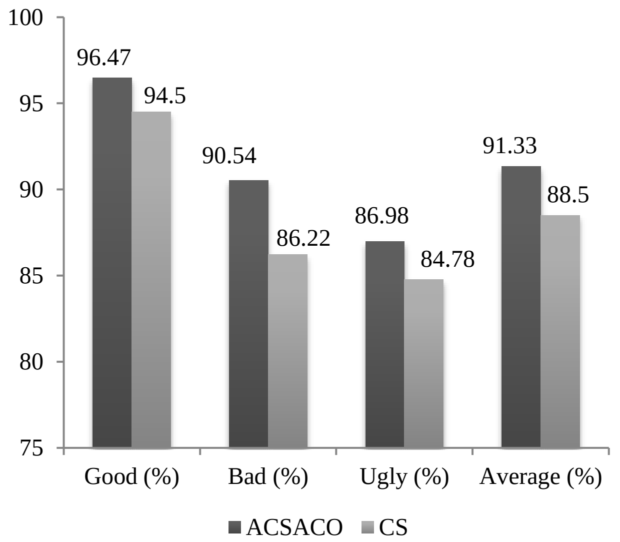

Figure 4. Similarity Score of proposed ACSACO technique with CS algorithm.

The results evaluated in Figure 4 illustrate that the proposed ACSACO technique has an average similarity score of 91.33% which is quite higher than the CS algorithm (88.5%). Although the similarity score of all the quality type images is higher, the bad quality fingerprints attained a greater improvement for matching.

Further, the identification rate and confusion matrix parameters of recall, precision, and f-measure are calculated. The latent fingerprint images with a similarity score of 75% or higher with a rolled fingerprint are considered to be a match of the fingerprint. The identification rate is calculated as the ratio of the fingerprint matches found to the total number of images. The evaluation of the identification rate of the proposed ACSACO technique with the CS algorithm is illustrated in Figure 5.

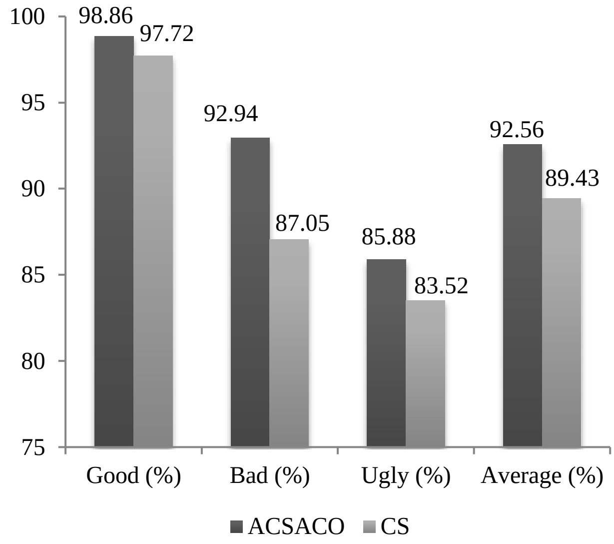

Figure 5. Identification rate of proposed ACSACO technique with CS algorithm.

The identification rate evaluation depicted in Figure 5 indicates the average identification rate of 92.56% which is higher than the CS algorithm. The category wise improvement in the identification rate can also be noted (Figure 5).

Table 3. Confusion matrix of good quality images using proposed ACSACO technique.

	Evaluated Result Values	
Actual Values	TP = 87	FN = 01
	FP = 19	TN = 7637

Table 4. Confusion matrix of bad quality images using proposed ACSACO technique.

	Evaluated Result Values	
Actual Values	TP = 79	FN = 06
	FP = 27	TN = 7113

Table 5. Confusion matrix of ugly quality images using proposed ACSACO technique.

	Evaluated Result Values	
Actual Values	TP = 73	FN = 12
	FP = 32	TN = 7108

Furthermore, the confusion matrix results are calculated in terms of True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN). These measures are the formulation requirements for the calculation of recall, precision, and f-measure. The confusion matrix results are evaluated by matching each fingerprint image with all the other images. The confusion matrices for all the categories of the NIST SD-27 dataset are illustrated in Tables 3, 4, and 5.

These confusion measures are used for the calculation of recall, precision, and f-measure. These performance calculations are illustrated in Table 6.

Table 6. Performance metrics using proposed ACSACO technique.

Database Category	Good	Bad	Ugly
Precision (%)	82.07	74.52	69.52
Recall (%)	98.86	92.94	85.88
F-score (%)	89.68	82.71	76.83

The performance results depicted in Table 6 indicate that the ugly quality images have lower values than the good and bad quality images. The lower value of the ugly category is due to the worst level of noise in those images. The average precision, recall, and f-measure values using the proposed ACSACO technique are 75.37%, 92.56%, and 83.07%.

The proposed ACSACO technique is also analyzed by making a comparison with the state-of-the-art techniques as discussed in the next sub-section.

7.1. State-of-the-Art Comparison

The proposed ACSACO technique is validated by making a comparison with the CS algorithm and other state-of-the-art techniques for the identification rate measure.

Table 7. Comparison of proposed ACSACO technique with state-of-the-art techniques.

	Good	Bad	Ugly
Proposed ACSACO Technique	98.86%	92.94%	85.88%
Gu et al. [7]	88.97 %	84.73 %	80.83 %
CS [10]	97.72%	87.05%	83.52%
Paulino et al. [16]	81.4%	67%	39%
Venkatesh et al. [20]	92.6%	58.5%	55.6%
Xu et al. [21]	71.6%	63.83%	60.89%

The considered techniques for the state-of-the-art comparison are Gu *et al*. [7], CS [10], Paulino *et al*. [16], Venkatesh *et al*. [20], and Xu *et al*. [21]. The comparison is illustrated in Table 7.

To have a clear view of the dominating and lacking techniques, the results calculated in Table 7 are pictured in Figures 6, 7, and 8 for the good, bad, and ugly categories respectively.

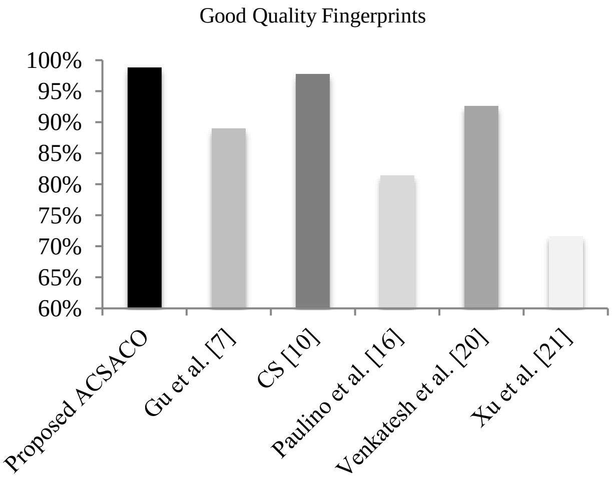

Figure 6. State-of- the-art comparison for good quality fingerprints.

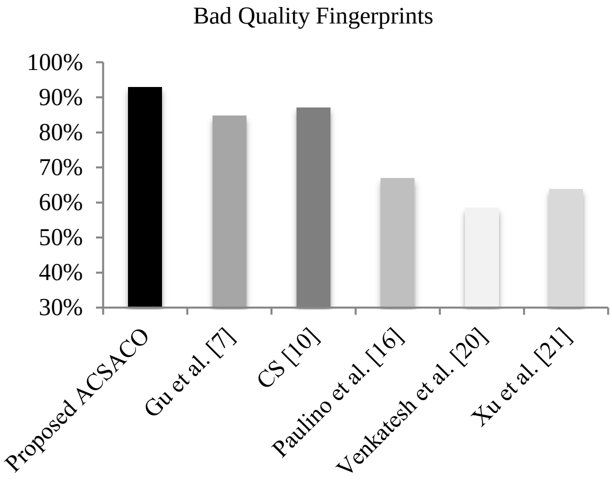

Figure 7. State-of- the-art comparison for bad quality fingerprints.

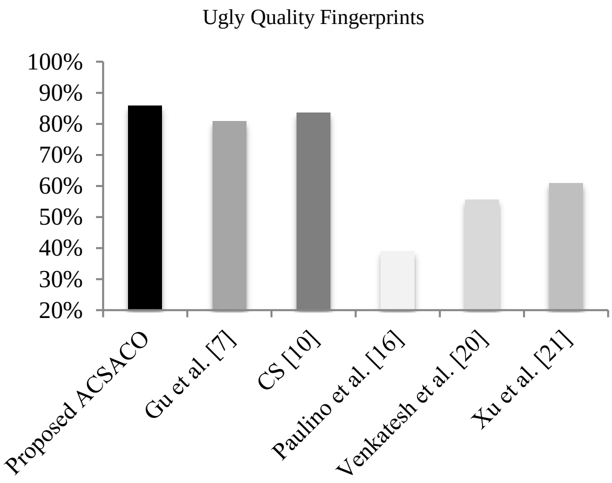

Figure 8. State-of-the-art comparison for ugly quality fingerprints.

The comparison for the good quality images illustrated in Figure 6 clearly demonstrates the outperformed matching with the proposed ACSACO technique. The identification rate for the technique used by Xu *et al*. [21] was lower. Further, the comparison for bad and ugly quality images also clearly indicates the outperformed results of the proposed technique. The lower values of Venkatesh *et al*. [20] and Paulino *et al*. [16] were relevant to the bad and ugly quality images.

8. Conclusions

Latent fingerprint recognition is a challenging task due to poor quality impressions with incomplete finger patterns. The current work has proposed the latent fingerprint recognition techniques of ACSACO which is an amalgamation of the swarm intelligence algorithms of cuckoo search and ant colony optimization. The amalgamation technique was proposed to surpass the drawbacks of the individual cuckoo search algorithm for latent fingerprint recognition. Initially, the proposed ACSACO technique was tested with benchmark functions of

Griewank, De Jong, Easom, Michalewicz, Schwefel, Rosenbrock, Rastrigin, and Ackley. Then, it was employed for the latent fingerprint recognition application with experimentation on the NIST SD-27 dataset of latent fingerprint images. Both the benchmark testing and fingerprint matching outcomes indicate that the proposed technique is efficient to attain higher performance than the individual CS algorithm. The state-of-the-art comparison also demonstrates the outperformed performance of the proposed ACSACO technique. In the future, the proposed ACSACO technique could be employed for popular applications of optimization such as face recognition, imagery document analysis, speech recognition, etc.

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