Optimize Control Points Selection based on A hybrid Meta Heuristic Algorithm for Enhancing SIFT Matching

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Abstract

One of the common methods of feature extraction is SIFT (Scale Invariant Feature Transform) in computer vision that use for image's control points, or local features. These invariant control points may be utilized for image matching, object identification, scene detection, …, etc. Due to the local similarity of images, the SIFT matching of control points results from some false matches. The aim of the study is to improve the performance of the SIFT algorithm for extracting and selecting the strongest control points from palm print images using shark small optimization (SSO) and genetic algorithm (GA). The proposed system consists of seven steps, namely, input palm print images; preprocessing by converting color to gray scalar image; extraction of control points using SIFT algorithm; selection of control points using SSO; weighting using GA; creation of a hand palm print dataset; and saving control points into the dataset. The proposed method uses the THUPALMLAB publicly available database which contains 1,280 palm print images from eighty subjects (two palms per person and eight impressions per palm) captured using a commercial palm print scanner of Hisign. The results of error rate metrics of the proposed method show an excellent palm print matching as it offered a higher CVR of 99.80%, and lowered FAR and FRR of 0.00 and 0.0020, respectively. This proves that the enhancement method is more effective and accurate.

الخلاصة

من الطرق المهمة في إيجاد النقاط المهمة في الصورة الرقمية والتي)SIFTتعتبر طريقة إيجاد خصائص الصورة (تسمى نقاط التحكم في الصورة، أو الميزات المحلية. يمكن استخدام نقاط التحكم الثابتة هذه لمطابقة الصور وتحديد الكائن في لنقاط التحكم بعض الأخطاء. لذلك SIFT الصورة واكتشاف المشاهد، ... إلخ. نظرًا للشبه المناطقية للصور، ينتج عن مطابقة لاستخراج واختيار أقوى النقاط من صور مأخوذة لبصمات الكف عن طريق SIFT تم اقتراح طريقة لتحسين أداء خوارزمية يتكون النظام . (GA) من خلال الخوارزمية الجينية(SSO) استخدام طريقة مبتكرة لتحسين خوارزمية سمك القرش الصغير المقترح من عدة خطوات هي: إدخال صور بصمة الكف والمعالجة الأولية من خلال تحويل اللون إلى صورة رمادية ومن ثم وإعطاء اوزان للنقاط من خلال SSOواختيار نقاط التحكم باستخدام SIFT استخراج نقاط التحكم باستخدام خوارزمية الخوارزمية الجينية. مجموعة بيانات النهائية لليد من خلال حفظ نقاط التحكم في مجموعة البيانات. تم استخدم قاعدة بيانات

والتي تحتوي على ١،٢٨٠ صورة بصمة لليد من ثمانين حالة (كفتان لكل شخص وثمانية حالات لكل THUPALMLAB راحة يد) تم التقاطها باستخدام ماسح ضوئي تجاري لبصمة راحة اليد. تُظهر نتائج مقاييس معدل الخطأ للطريقة المقترحة مطابقة مقدار FRRو FAR) بنسبة ٩٩,٨٠٪، وخفضت نسبةCVR(ممتازة لبصمة راحة اليد حيث أنها قدمت معدل أعلى في معدل ٠,٠١ و٠,٠٠٢٠ على التوالي. هذا يثبت أن طريقة التحسين أكثر فعالية ودقة.

Keywords: SIFT, Biometric, Shark Smell Optimization (SSO), Genetic Algorithm (GA).

1. Introduction

Computer vision is a mimic of biological vision, and in computer vision applications, positioning and image matching are crucial. A branch of image matching that relies on a matching algorithm based on features provides the benefits of quick computation speed. It is now the most extensively researched and used matching approach [1]. Typically, image matching algorithms consist of three components: feature detection, feature description, and matching. The SIFT descriptor has shown its superiority over hundreds of other descriptors, including distribution-based form context, geometric histogram descriptors, derivative-based complex fillers, and moment invariants [2]. D. G. Lowe introduced the SIFT approach [3], which extracts invariant characteristics from images for accurate item or scene matching. It combines a scale-invariant area detector with a gradient-based descriptor for high image matching rate and stability. SIFT creates a several interesting points for each image and compares their similarity [4]. Palm print are a widely effective biometric approach. SIFT-based features are resistant to image modifications and deformations, but not palm print identification. SIFT-based biometrics has been criticized for its high false match rate [5]. Many studies try to development SIFT feature selection using swarm intelligence algorithms [6]. Swarm-Intelligence (SI) is an AI technique that uses group behavior from nature. It is a system where cooperative agent actions locally cooperate with their surroundings, such as ant-colony seeking, birds flocking, microorganisms developing, and fish schooling [7] [8]. There are six algorithms in the SI: ant colonies, particle swarms, artificial-bee colonies, bacterial-foraging algorithms, fireflies, artificial fish swarms, and Shark Smell Optimization Algorithm [9]. Cao et al in 2014 [10] offered a FSIFT (Affine SIFT) method based on particle swarm optimization. ASIFT allows image matching with extreme viewpoint shift and beats current approaches. It did this by mimicking several images. Senthilnathand and Prasad in 2015 [11] introduced a novel multi-objective function for SIFT feature matching and implemented it in a Genetic Algorithm using an objective switching approach. Pachouri and Barve in 2015 [12] proposed new feature selection method based on combine the SIFT feature matching using genetic algorithm. Bidi and Elberrichi in 2016 [13] introduced improved features selection based on GA. This research compares several text representations of a genetic algorithm-based wrapper feature selection approach. This feature selection technique finds the smallest feature subset, which improves classification accuracy. In 2019, Eleyan [14] PSO was suggested as a feature selection algorithm by the author of this article. To evaluate the PSO technique, face recognition is used as a test case. Facial pictures have a great degree of dimensionality in face recognition applications. In 2020, Ahmed and Abdulhameed [6] mixing between shark small optimization and GA to selection the strongest features from fingerprint images. Lie and Liu in 2020 [15] focusing on the "edge spots" is the goal of the writers. These edges may be better detected by comparing SIFT method derived feature points and generating edge points using the cuckoo algorithm, which has been developed. Improve SIFT is the most accurate and fastest algorithm, whereas HSIFT and

BSIFT are both better than SIFT, and BSIFT is better than ISIFT. BSIFT is also better than SIFT. A detailed study on employing metaheuristic algorithms to solve the feature-selection problems is presented by Agrawal et al. in 2021 [16]. Si et al. in 2022 [17] improved matching images for pattern identification based on GA.

Researchers have used SSO (Shark Small Optimization) and GA (Genetic Algorithm) to enhance feature selection and matching. AI will minimize features and minimize computational costs. This avoids matching errors.

In this paper present a hybrid method for optimization that are using SSO and GA in enhancement the selection numbers of control points from palm print using SIFT algorithm.

The organization of the paper as follows: Section 2 and 3 presents the preliminaries for the SIFT and meta heuristic algorithms. The proposed method illustrated in section 4 and the results of the proposed method introduced in section 5. Finally, the conclusion shows in section6.

2. SIFT (Scale Invariant Feature Transform) Algorithm

The control point detection module and the descriptor generating module are the two main components of the SIFT algorithm. There are five key stages in the SIFT algorithm. [19,20,4]:

- **Scale-Space Extrema Detection**

The interest spots, which are crucial components of the SIFT framework, are discovered at this step. The Gaussian filter is applied at various strengths at each step, and the difference between subsequent Gaussian blurred pictures is then measured. Then, at various scales, the important maximum or minimum points occur. A DoG of the picture is expressed specifically as:

$$D(x,y,\sigma) = D(x,y,k_i\sigma) - D(x,y,k_j\sigma) \quad (3)$$

Convolution of the image is L (x, y, kσ) where the image (I (x, y)) is depicted as I (x, y) and its Gaussian blur G (x, y σ) at scale i.e.

$$L(x,y,k\sigma) = G(x,y,K\sigma) \times I(x,y,) \quad (4)$$

A DoG image is thus the difference between the Gaussian blurred images at weights ki$\sigma$and kjσ. The convolution images are sorted by octave and the Gaussian blur is performed at various scales. The DoG is computed from a predetermined number of convolved images. control point Localization. Next, a thorough allocation is calculated utilizing nearby data and location. High-contrast important points are selected. Taylor expansion of DOG scale-space function with candidate control point as origin.

- **Orientation Assignment**

In the third step, critical spots are allocated orientations based on regional image gradients. The calculations are done after taking the gradient-smoothed picture L (x, y, σ). Calculations for magnitude and direction are as follows:

$$M(x,y) = \sqrt{\big(l(x+1,y)l(x-1,y)\big)^2 + \big(l(x,y+1)l(x,y-1)\big)^2} \quad (5)$$

$$\theta(x,y) = atan^2\big(l(x,y+1) - l(x,y-1), l(x1,y)l(x1,y)\big) \quad (6)$$

The orientations are determined for each control point in accordance with their vicinity to produce rotation invariant control points. The steps in this procedure are defining the neighborhood; calculating the 360-degree orientation histogram; weighting the histogram; picking the tallest peak and giving it a value greater than 80% of the histogram; and then computing the orientation. As a result, control points of various orientations are acquired at the same position and scale.

- **Control point Descriptor**

The control points with size, orientation, and image position information were gathered in the earlier phases. To put it another way, the main points are no longer dependent on these factors. In this step descriptor for the local image region which is invariant to remaining variables such as illumination change and local shape distortion too, is calculated. The obtained descriptors are 128-dimensional vectors. Information in the control point descriptor comes from 16 × 16 neighborhood of the control point. 8 bin orientation histogram value is computed for each 4 × 4 sized sub-blocks which are the pieces of 16 × 16 neighborhood.

- **Matching**

When using the SIFT algorithm for object recognition, each control point descriptor extracted from the test image is matched to the descriptor database from the train image. To eliminate control points whose descriptors do not have a good enough match in the other image, a subsequent threshold is used, based on which matches that are too ambiguous are rejected. The match is accepted if the Euclidean distance ratio between the closest neighbor and the second closest neighbor is less than the predetermined threshold.

3. Meta Heuristic Algorithms

The Metaheuristic algorithms are used for solving optimization problem and it considered as computational intelligence paradigms. One of the metaheuristic problems is Shark Smell Optimization Algorithm.

3.1 Shark Smell Optimization Algorithm

Shark Smell Optimization (SSO) has relied on the Shark's ability because it has superiority in catching prey by using a strong smell sense in an abbreviated time [6,20,21,22]. SSO algorithm consists of basic steps as follows

- **Initialization of SSO**

The search procedure starts when a shark finds a smell of an injured prey odor particle. A population of initial solutions is produced haphazardly within the possible seeking environment. Each response illustrates a location of the shark. The start position vector is presented by:

$X_i = [X_1^1, X_2^1, \ldots\ldots, X_{NP}^1]$ and NP=population **size** (7)

Where X_i^i is the *i*th first candidate solution's (i.e., beginning position vector) ith instance? The population's average speed is reported as follows:

$SP_i = [SP_{i.1}^1 . SP_{i.2}^1 . \ldots ,, . SP_{i.ND}^1]$,*i=1, NP* (8)

Where ND = number of decision variables in the optimization issue and $SP_{i,j}^1$ is *j*th dimension of the shark's *i*th location or *j*th choice variable of *i*th position of the shark X_i^1 . However, following iteration, everyone will have the same objective function, which may be described as OF (X_{NP}) for the appropriate person. The algorithm is said to start at iteration zero.

- **Shark Movement Toward the Prey**

After initialization, the shark moves to find its victim. Sharks may turn and move forward at the same time. The shark approaches its prey in a premeditated and odor-concentrated manner by:

$$SP_{i,j}^{m} = \mu_m . R1. \frac{\vartheta(OF)}{\vartheta X_j}\left[X_{i,j}^{m} + \alpha m. R2. SP_{i,j}^{m-1}\right] \quad (9)$$

Where I = 1, NP, j = 1, ND, m = 1, M, ∇(OF) is the objective function's gradient, μ _mis is the gradient coefficient, m is the number of stages, M denotes the maximum number of stages in the shark's forward movement, μ -m, and am belong to the [0, 1] interval, and R1 and R2 are randomly generated constants. The shark speed is subject to the following restriction:

$$\left|SP_{i,j}^{m}\right| = \left[\mu_m . R1. \frac{\vartheta(OF)}{\vartheta X_j}\left|X_{i,j}^{m} + \alpha m. r2. SP_{i,j}^{m-1}, \left|\gamma_m . SP_{i,j}^{m-1}\right|\right|\right] \quad (10)$$

Where i = 1, NP, j = 1, ND, and m = 1, M, the parameter γ_m denotes the upper limit of the present speed in relation to the previous speed. Equation (11) calculates the $SP_{i,j}^{m}$ of each element of the SP_{i}^{m} .The most recent position evaluation might be provided as:

$$GY_i^{m+1} = X_i^m + SP_i^m . \boldsymbol{\Delta tm} \quad (11)$$

The time interval for the *mth* stage is referred as Δtm. So,the local seeking of the shark can be presented as:

$$NX_i^{m+1,l} = GY_i^{m+1} + R3. \Delta \mathbf{GY_i^{m+1}} \quad (12)$$

L is the number of points in the local search of each stage, while R3is a random constant produced arbitrarily in the (1, +1) interval. The shark selects the best places to hunt for in the forward movement and local search, which are represented in the shark scent optimization algorithms as:

$$X_i^{K+1} = \text{org max } \{OF(GY_i^{m+1}). OF(NX_i^{m+1.1}).,,.OF(NX_i^{m+1.L})\} . \quad i = 1,2, \ldots, NP \quad (13)$$

3.2 Genetic Algorithm (GA)

Genetic algorithms are search methods based on the principles of natural selection and natural genetics, according to Dr. David Goldberg's 1989 definition. [23]. An optimization and random search method based on the idea of natural selection systems is known as a genetic algorithm. The decision to select the chromosomes from a population that will reproduce, a quantitative criterion based on fitness value is used. The crossover process involves taking two chromosomes and creating a new one by taking certain characteristics from the first chromosome and the remainder from the second. Crossover operations come in three different varieties. Uniform Crossover, Single Point Crossover, and Two Point Crossover [24]. To preserve genetic variation from one population generation to the next, the mutation is utilized. Comparable to biological mutation GAs entails making string-based adjustments to a potential solution's constituent parts. Bit-reversal in bit-string GAs is one of them. A chromosome's bits are randomly flipped using this operator. The fundamental GA Cycle is shown in Figure 1[25].

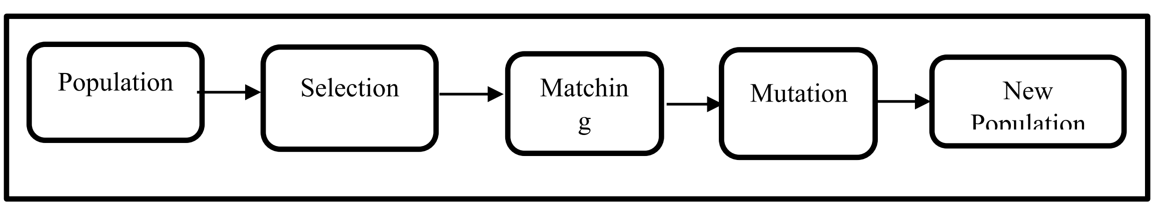


Figure 1: Basic Model of Genetic Algorithm [25].

4. The Enhancement Control Points Selection Method

The steps of the proposed model are shown in this section. From the user's palm print picture, features are extracted using the SIFT and Shark Smell Optimization (SSO) algorithms, and the best features are chosen using a Genetic Algorithm (GA). Seven phases make up the suggested model: Load palm print image, palm print image pre-processing, feature extraction, weight generation, feature selection, building a user's database, and the matching procedure. Figure 2 shows a detailed illustration of each level.

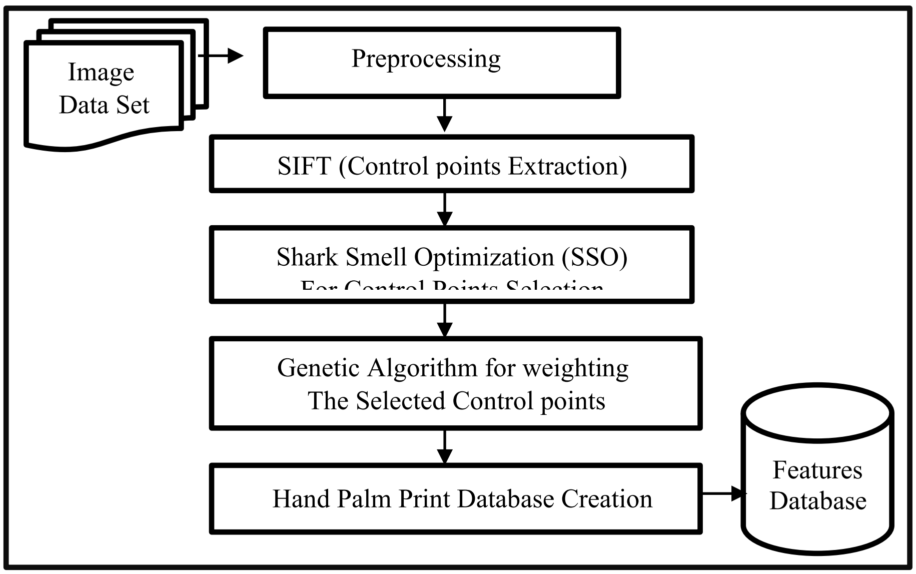
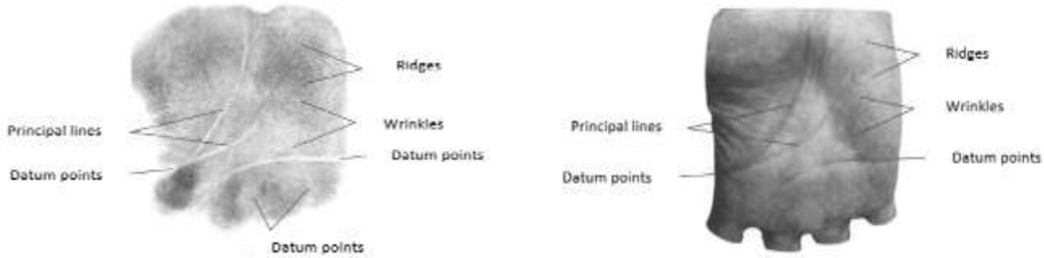


Figure 2 General Framework of Proposed Method.

4.1 Load Palm Print Image Step

The suggested method's first step is to import an image from a dataset. This collection includes 1,280 palm print biometric images from eighty people (2 palms and eight impressions per palm), all of whom were photographed using a Hisign palm print scanner. Each palm print picture is 2040 × 2040 pixels and 500 dots per inch [26]. The palm is the hand's interior surface from the wrist to the fingernails. Non-forensic and forensic palm print studies exist. Crime scene palm prints are important for forensic inquiry, while non-forensic research may employ imaging methods to generate human palm "prints." Palm print authentication employs distinctive, non-obvious palm print traits for personal authentication. It can be done by building a palm print-based algorithm. Palm prints have main lines, wrinkles, ridges, solitary points, and minutiae points as shown in Figure 3. Palm prints are bigger than fingertip prints but have the same skin. Palm dataset 1-0 of 100 participants [27].



(a) (b)

Figure 3: Unique features of palm print (a) inked palm print (b) inked less palm print.

4.2 Palm Print Image Pre-processing Step

The second step in the proposed method is preprocessing palm print image to prepare image to next step. **Image enhancement techniques improve its quality to get detail that is obscured in image. The main purpose is to bring out detail that is hidden in an image or to increase contrast in a low contrast image. The pre-processing image includes two phases:**

- **Converting palm print image to grayscale color space is important to less amount of data** using the luminosity method that it forms a weighted average to account for human perception. The most heavily is the green because they are more sensitive to it. The luminosity formula is shown in equation (14) [28]:

$$Grayscale(i,j) = (0.2989 * R) + (0.5870 * G) + (0.1140 * B) \qquad (14)$$

- Apply median filter is used to removed noise from image before binarizing the image. Contrary to linear mean filters, the median filter is a nonlinear filter that does not substitute the processed pixel with an average value. The boundary tracing stage is more accurate because to the median filter's ability to preserve the palm's border features without replacing them with artificial values. The suggested approach uses a 2020-pixel-wide frame window. To make up for the missing necessary pixels, the corners of the pixels are paddinged with zeros. The median filtering is shown by the following equation [29]:

$$M(x, y) = Med(f(x, y)) \qquad (15)$$

where M (x, y) is the image after convolving with median filter, and f (x, y) is the input image.

4.3 Enhancement SIFT Control Points Selection Step

The main aim of the proposed control point selection is to enhance SIFT performance by extracting and selecting the most important feature from the palm print image. This aim is achieved by combining SIFT with SSO and GA algorithms. The detail of the proposed method illustrated in algorithm one.

Algorithm 1 A Proposed Enhancement Control Points Selection Method

Input: image, number iteration, k-Variable, No. of control points' sets
Output: best key point feature

Begin
Step 1: Read palm-print image
Step 2: Preprocessing
Applying median filter as first step in preprocessing

Applying Otsu threshold algorithm to find best threshold value
Step 3: Feature extraction
Applying SIFT algorithm to find the control points
Step 4: Applying Shark Smell Optimization
Step 4-1: Initialized shark optimization parameters
Select random point as Shark Starting point for searching fish
Select Random points as fish that will used to specify the direction of shark
Step 4-2: Move direction of shark path depends on the distance to reach each fish
Step 4-3: Storing all points in each path for reaching the fish
Step 5: Applying genetic algorithm
Step 5-1: divide the total paths into groups
Step 5-2: initialized random weights for all sets as initial populations
Step 5-3: calculate fitness function for each chromosome in the initial population
Step 5-4: find the best fitness in all groups
Step 5-5: applying Crossover for finding new weights
Step 5-6: Applying mutation (population) under a random probability
Step 5-7: Calculating Fitness
Step 5-8: Applying Selection to find new generation
: iterating step 5-4to Step 5-8 until find the optimized weights for selected number of key points
return best weight
End Algorithm

It is then employed in the shark algorithm, which is assumed to infect the prey and pump blood into the sea, after the figurines from the palm of the hand, which was certified by SIFT and provides a description of the figurines that were selected, have been removed (the search environment). The first step is to choose the coordinates of the shark, which is challenged through head clustering, while the rest of the coordinates are the fish. The second step is the process of evaluating and finding the shark's direction towards the least distance to the mare, which represents the coordinates of the confused dawn, where a set of solutions are formed between the two neighbors and all the foggers and choosing the best.

The third step, which is determining the direction of the shark towards it, is the best solution and the one through which the path is stored. The path of the shark was determined, represented by the sites chosen for this path. The Junk algorithm is applied, which depends on dividing the coordinates of the path into groups, and for each group, an initial value of randomness is made. Then we generate the number of generations from the Junk algorithm, which depends on (and mutation crossover), and that the evaluation of all generations depends on the largest error value in weights.

4.4 Hand Palm Print Database Creation

A palm print is defined as the patterns of skin of a palm, composed of the physical characteristics such as texture, points and lines. Palm prints may exist on the object surface, due to the perspiration. Less observable “prints” are generated for a dryer hand. This point will be used for feature extraction.

4.5 Matching

process of matching and resemblance the reliability of any palm print identification depends on the matching procedure, making it the last and most crucial step in the suggested technique. This research uses the Euclidean Distance to construct the match (similar) operation (ED). As shown in (16), ED is a mathematical formula that may be used to determine the similarity ratio between two points. It is the Euclidean distance between points p and q at (x, y) coordinates [30].

$$ED(q,p) = \sqrt{(px - qx)^2 + (py - qy)^2} \qquad (16)$$

Due to its unique property of being rotation invariant, the ED is the sole metric that is employed. There are two iterations of similarity (matching). First, while inputting data for an authorized user, identification takes place when the person's fitness value is compared to all other fitness values in the database (1:M). The second, known as verification, occurs between the user's fitness value that they claim to be approved and the authorized user's fitness value that is kept in the database (1:1).

5. Experimental Results and Discussion

The proposed system is implemented on the computer (laptop) with Processor: Intel(R) Core (TM) i5-7200U, CPU @ 2.50 GHz 2.70 GHz, Ram (4.00 GB),64-bit operating system, operating system version (windows 10), C# language with version Microsoft Visual Studio 2013 Visual, and Microsoft 2016. **Figure 4 depicts the sample of tests conducted on a recommended approach for examining hand palm print datasets.**

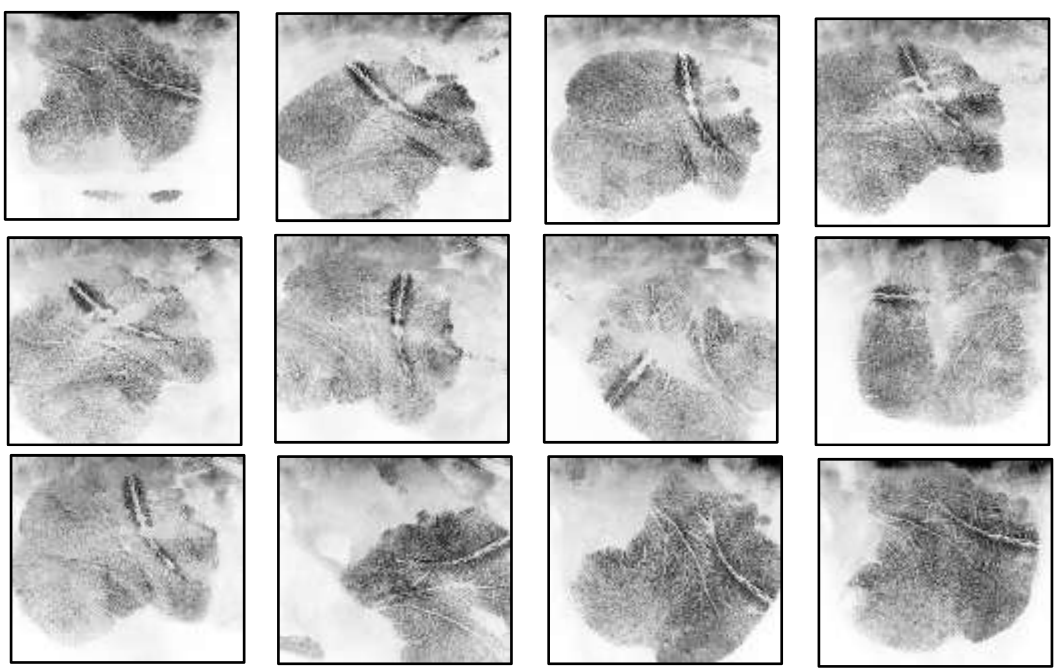


Figure 4: Samples of hand palm print data set

At this stage, a preliminary image processing was done through the application of convert image from RGB to gray scale color space using equation (14) and median filter with kernel size 3×3 using equation (15). The results of the pre-processing step are shown in Figure 5.

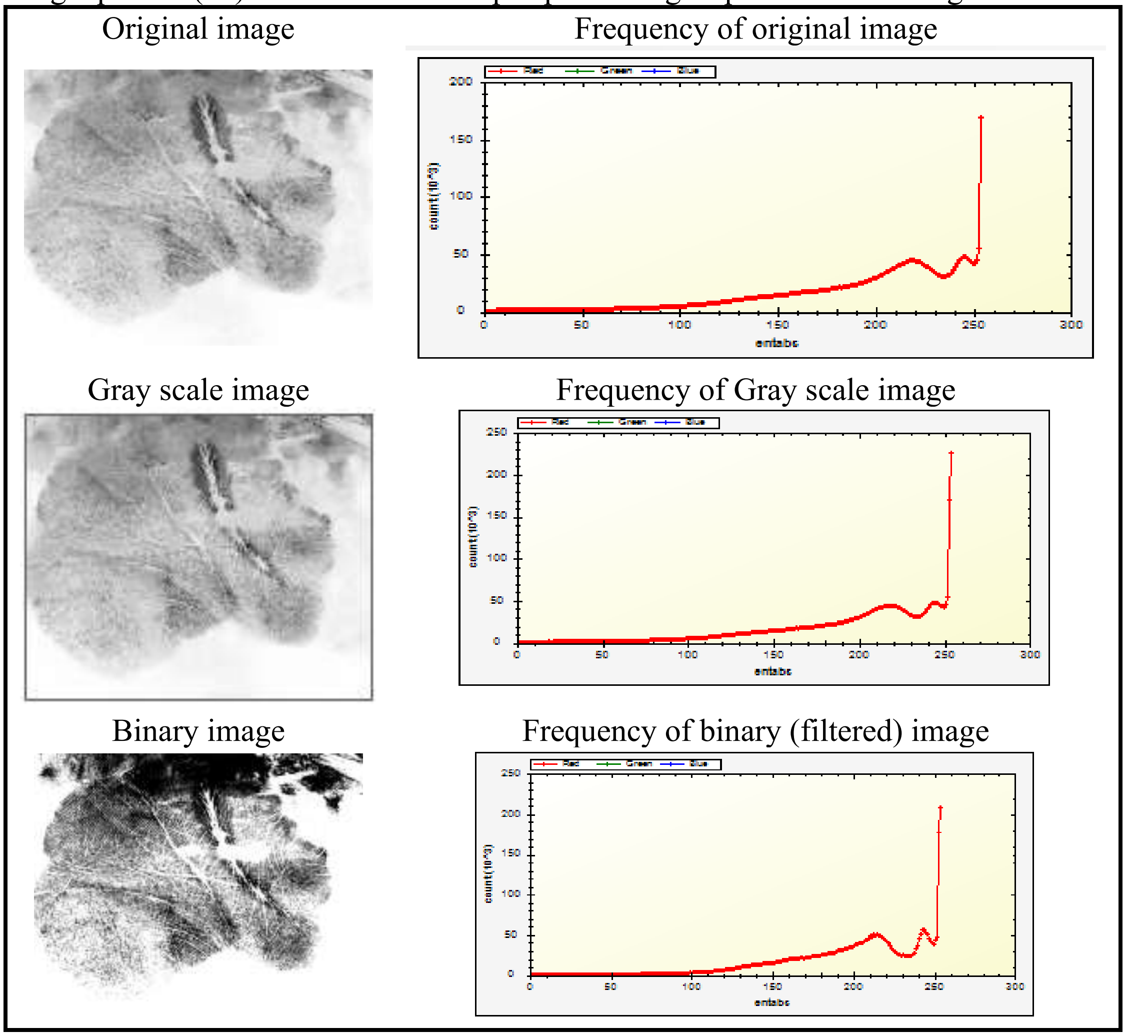


Figure 5: Results of the Pre-processing Step.

In this stage, SIFT is applied, through which the features of the hand image are extracted, and through which the density of the negative pixels is extracted according to the SIFT descriptor, where this was collected for converging points based on the description of these points and extracted from SIFT. The clustering and the selection of the medium from these points are used through this process the number of points extracted from the image of the palm of the hand and Table 1 is reduced between each image and the number of the selected features.

Table 1: Results of the SIFT Feature Extraction Methods

Image	SIFT	Sift Descriptor	No of features

		#	X	Y	Size	Angle	Octave	
		0	176.043	5.386847	3.835294	22.38068	4718848	523
		1	354.7514	5.108521	3.767121	314.4171	3473664	
		2	496.394	6.487955	4.526007	142.8751	512	
		3	445.8378	7.059464	4.027468	308.5178	8257792	
		4	75.07614	8.302411	4.120183	220.4666	9896192	
		5	366.3455	8.837465	3.846777	319.5121	4980992	
		.	.	.	.	.	.	
		.	.	.	.	.	.	
		0	338.933	23.16631	3.630318	83.14227	786688	348
		1	48.0436	30.27341	3.599239	170.0439	131328	
		2	281.8009	37.60046	4.076751	123.0856	9175296	
		3	335.2599	37.56135	4.072944	295.6616	9109760	
		4	180.7691	56.14002	4.049371	234.03	8651008	
		5	210.8462	63.06335	3.66761	185.4595	1507584	
		.	.	.	.	.	.	
		.	.	.	.	.	.	
		0	23.29123	7.161402	4.404711	74.68121	14745856	274
		1	405.847	8.241916	4.406778	316.0843	14811392	
		2	15.88398	9.367002	3.985529	81.31192	7536896	
		3	10.78605	14.56115	3.632002	92.02753	786688	
		4	426.6104	18.16258	3.86993	348.0798	5374208	
		5	412.9822	19.47658	3.640372	298.2279	983296	
		.	.	.	.	.	.	
		.	.	.	.	.	.	
		0	109.4188	5.080375	4.248142	125.77	12124416	513
		1	199.7178	6.207732	3.823704	20.27112	4522240	
		2	5.345904	10.92307	4.259367	26.60913	12321024	
		3	239.2094	10.20343	3.815397	98.39642	4391168	
		4	239.2094	10.20343	3.815397	16.83072	4391168	
		5	75.0865	12.09008	3.741705	222.922	2949376	
		.	.	.	.	.	.	
		.	.	.	.	.	.	

The population size utilized to determine the optimal locations for selection was 261121; there were 263 choice variables; one velocity limiter; and three-time intervals. To regulate the algorithm's output, certain parameters are fixed. The midpoint of a group of points was filtered by SIFT in between the random values and the random distribution of the variables that you require in the shark movement in the direction of the fish. The random behavior of SSO algorithm shows in Figures 6 and 7, where the inputs parameters to SSO algorithm are NP (number of population size) =24336, ND (number of decision variables) =50, βk(the velocity limiter)= 1 ,Δk (time interval) =3 ,k=1,0,-1,and R1,R2,R3 represents random parameters .

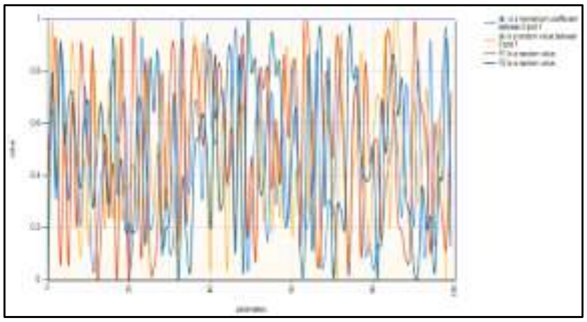


Figure 6 Behavior of SSO based on Randomly Parameter: number of iterations =100; αk is momentum coefficient [0-1]; η_k random value [0-1], R1, R2 random value

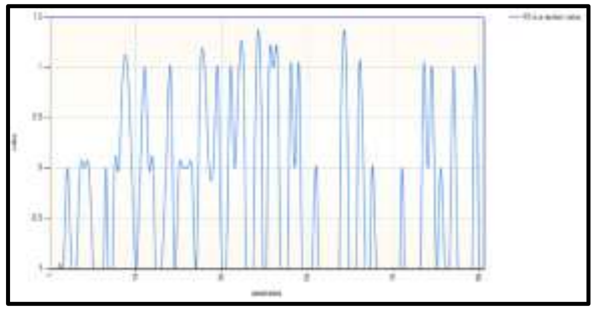
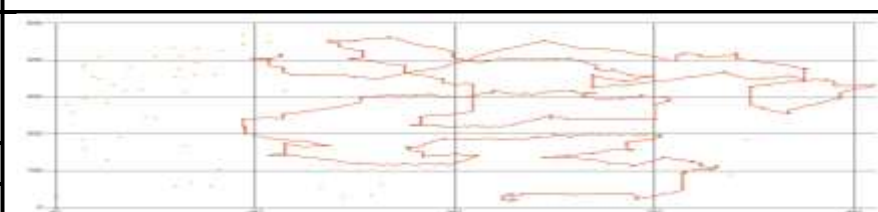
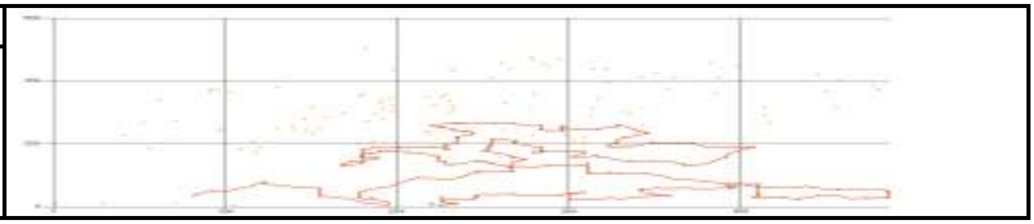


Figure 7 Behavior of SSO based on R3 Randomly Parameter**.**

According to the shark algorithm, as the path that the shark adopts in the prey is considered the best solution for it and according to the number of iterations and in the proposed method and that are specified.

Table 2: The Best Control Points using Enhancement Selection Method.

Image	Select best Control Point
	
iteration	
1168	
	
iteration	
3002	
	
iteration	
2296	
	

iteration	
2172	

The fitness for each pixel in the picture is determined by first calculating the mean for all the images, and this value is then multiplied by the product of the sound pixels' total number and the image's coordinates. An application is used to extract the object function. Gradient of the Objective Function in the diagram below, among the values of the object function chosen for enemy samples from the palm of the hand used in the proposed system, which the SSO needs in finding the best solution.

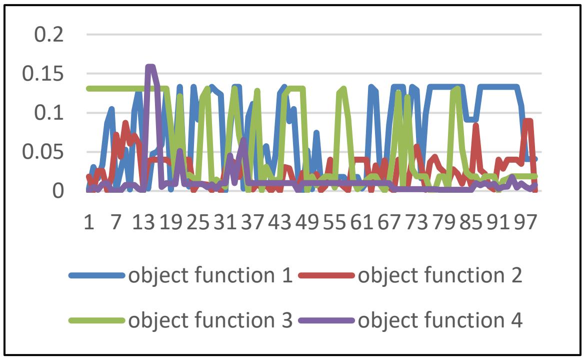


Figure 8: An Objective Function of the Proposed Method.

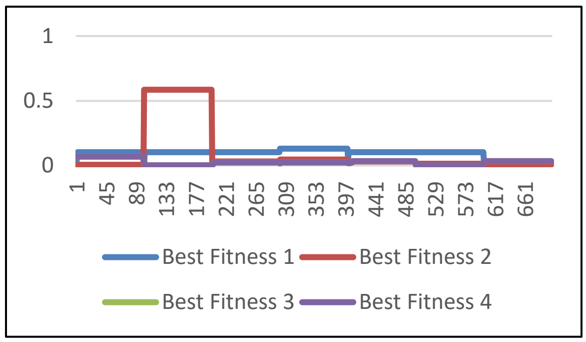


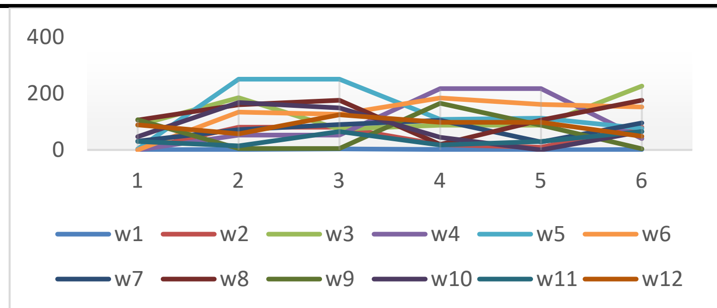
Figure 9: A Best Fitness of the Proposed Method.

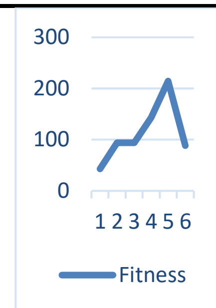
In the pattern among the best object fitness for several samples used in the proposed system. The best solution test process where the points extracted from the sift are the target points (the fish) where the lowest distance is determined between the shark and this sample, which determines the direction of the shark for the target time and then depends on the shark on (object fitness and object function) in the direction of the movement of the shark and the spin, which depends on it in finding the second-best solution.

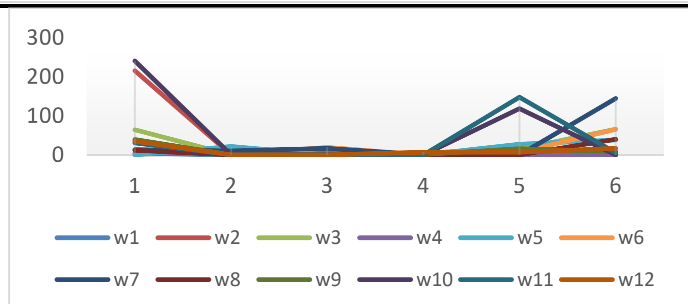
After applied-SIFT and SSO algorithms to extraction and selection the best control points from palm print images, Table 3 show histogram of the generation weights and fitness values using genetic algorithms for reduced number of the best control points.

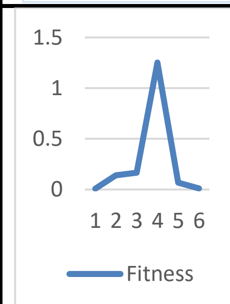
Table 3: Wight and Fitness Generation from Genetic Algorithm.

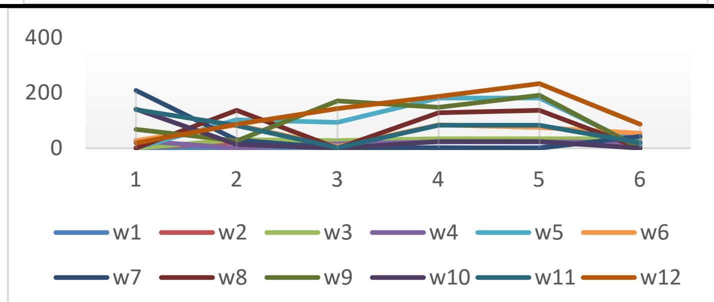
Image	Ganaration wight from genetic algorithm	Fiteness

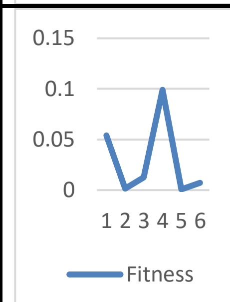


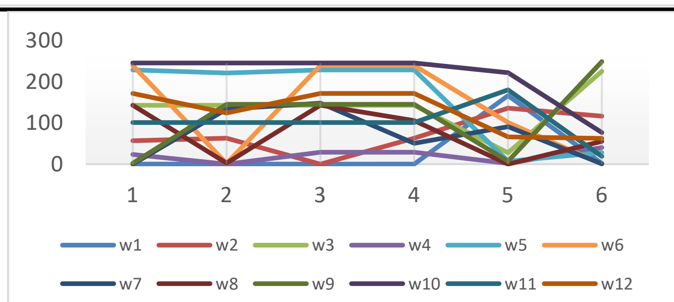












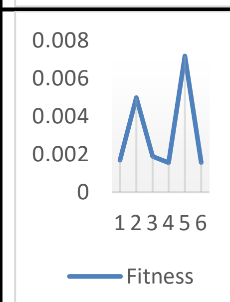


Table 4 shows the effect of the Genetic algorithm in reducing the control points for each iteration. For example, in palm print image 1, the number of control points that extract using SIFT and SSO algorithm are =523, then after applying genetic algorithm the number of control point become =100 and so on.

Table 4: Optimize Number of Control Points using Genetic Algorithm.

Image #	No. of Control Points	Selected Control Points	Iterations
1	523	100	1986

		150	2277
		200	3303
2	348	100	1920
		150	3024
		200	2863
3	274	100	2296
		150	3780
		200	5047
4	513	100	1757
		150	2565
		200	3630

The hand palm print dataset will include the control points that the genetic algorithm chooses. The proposed method's last step involves matching every palm print picture in the dataset to the input palm print image. Table 4 shows that each user had control points that GA had chosen and that showed how effective the algorithm was.

The final metrics used to assess the performance of the proposed model are the "False Acceptance Ratio (FAR)", "False Rejection Ratio (FRR)", and "Correct Verification Rate (CVR)". Calculating FAR, FRR, and CVR [31] is as follows:

$$FAR = number\ of\ false\ acceptation\ /\ total\ number\ of\ the\ test\ sample \quad (18)$$

And

$$FRR = number\ of\ false\ rejection\ /\ total\ number\ of\ the\ test\ sample \quad (19)$$

Finally;

$$CVR = (1 - FAR - FRR) * 100\ \% \quad (20)$$

To test our suggested model, we ran it through a series of tests utilizing 10, 50, 100, and 150 hand palm print images, respectively. As shown in Table 5, the suggested model was exceptionally accurate when measured by FAR, FRR, and CVR.

Table 5: Compare Between the Proposed Model Performance and Cross-ponding Its original SIFT Through Error Rate Metrics.

Error Rate Metrics	Batch Images	Original SIFT	Enhancement SIFT
FAR	10	0.01	0.00
	50	0.03	0.00
	100	0.002	0.01
	150	0.0030	0.00
FRR	10	0.00	0.00
	50	0.00	0.00
	100	0.001	0.00

	150	0.00324	0.0020
CVR	10	99	100
	50	97.01	100
	100	99.00	99
	150	99.37	99.80

Table 5 proves that the proposed algorithm was able to achieve the highest accuracy of comparison with the original, and this indicates the efficiency of the proposed method and the possibility of its application in various fields. There are several studies have been concerned about enhancement SIFT feature selection for images using different methods and techniques that have been adoptive in previous years. Table 6 illustrated the compared the proposed method and related works based on set of parameters.

Table 6: Comparison Between the Proposed Methods and Related Methods.

Reference	Year	Feature selection method	Meta heuristic algorithms	Data type
Cao et al [10]	2014	Affine SIFT	particle swarm optimization	image
Senthilnathand and Prasad [11]	2015	SIFT	Genetic algorithm	image
Pachouri and Barve [12]	2015	New SIFT	Genetic algorithm	image
Bidi and Elberrichi [13]	2016	New wrapper feature selection	Genetic algorithm	text
Eleyan [14]	2019	New feature selection	particle swarm optimization	Face biometric image
Ahmed and Abdulhameed [6]	2020	New feature selection	Shark small optimization +Genetic algorithm	Fingerprint biometric image
Lie and Liu [15]	2020	New SIFT	Cuckoo optimization algorithm	image
Si [17]	2022	Enhancement SIFT matching	Genetic algorithm	Biometric images
The proposed method	2022	Enhancement SIFT	Shark small optimization +Genetic algorithm	Palm print biometric image

According to the table 6, a novel way of meta-heuristic algorithms was used to improve the SIFT feature extraction and matching algorithm's performance (SSO and GA).

6. Conclusion

The SIFT matching of control points results a false match sometimes, this paper proposed an improving of the performance of the SIFT algorithm. the strongest control points from palm print images are present using shark small optimization (SSO) and genetic algorithm (GA). The THUPALMLAB dataset database of palm print images is used. In this study, a shark smell optimization (SSO) technique and a genetic algorithm are combined to create an improved SIFT matching system (GA). A median filter with a kernel size of 3×3 was found to be a useful filter for noise reduction and palm print picture enhancement in this part. A median filter with a kernel size of 3×3 was found to be a useful filter for noise reduction and palm print picture enhancement in this part. SIFT and SSO techniques were used in an intelligent and random way to extract and choose the control points. The greatest features that GA has optimized for each user may be found in the control points. A CVR of 99.80%, a FAR of 0.00, and an FRR of 0.0020, respectively, were achieved using the suggested technique, which included intelligent algorithms. It shows that the suggested palm print matching algorithm has a higher CVR rate than the original methods since its performance was better than the original versions.

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