Performance Analysis of Particle Swarm Optimization Algorithm-Based Parameter Tuning for Fingerprint Image Enhancement

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***Abstract*—Existing algorithms designed for Fingerprint Image Enhancement either lack the ability to enhance poor quality image or are computationally expensive. Evolutionary algorithms are often used to enhance images. Particle Swarm Optimization (PSO) is one of the most progressive algorithms but has parameters, which are not properly tuned to reduce the number of iterations. In this paper, PSO parameters; inertia weight (w) and acceleration constants (c_1 and c_2) were fine-tuned. PSO-based parameterized transformation function, which incorporates both the global and local information of an image was developed to maximize the information content of the fingerprint image. In the transformation function, a threshold of 0.99 was set to control the contrast effect of the enhanced image. The intensity values of pixels that are less than the threshold were transformed. The image quality was evaluated using an Objective Function in term of Number of Edges, Sum of Edge intensities and the exponential of the entropy. The commonly-well-known database FVC-2004 is used in this study. It was observed from the experiments that the best PSO parameters set used for successful convergence of the PSO Algorithm were $w \in [0.7, 0.75]$ and $(c_1, c_2) \in [1.2, 1.3]$. Therefore, any set of values used outside these ranges would result to local minimum convergence and increase the computational effort by searching in unwanted areas.**

Keywords*—particle swarm optimization; fingerprint image enhancement; parameter tuning; transformation function

I. INTRODUCTION

Biometric are personal attributes in every human being. These attributes are classified into individual physiological character such as palm print, fingerprint, iris, facial, DNA and behavioural character such as voice, signature, gait, keystroke, which are used for identification [1-2]. Among these several biometric attributes, fingerprint is the most progressive attribute applied in various domains to authenticate and identify human being [3]. The diverse use of fingerprint as biometric attribute to authenticate individuals is because of their uniqueness, reliability, easy to use, more secure and generally acceptable. The quality of fingerprint image vary, due to noise element that corrupt the ridge structure clarity as a result of variation in skin and impression situation like dirt, scars, holes, humidity, creases, abnormal formations of epidermal ridges of fingerprints, occupational marks and inconsistent acquisition devices [4-6]. Basically, there are good quality fingerprint images with ridge and valley clearly defined and poor quality images where the ridge and valleys are corrupted by little or large amount of noise [4]. Most automated systems depend extremely on the quality of the input image [7]. Therefore, the need for an enhancement algorithm became important to improve the quality of the fingerprint image for further processes. Image Enhancement is the process of manipulating the image for further operations [8]. The aim of fingerprint image enhancement algorithm is to advance the contrast between ridges and valley, so as to obtain clear and more fitting image that is better than the original image thereby increasing the visual quality of the original image [9]. Essentially, there are two domain techniques widely used for enhancement, which are spatial and frequency domains [10]. The choice of appropriate techniques depends deeply on the task at hand, Image modality and viewing conditions [11]. Various fingerprint image enhancement algorithms were developed in both domains, but it is either unable to enhance poor quality image or is computationally expensive. To address these weaknesses, it leads to the use of evolutionary algorithm to enhance gray-level images such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC). Among these evolutionary algorithms; PSO is one of the successive Evolutionary Algorithm applied in various domains for optimisation problems [12]. However, PSO major contributing factors: inertia weight and acceleration constants are not properly fine-tuned to obtain the best optimal solution. This paper proposes to fine-tune the two dependent PSO parameters after considering fingerprint image enhancement as an optimization problem using spatial domain to maximize the information content of fingerprint image. Despite the fact that there is no well-defined theory for image enhancement [10]. Enhancement can either be conducted on binary or gray-level image [13]. In [14], it was assumed that the ridge orientation and ridge frequency can reliably be estimated in gray-level image.

The remainder of this paper are organised as follows: related work in terms of frequency domain, spatial domain and evolutionary algorithms were presented in section 2. Section 3 describes the fingerprint image enhancement functions used. Section 4 presented the PSO algorithm-based fingerprint image enhancement. The results and discussion of the algorithm were presented in section 5. Section 6 gives the concluding remarks.

II. RELATED WORK

1) Frequency Domain Based Enhancement Techniques: The use of directional filter was proposed by [15] consisting of two stages of enhancement algorithm: the filtering stages and thresholding stage, which are dependent on one another, but the approach ignored the use of ridge frequency. A new approach was developed in [16] for fingerprint enhancement by using directional filters and binarization. It is adaptive algorithm, which indicates a good ability to tune itself for each fingerprint image automatically. However, the results presented by algorithm were either not reactive to selection in acquisition device (sensor) or variation in skin. Reference [17] developed an enhancement technique based on Short Time Fourier Transform (STFT). The algorithm simultaneously estimates the ridge orientation, ridge frequency and region mask to facilitate contextual filtering performed in Frequency Domain, which employed full contextual information of the image for enhancement. 17% increase in the accuracy was observed in the comparative study but more robust orientation smoothening algorithm is needed at earlier stage to enhance fingerprint image. Reference [2] proposed a fingerprint image enhancement techniques using Adaptive Filter in Frequency Domain. The enhanced image was binarized and compared the result with other existing techniques, which showed that the proposed techniques performed better. But failed when fingerprint images are corrupted with heavy noises. Reference [18] developed a fingerprint image enhancement technique using Directional wavelet transform and second derivative of a Gaussian filter. The ridge and valley with core point detection of fingerprint were improved, but complex in computation. Yet the result may not be as good as when the directional wavelet transform is also employed. Similarly, [19] developed a new technique for Fingerprint image enhancement based on the Discrete Wavelet Transform (DWT) and Singular Value decomposition (SVD). The contrast between ridges and valleys of the Well-defined, Recoverable corrupted and Unrecoverable corrupted fingerprint images were significantly improved and maximum recognition rate was obtained using fuzziness measure, but it was computationally complex. Reference [5] presented a fingerprint image enhancement algorithm based on energy minimization principle. Two distinct Filters were designed considering both ridge direction and ridge frequency due to numerous peaks and valleys existing on the surface of fingerprint image. These separable filters facilitated the computational speed, but filter design was computationally difficult. Reference [20] proposed a fingerprint image enhancement technique using Iterative Fast Fourier Transform (IFFT). The intensity pixel of the fingerprint image was enhanced by maintaining the orientation and frequency selective property, which increased the clarity of ridge and valley. But using the texture filtering cannot provide suitable end result, which may lead to erroneous false minutiae in the process of minutiae extraction.

2) Spatial Domain Based Enhancement Techniques: One of the most widely quoted fingerprint image enhancement algorithms in spatial domain is in [4]. It uses Gabor Filter that is based on ridge orientation and ridge frequency estimation on the convolution of the image. The algorithm was able to identify the poor quality fingerprint image and remove the noises. But it involves spatial convolution of filters, which was computationally expensive. Furthermore, [14] modified the Gabor Filter approach employed by [4] using unique anisotropic filter. This technique only considers the ridge orientation and replaces Gabor filter with the anisotropic filter. But cannot tune the filters properly due to the absence of the ridge frequency estimation. Similarly, [6] built on the work of [4] by adding three new stages to the four existing stages. The additional stages include; segmentation, binarization and thinning, which was employed to alleviate the drawback in [4]. Similarly, [21] proposed a Modified Gabor Filter (MGF) to overcome the short coming of the Traditional Gabor Filter (TGF) used by [4], which assume that the parallel ridge and valleys structure exhibit some ideal sinusoida-shape plane waves associated with noises. However, both the TGF and MGF failed when used for highly corrupted image with noises. In addition, [22] integrated the Anisotropic Filter (AF) and Directional Median Filter (DMF). An improved smoothing capability with comprehensive filled of broken ridges was observed in the experiment. However, the algorithm failed when the fingerprint image is highly corrupted with heavy noises. Reference [13] suggested the use of image-based pyramid and directional filtering in spatial domain for fingerprint image enhancement; this is to improve the recognition performance. When compared with two well-known algorithms [4] and [17], it shows that the proposed pyramid-based method has a lower Equal Error Rate (EER) using an independent fingerprint matcher in the entire tested database. However, the technique was unable to yield a better result when the image is heavily corrupted with noises. Reference [23] proposed a new framework that applied a pre-processing step, intermediate steps and post-processing steps to achieve an enhanced image thereby improving the clarity of ridge and valley structure. However, the experimental result applied to a database of 100 images showed that 80-92% are successfully enhanced while 8-20% where not successfully enhanced due to heavy amount of noise. Reference [24] integrated existing algorithms of the fingerprint image enhancement by [4] and [6] to obtained a new improved version of algorithm. But it was computationally expensive. Reference [25] employed three different image enhancement filtering techniques: Gabor filter (GF), Log base Gabor (LGF) filter and Modified Gabor filter (MGF) together. From the analysis the result showed that MGF performed better than the other two filters. But it consumed time. These drawbacks lead to the use of evolutionary algorithms reviewed as follows.

3) Evolutionary Based Enhancement Algorithms: Reference [26] applied a parameterized transformation function to the original image in spatial domain, to obtain an enhanced image. A real coded Genetic Algorithm (GA) was used to find the best combination of these parameters for best enhancement. To automate the analysis of the enhanced image without been intervene by human being, an evaluation criterion was used. Conversely, in this paper, the transformation function was slightly modified and used instead. References [27-30] considered gray-level image enhancement hitch as an optimization problem. Particle Swarm Optimization (PSO) Algorithm was used in spatial domain to maximize the information content of the image, by incorporating the global and local information of the original image to transform the intensity of the image using a transformation function. To assess the enhanced image, entropy and edge information of the image were considered in the objective criterion. Conversely, in this paper, the exponent of entropy was taken instead of just the entropy value to strengthen its contribution on the enhanced image. Experimental results in the literatures indicate that the proposed approach achieved better result when compared with other existing techniques such as Histogram Equalization (HE), Contrast Stretching (CS) and Genetic Algorithm (GA).

But the parameters are not properly tune to yield a better result. Similarly, [31] considers fingerprint image enhancement problem as an optimization problem, and uses Particle Swarm Optimization (PSO) to solve it. The PSO maximizes the information content in the enhanced image with image intensity transformation function achieved in spatial domain. Experimental result showed that it outperforms the existing approaches but PSO parameters are not properly tuned. Reference [32] used Artificial Bee Colony (ABC) Algorithm to solve image enhancement problem after considering the problem to be an optimization problem. The transformation function proposed by [26] was employed to transform the image and applied ABC optimization technique to optimize the parameters used in the transformation function. The enhancement process was automated using an objective criterion in [26] to access the image quality. But the tuning parameter process was considered as exploration process of the bee colony.

III. Fingerprint Image Enhancement Functions

Fingerprint image enhancement uses a parameterized transformation function that transformed the intensity value for each pixel of $M \times N$ original image and produce a new intensity value of the corresponding pixel, thereby resulting to an enhanced image. Where M represent the number of columns and N represent number of rows. An objective function is derived to evaluate the enhanced image quality. In this section, the functions used for image enhancement in the proposed study is described.

A. Initialization and Computation of Image Parameters

The gray-level fingerprint image is read by executing the PSO algorithm and resize the input fingerprint image (row = 100 and column = 200). So as to have a specified number of rows and columns, Initialize N numbers of particles of 4-dimension, i.e. each with four parameters $(\alpha, \beta, \gamma, \eta)$ contained in the transformation function, generate random values for these parameters within their ranges and their equivalent velocities. Meaning that, position vectors for each particle has four components $(\alpha, \beta, \gamma, \eta)$.

B. Application of Transformation Function in Spatial Domain

The fingerprint image enhancement was done on spatial domain. A transformation function was employed to produce a new intensity value for each pixel of $M \times N$ original image to produce an enhanced image. The enhancement process equation is given by:

$$g(x, y) = T\left[f(x, y)\right] \quad (1)$$

where $f(x, y)$ is the original image, T is the transformation function and $g(x, y)$ is the enhanced image. The designed transformation function proposed in the literature that takes into account both the global and local information to generate enhanced image was employed. However, it was slightly modified by setting a threshold of 0.99 to control the contrast effect of the enhanced image, which prevent it from transforming toward either total dark or total white region. Therefore, it transformed the intensity values of pixel that are less than the threshold. This means that each input pixel value was analyzed and compared with the threshold before executing the process. The transformation function T is defined as:

$$g(x, y) = z(x, y)\left[f(x, y) - \gamma * m(x, y)\right] + m(x, y)^{\alpha} \quad (2)$$

where α and γ are parameters whose values are to be optimized. $m(x, y)$ is the local mean of the original image over a user-defined $n \times n$ window size and it is given by:

$$m(x, y) = \frac{1}{n \times n} \sum_{i=1}^{n-1} \sum_{j=1}^{n-1} f(i, j) \quad (3)$$

z(x,y) is the enhancement function that takes both local and global information into account and it is defined as:

$$z(x, y) = \frac{\eta * D}{\sigma(x, y) + \beta} \quad (4)$$

where η and β are parameters whose values are to be optimized, D represents the global mean of the original image and $\sigma(x, y)$ represents the local standard deviation of the original image over $n \times n$ window. The global mean D is defined as:

$$D = \frac{1}{M \times N} \sum_{x=1}^{M-1} \sum_{y=1}^{N-1} f(x, y) \quad (5)$$

and $\sigma(x, y)$ is defined as:

$$\sigma(x, y) = \sqrt{\frac{1}{n \times n} \sum_{i=1}^{n} \sum_{j=1}^{n} (f(i, j) - m(x, y))^2} \quad (6)$$

Therefore, the final transformation function is defined as:

$$g(x, y) = \frac{\eta * D}{\sigma(x, y) + \beta}\left[f(x, y) - \gamma * m(x, y)\right] + m(x, y)^{\alpha} \quad (7)$$

with the final transformation in (7), contrast of the image is stretched considering local mean as the center of stretch. Four parameters $(\alpha, \beta, \gamma, \eta)$ were introduced in the transformation function to generate large variations in the processed enhanced image.

C. Assessing Image Quality using Evaluation Function

Intuitively, image quality is measured, without human intervention, using an objective function (or fitness function) comprising entropy value, sum of edge intensities and number of edgels (i.e. number of edge pixels). However, in this paper, the objective function was formulated using the exponent of the entropy value, sum of edge intensities and number of edgels. Because it was observed from the experiment that for each runs of the PSO algorithm it gives different entropy$(H(I_e))$, which affects other components of the fitness function in the enhanced image. Therefore, exponential of entropy $(e^{H(I_e)})$ was to balance the contribution of the $(H(I_e))$ with respect to other fitness function components in the enhanced image. The fitness function is defined as:

$$F(I_e) = log(log(E(I_s))) \times \frac{n\_edgels(I_s)}{M \times N} \times e^{H(I_e)} \quad (8)$$

where $F(I_e)$ is the fitness function, I_e is the enhanced image equivalent to $g(x, y)$, $E(I_s)$ is the sum of $M \times N$ pixel intensities of Sobel edge image, $n\_edgels(I_s)$ are the number of edge pixels, whose the intensity values were above a threshold in the Sobel edge image, which were detected using Sobel edge operator that was used as an automatic threshold detector. The Sobel operator was used because its larger convolution kernel smooths the original image to a greater extent and so makes the operator less sensitive to noise and it also generally produces considerably higher output values for similar edges. Using the Sobel pseudo-convolution kernels, the approximate gradient magnitude was computed as:

$$\nabla f \approx |(q_1 + 2 \times q_2 + q_3) - (q_7 + 2 \times q_8 + q_9)| \\ + |(q_3 + 2 \times q_6 + q_9) - (q_1 + 2 \times q_4 + q_7)| \quad (9)$$

After the use of Sobel edge operator, an edge image was produced on the enhanced image using:

$$I_s(x, y) = \sqrt{qmI_e(x, y)^2 + qnI_e(x, y)^2} \quad (10)$$

where

$$qmI_e(x, y) = qI_e(x+1, y-1) + 2qI_e(x+1, y) \\ + qI_e(x+1, y+1) - qI_e(x-1, y-1) \\ - 2qI_e(x-1, y) - qI_e(x-1, y+1).$$

and

$$qnI_e(x, y) = qI_e(x-1, y+1) + 2qI_e(x, y-1) \\ + qI_e(x+1, y+1) - qI_e(x-1, y-1) \\ - 2qI_e(x, y-1) - qI_e(x+1, y-1).$$

$H(I_e)$ is the entropy value computed on the enhanced image as:

$$H(I_e) = -\sum_{i=0}^{255} e_i \quad (11)$$

where

$$e_i = \begin{cases} h_i log_2(h_i), & \text{if } h_i \neq 0. \\ 0, & \text{otherwise.} \end{cases}$$

and h_i is the probability of occurrence of x^{th} intensity value of enhanced image (I_e) between 0 to 255, which are shades of gray levels in the original image.

IV. PSO Algorithm-based Image Enhancement

A Particle Swarm Optimizer (PSO) is a nature-inspired swarm intelligence algorithm. Every PSO uses a population of particles. The number of particle in a swarm is typically far less than the number of individuals in an evolutionary algorithm. A particle in this population is interconnected to other particles. This interconnection is called the neighborhood topology. Neighborhood refers to a communication structure rather than a geographical neighborhood. To use these particles to explore the search space we need a so-called change rule as shown in (12). This rule moves the particles through the search space at a given moment t in time depending on its position at moment $t-1$ as well as the position of its previous best location. This is the cognitive aspect of the PSO. The social aspect is introduced by an interaction rule. A particles position is not only dependent on its own best position in history, but also on the best position in history of its neighbors.

A. Initialization and Computation of PSO Parameters

Since there exists no better way to position the particles in the search space; they are most commonly initialized in a uniform random fashion within the search space. If one chooses to initialize the velocities, $\vec{V}_i^t$, to a vector of zeroes then $pbest_i$ should be different from $\vec{X}_i^t$ to enable the particles to start moving, but commonly $\vec{X}_i^t$ and $\vec{V}_i^t$ are initialized randomly while $pbest_i$, which is the the individual best candidate solution for particle i at time t, is initialized as $\vec{X}_i^t$ for the first iteration. The nonzero velocities move the particles through the search space in a randomly chosen direction and magnitude. $gbest^t$ contains the objective function value of the best position of a particle at iteration t. At initialization, it is set to infinity to always allow an improvement in the first iteration.

The first phase is to evaluate all particles and update their personal bests according to their fitness values. The variable $gbest^t$ is the swarms global best candidate solution at iteration t. The second phase is to adjust the positions of the particles; since in each iteration, a swarm of N number of new particles are generated. In algorithm 1, first the velocity $\vec{V}_i^{t+1}$ of each particle is updated to get new solution using (12) as follows:

$$\vec{V}_i^{t+1} = w * \vec{V}_i^t + c_1 * r_1 * (pbest_i^t - \vec{X}_i^t) \\ + c_2 * r_2 * (gbest^t - \vec{X}_i^t) \quad (12)$$

Then the new positions of the particles are updated using (13) as follows:

$$\vec{X}_i^{t+1} = \vec{X}_i^t + \vec{V}_i^{t+1} \quad (13)$$

This process is repeated until a number of iterations when the last update of the global best candidate solution(i.e. maximum fitness value) was reached. When the process is completed the enhanced image is created by the particle, as it provides the maximum fitness value and the image is displayed as the final result.

Algorithm 1: PSO Based Image Enhancement

Input: N, $d \leftarrow (\alpha, \beta, \gamma, \eta)$, $\vec{V}_i^0$, $\vec{X}_i^0$, w, c_1, c_2, r_1, r_2
Output: *gbest* and $g(x, y)$
Create N number of particles of d dimension
for ($i \leftarrow 1$ **to** N) **do** //each particle i
  Initialize $\vec{X}_i^t \sim [\alpha, \beta, \gamma, \eta]$ within their ranges and corresponding random V_i^t
end for
while (Termination condition $\neq true$) **do**
  for ($i \leftarrow 1$ **to** N) **do** //each particle i
    Generate $g(x, y) = \frac{\eta * D}{\sigma(x,y)+\beta} [f(x, y) - \gamma * m(x, y)] + m(x, y)^\alpha$
    Compute $F(I_e) = log(log(E(I_s))) \times \frac{n\_edgels(I_s)}{M \times N} \times e^{H(I_e)}$
    {Update personal best positions}
    if $F((I_e)_i) > pbest_i$ **then**
      $pbest_i = F((I_e)_i)$
    end if
    {Update best particle in each neighborhood}
    if $F((I_e)_i) > gbest^t$ **then**
      $gbest^t = F((I_e)_i)$
    end if
  end for
  {Update velocities and positions}
  for ($i \leftarrow 1$ **to** N) **do** //each particle i
    $\vec{V}_i^{t+1} = w * \vec{V}_i^t + c_1 * r_1 * (pbest_i^t - \vec{X}_i^t) + c_2 * r_2 * (gbest^t - \vec{X}_i^t)$
    $\vec{X}_i^{t+1} = \vec{X}_i^t + \vec{V}_i^{t+1}$
  end for
end while

1) PSO Algorithm Parameter Setting: The performance of PSO Algorithm depend solely on parameters. Therefore, if the parameters were properly fine-tuned, it provides better result compared to other optimization algorithms. These parameters

TABLE I. THE PARAMETERS OF THE DATABASE

Database Name	2004 DBI
Sensor Type	Optical Sensor
Image Size	640x480
Resolution (*dots per inch - dpi*)	500

include: inertia weight w, with maximum and minimum values set to 2 and 0, respectively, which were the same for all particles. The values of c_1 and c_2 are positive acceleration constants randomly assigned in [0, 2], which are fixed when executing the algorithm for each particle throughout the experiment. The values of r_1 and r_2 are randomly generated in [0, 1], which varies for each particle in every generation. The parameterized transformation function used four parameters $(\alpha, \beta, \gamma, \eta)$, which are also generated within their range of values as follows, respectively: $\alpha \in [0, 1.5]$, $\beta \in [\frac{D}{2}, 0.5]$, $\gamma \in [0, 1]$, and $\eta \in [0.5, 1.5]$, where D is the global mean.

Optimal performance of the PSO algorithm lies on the proper fine-tuning of the two important PSO control parameters, which are inertia weight and acceleration constants. This is because acceleration constants control the magnitude of the adjustments towards the particles personal best and its global best. While inertia weight is necessary to keep velocities under control, as they would quickly increase to unacceptable levels within a few iterations. w is dependent on c_1 and c_2, which eliminates the need to set another parameter [33].

V. RESULTS AND DISCUSSION

In this study, the performance of the PSO algorithm was investigated based on the PSO control parameters using their different set of values. Thus, a PSO Algorithm was developed for fingerprint image enhancement using a parameterized transformation function in spatial domain.

The algorithm was set to run three times for a particular set of PSO control parameters to investigate the changes in the resulted enhanced image. The three best results were presented in this section as best, average and worst enhanced images, respectively. The parameters were tuned either by increasing or decreasing the parameter values to examine the changes in the resulted enhanced image. The implementation was performed using Matrix Laboratory (MATLAB) R2013a.

A. Fingerprint Database used

The poor quality images contained in a public obtainable fingerprint image database for Fingerprint Verification Competition (FVC) in 2004 was used. The summary of the database used is shown in Table I. The image stored in the database were in *tif* picture format and open in JPEG format for easy display and result representation. In the pre-processing stage, the image was resized to have a specified number of rows and columns. The original image was then converted to gray scale.

B. Transformed Image

The transformation was based on a set threshold 0.99, which triggered when the intensity value is less than the threshold to control the contrast effect in the resulted image. It was observed that the lower part of the original image in Fig. 1(a) was not clearly visible and cannot be used in the subsequent steps of processing such as in automated systems.

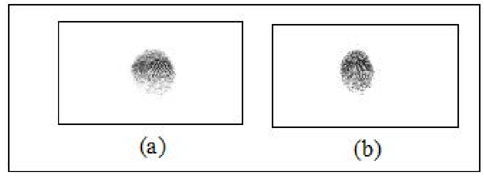

Fig. 1. Original (a) and transformed image (b)

However, the edges where cleared and information needed are visible in the transformed image as shown in Fig. 1(b).

C. Objective Evaluation

The metrics used to analyse the performance of the algorithm were Detailed Variance (DV) and Background Variance (BV). These variance values were obtained using the following steps:

1) Evaluate the variance of the enhanced image, taking into account the neighbours of each pixel over $n \times n$ window sixe, where $n = 3$.
2) Classify the pixel with variance less than the threshold as a background pixel, otherwise, classify it as a foreground pixel.
3) Compute the average variance of all pixels belonging to the foreground group as DV.
4) Compute the average variance of all pixels belonging to background group as BV.

Intuitively, the Detailed Variance of Enhanced image (DVE) increased when compared with Detailed Variance of Original image (DVO) for any successful enhanced image. While Background Variance of Enhanced image (BVE) should either decrease or almost the same when compared with the Background Variance of Original image (BVO). Similarly, by computing the number of edges detected by sobel automatic threshold edge operator, the Enhanced Image Number of Edges (EI NE) should increase for efficiently enhanced fingerprint image when compared with Original Image Number of Edges (OI NE). The fitness of each round converges at almost the same or closer fitness value for successful fingerprint image enhancement.

The results for three different runs of the algorithm using the same fixed parameter values of inertia weight $(w = 2)$ and acceleration constants $(c_1 = c_2 = 1)$ of the PSO algorithm are shown in Fig. 2 and Table II. The values obtained in the three rounds for BVE, DVO, BVO, EI NE and OI NE are 2.56E-08, 0.05457, 0.00116, 542 and 815, respectively.

TABLE II. THE VALUE OF PARAMETER $w = 2$ AND $c_1 = c_2 = 1$

ROUND	DVE	ROUND FITNESS
First	1.16E+20	1317757.4
Second	6.15E+21	364609946
Third	1.60E+22	21299211

Fig. 2(a) is the original image. In Fig. 2(b, c and d) it was observed that this set of values $w = 2$ and $c_1 = c_2 = 1$ were not good for fingerprint image enhancement. The resulted images look the same and the needed information were lost. The number of edges in the original image was more than that of the enhanced image, this indicated that the result was very

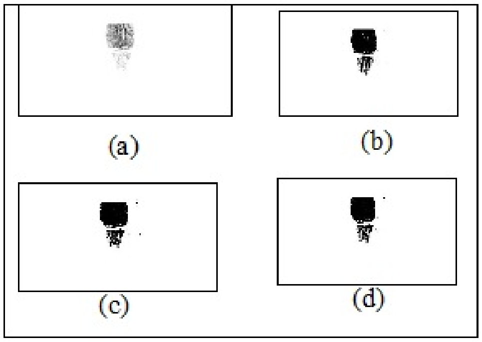

Fig. 2. The value of parameter $w = 2$ and $c_1 = c_2 = 1$

poor. By implication, the inertia weight, $w = 2$ explore larger area in the solution search space and result was far from the best optimal solution. Similarly, small value of acceleration constants limits movement, since $c_1 = c_2 = 1$ were the factors that control the speed of the particle. Consequently, there is neither optimization nor convergence using this set of parameter values for fingerprint image enhancement.

The results for three different runs of the algorithm when the values of parameter set were $w = 0.9$ and $c_1 = c_2 = 1$ are shown in Fig. 3 and Table III. The values obtained in the three rounds for DVO, BVO and OI NE are 0.054571, 0.001162 and 815, respectively.

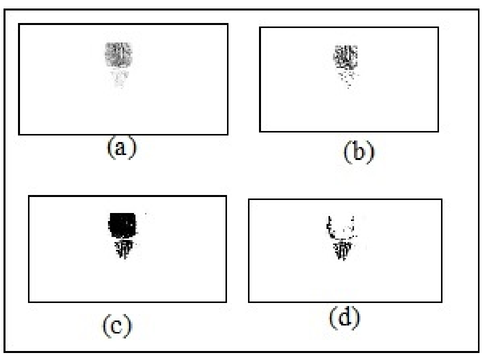

Fig. 3. The value of parameter $w = 0.9$ and $c_1 = c_2 = 1$

TABLE III. THE VALUE OF PARAMETER $w = 0.9$ AND $c_1 = c_2 = 1$

RESULT RANK	DVE	BVE	EI NE	ROUND FITNESS
Best	1.047314	2.08E-05	936	4.967891
Average	4.821404	9.61E-07	566	2.887843
Worst	3.75E+21	2.56E-08	6	0.489196

Table III presents results obtained from Fig. 3 when the values of parameters were tuned to $w = 0.9$ and $c_1 = c_2 = 1$. From Table III, it was observed that only the first round has higher number of edges but yet not improved. In fact, the inertial weights have to balance the exploration and exploitation, but there was no balance between this two conflicting goals. If the inertia weight was small, it pulled toward exploitation and if large it pulled toward exploration. This indicated that the pull was toward exploitation, so there is need to tune these parameters so as to balance those two conflicting goals. The acceleration constants are to pull the particle toward local best position and global best position, respectively. However,

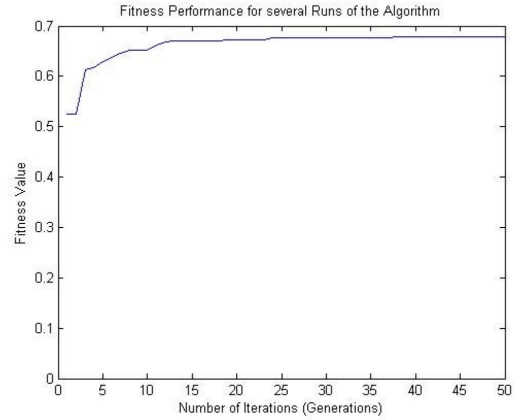

Fig. 4. Fitness performance when $w = 0.9$ and $c_1 = c_2 = 1$

for $c_1 = c_2 = 1$, it implies that their values are small, which resulted in slow movement of the particles, increase in computational effort and lack of convergence in the PSO algorithm. It can also be observed from the Fitness graph in Fig. 4, which shows that the Fitness Performance for three runs of the PSO algorithms have neither optimisation nor convergence.

The results for three different runs of the algorithm when the values of parameter set were $w = 0.75$ and $c_1 = c_2 = 1.2$ are shown in Fig. 5. The first image in Fig. 5(a) presents the best result, since it was clearly visible with highest increase in DVE and higher number of edges as shown in Fig. 6 and Fig. 8, respectively.

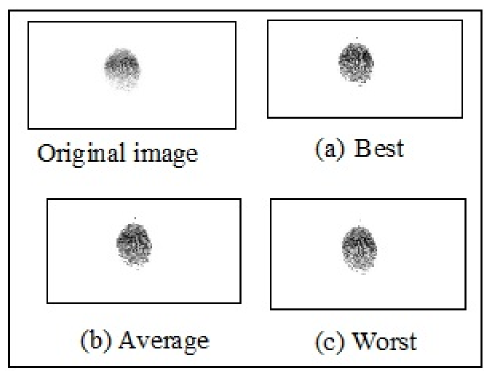

Fig. 5. The value of Parameter $w = 0.75$ and $c_1 = c_2 = 1.2$

In Fig. 6 it was observed that there was an increase in the Detailed Variance of the enhanced image when compared with the Detailed Variance of the original image as clearly shown for the three rank of the resulted images. A decrease was observed in the Background Variance of the enhanced image as shown in Fig. 7 when compared with the original image.

The three runs of the PSO algorithm using this same set of parameters values converged at almost the same fitness value as shown in Fig. 9. By implication, there is a balance between the cognitive factor c_1, which controls the pull towards personal best position and social factor c_2, which controls the pull towards the global best position. The convergence was also

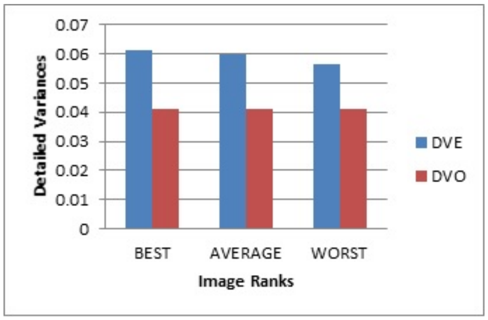

Fig. 6. Detail Variance when $w = 0.75$ and $c_1 = c_2 = 1.2$

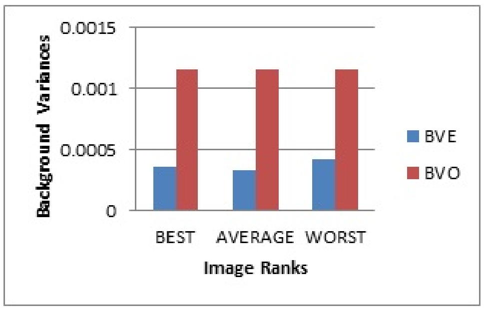

Fig. 7. Background Variance when $w = 0.75$ and $c_1 = c_2 = 1.2$

as a result of balance between exploitation and exploration, which was based on the set inertia value $w = 0.75$.

From the results in Fig. 9 it was observed that these parameters $w = 0.75$ and $c_1 = c_2 = 1.2$ presents optimal solution, because there is convergence.

The results for three different runs of the algorithm when the values of parameter set were $w = 0.73$ and $c_1 = c_2 = 1.3$ are shown in Fig. 10.

In Fig. 11 it was observed that there was an increase in the Detailed Variance of the enhanced image when compared with the Detailed Variance of the original image as clearly shown for the three rank of the resulted image. A decrease was observed in the Background Variance of the enhanced image when compared with the original image as shown in Fig. 12. There is an increase in the number of edges, which presents the best detailed of an enhanced image as shown in Fig. 13.

The three runs of the PSO algorithm using this same set of parameters converged at almost the same fitness value

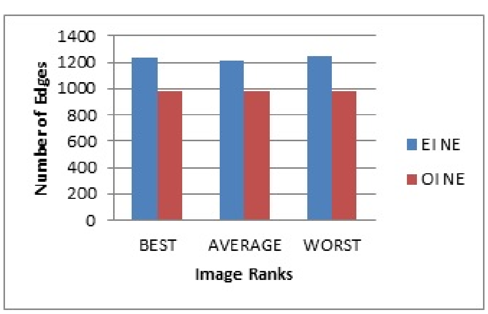

Fig. 8. Number of Edges when $w = 0.75$ and $c_1 = c_2 = 1.2$

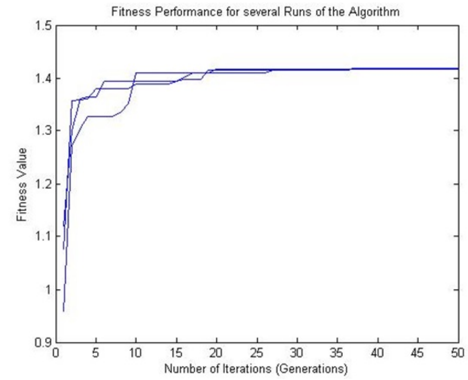

Fig. 9. Fitness performance when $w = 0.75$ and $c_1 = c_2 = 1.2$

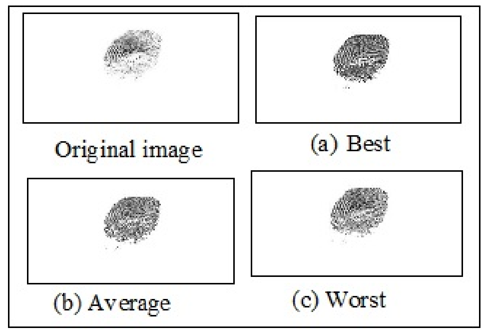

Fig. 10. The value of Parameter $w = 0.73$ and $c_1 = c_2 = 1.3$

after fifty iterations as shown in Fig. 14. By implication, there is a balance between the cognitive factor c_1, which controls the pull towards personal best position and social

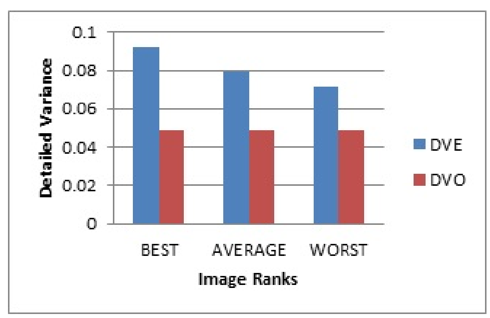

Fig. 11. Detail Variance when $w = 0.73$ and $c_1 = c_2 = 1.3$

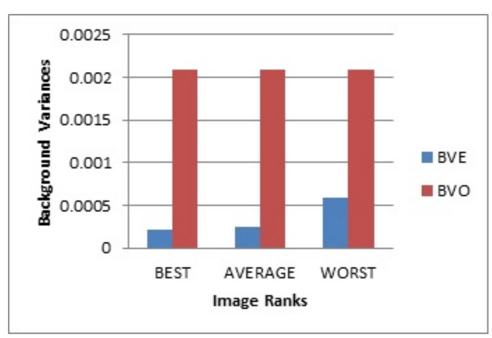

Fig. 12. Background Variance when $w = 0.73$ and $c_1 = c_2 = 1.3$

Fig. 13. Number of Edges when $w = 0.73$ and $c_1 = c_2 = 1.3$

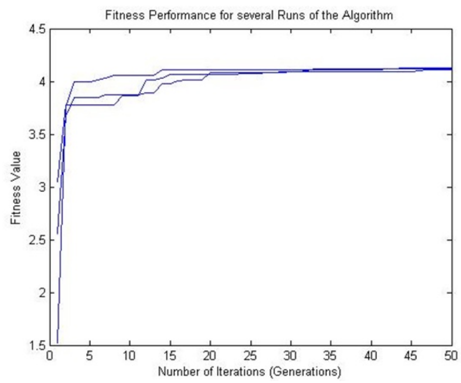

Fig. 14. Fitness performance when $w = 0.73$ and $c_1 = c_2 = 1.3$

factor c_2, which controls the pull towards the global best position. The convergence was also as a result of balance between exploitation and exploration, which was based on the set inertia value $w = 0.73$. From the result, it was observed that this set of parameters values $w = 0.73$ and $c_1 = c_2 = 1.3$ presents optimal solution.

D. Visual Analysis of the Enhanced Image

The visual analysis of the enhanced image was done from the presented results in Fig. 5 when $w = 0.75$ and $c_1 = c_2 = 1.2$. It visually shows that (b), the averagely ranked was the best due to the brightness effects in the resulted image, followed by (a), the best ranked due to the contrast effect in the resulted image. But from the objective evaluation it is opposite. From Fig. 10 when $w = 0.73$ and $c_1 = c_2 = 1.3$, also visually indicated that (b) the averagely ranked fingerprint image was the best followed by (c); the worst objectively ranked was the averagely ranked visually due the brightness effect in the resulted image. From The visual analysis there is a contradiction with the objective evaluation, however, the objective evaluation presents the best results because the it considers some image qualities before ranking the resulted image, but that consideration is impossible visually.

VI. CONCLUSION

In this paper, performance comparative analysis of PSO-based enhancement algorithm for fingerprint images by tuning its two major control parameters was investigated. This was carried out after considering fingerprint image enhancement as an optimization problem. The two major PSO control parameters: inertia weight and acceleration constants were fine-tuned and run for different generations. More pleasant results were obtained. It was observed that if the parameters are properly tuned it absolutely converge to best optimal solution.

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