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A comparative study of two meta-heuristic approaches for image registration of printed circuit boards

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Informations	Abstract
Keywords : Gray Wolf Optimizer Printed Circuit Board Sine cosine algorithm *Correspondence : fel la.charif@gmail.com	Nowadays, printed circuit boards (PCBs) are so short and high density that diagnosing and detecting defects becomes an increasingly difficult task. In this paper, we suggest using two recent bio-inspired optimization methods called sine cosine algorithm (SCA) and Grey Wolf Optimizer (GWO) to find the optimal parameters for the rigid transformation of PCB images. The comparative performances of these methods have been studied and the best meta-heuristic optimization method is identified. Simulation results show that Grey Wolf Optimizer achieves extremely accurate and robust recording compared to SCA methods.

1. Introduction

Image registration is playing an increasingly important role in image processing and it has a variety of applications in the field of military automatic target recognition remote cartography, computer vision, image fusion, medical imaging [1,2], and the printed circuit board (PCB) layout technology[3]. A printed circuit board (PCB) is the electrical connection provider of electronic components. The use of PCB can greatly reduce layout and assembly errors [4]. In the automatic PCB defect detection system, image registration of PCB plays an important role. The goal of PCB image registration refers to the process of overlaying two comparison images.

Image registration consists to compute a spatial transformation function between two images to be superimposed by maximizing their resemblance criteria. One of the two images is referred to as the reference image and the second image is referred to as the target input image [5]. Image registration techniques can be divided into intensity-based and feature-based. In the intensity-based methods, the intensity patterns in the two images are compared utilizing correlation metrics, while in the feature-based methods, the image features such as points, lines, and contours are used to find correspondence between them. The intensity-based method is more robust and easy to realize than feature-based methods. Meanwhile, the

feature-based method is sensitive to the extracted features [5].

Intensity-based image registration is based on the calculation of a spatial transformation function between two images to be superimposed on the optimum of their resemblance criteria. This can be described by three components: a transformation model, a similarity metric, and an optimization method [4]. The spatial transformation can be rigid, affine, perspective, and elastic. Similarity metrics can be based on intensity difference, cross-correlation and mutual information (MI). Mutual information is a robust measure used in image registration [6]. It evaluates the relative independence of two images and does not depend on the specific dynamic range or intensity scaling of the images. High values of mutual information indicate a high dependence between images [5]. Usually, optimization in image registration means to maximize similarity. Many meta-heuristic methods have been introduced and adopted for the registration process [7], such as genetic algorithm [7], differential evolution [8], ant colony optimization [9], simulated annealing [7], Firefly algorithm [10], particle swarm optimization (PSO) [11,12], and Biogeography-Based Optimization Algorithm [13,14] have been applied to image registration.

In this paper, two recent bio-inspired optimization methods called sine cosine algorithm (SCA) [15] and Grey Wolf Optimizer

(GWO) [16] are used to compute the optimal geometric transformation that allows the target PCB image to overlay the reference PCB image. The sine cosine algorithm is a global optimization approach based on two trigonometric functions, the sine and the cosine functions. Grey Wolf Optimizer (GWO) is a new meta-heuristic algorithm proposed in 2014 [16]. This algorithm is inspired by the hunting process found in Grey Wolves.

The rest of this paper is organized as follows. In section 2, we will describe the proposed algorithm, including geometric transformation and similarity measure. The gray wolf and the sine cosine algorithms are discussed in section 3. Experimental results and comparative analysis are given in section 4. In section 5, some conclusions are presented.

2. Proposed algorithm to register PCB images

In this section, we describe the proposed algorithm to register PCB image pairs. The proposed image registration process can be described by three components: a transformation which relates the target and source images, a similarity measure which measures the similarity between target and source image, and an optimization algorithm which determines the optimal transformation parameters as a function of the similarity measure [5]. The flowchart of our method is given in Figure 1.

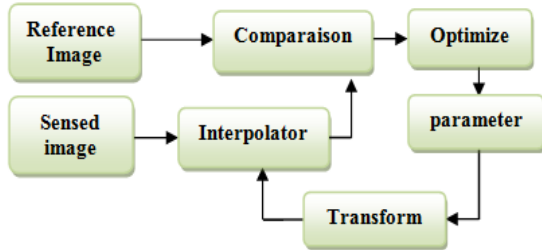


Fig.1:Block diagram of image registration process

2.1. Transformation

The transformation model determines which kind of geometrical transformation to be applied for the registration. In this paper, our study is limited to applying the rigid transformation, which contains a translation along x and y axes t_x , t_y , and rotation θ . This transformation is popular because in many common medical images the rigid body constraint leads to a good approximation. Furthermore, it has relatively few parameters to be determined and it can be defined as [1]:

$$M = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & t_x \\ \sin(\theta) & \cos(\theta) & t_y \\ 0 & 0 & 1 \end{bmatrix} \quad (1)$$

2.2. Similarity measure

To evaluate the similarity between model image A and registered source image B , the normalized mutual information (NMI) is used [6]:

$$NMI(A, B) = \frac{H(A) + H(B)}{H(A, B)} \quad (2)$$

where:

$$H(A) = -\sum_a P_A(a) \log_2 P_A(a) \quad (3)$$

$H(A, B) = -\sum_{a,b} P_{A,B}(a, b) \log_2 P_{A,B}(a, b)$ (4)
 $P_A(a)$ and $P_{A,B}(a, b)$ are the marginal probability distribution of A and the joint distribution of A and B respectively.

2.3. Objective function of image registration

Image registration determines spatial transformation $\hat{T}$ which maximizes the NMI of the reference I_r and floating I_f images. Previous description of image registration can be represented by the following equation [2]:

$$\hat{T} = \underset{T}{\operatorname{argmax}} NMI[I_r(x, y), I_f(T(x, y))] \quad (5)$$

In this equation (x, y) is the coordinates of the image.

3. Optimization algorithms

3.1 Sine Cosine algorithm

The sine cosine algorithm proposed by Mirjalili [15], is a population-based optimization technique. It begins by generating a set of random solution, and then, these solutions are updated based on the sine or cosine function as in equation (6).

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 < 0.5 \\ X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 \geq 0.5 \end{cases} \quad (6)$$

where t is the current iteration, P_i^t is the position of current solution at iteration t , X_i^t is the position of current solution, and r_2 , r_3 and r_4 are random variables and are uniformly distributed between 0 and 2π , 0 and 2, and between 0 and 1 respectively. The variable r_1 is updated as:

$$r_1 = a(1 - \frac{t}{T_{max}}) \quad (7)$$

where a is a constant, T_{max} and t respectively are the current and the maximum iterations. The sine cosine algorithm is summarized as follow [15,17]:

Algorithm 1: Sine Cosine Algorithm

1. **Initialize** a set of random solutions X .
2. **Calculate** the objective function of each solution.
3. **Select** the best solution that optimizes the objective function.
4. **Initialize** the parameters r_1, r_2, r_3 and r_4 .
5. **Initialize** the generation count $t = 0$.
6. **While** $t < \text{maximum number of iteration } T_{max}$
7. **For each** candidate solution
8. **Update** the solution using Eq. (6)
9. **Calculate** the objective function of updated solution.
10. **Update** the best solution.
11. **End for**
12. **Update** r_1, r_2, r_3 and r_4 .
13. $t = t + 1$
14. **End while**
15. **Return** the best solution obtained so far as the global optimum.

3.2 Grey wolf optimizer

The gray wolf belongs to a Canadian family. This type of wolf is considered predatory so it is at the top of the food chain. Gray wolves prefer to live in groups of 5 to 15 on average. They follow a strict social dominant hierarchy. The gray wolves are divided into three groups α, β, δ , each with a specific role that is different. Alpha wolves represent the best solution inside the group of possible solutions. [16,18]. This process is represented from equations 8 to 11.

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (8)$$

where $\vec{X}$ is the grey wolf position, t is the number of iteration, $\vec{X}_p$ is target position, and $\vec{D}$ is distance vector calculated as :

$$\vec{D} = |\vec{C} \cdot \vec{X}_p - \vec{X}(t)| \quad (9)$$

where $\vec{A}$ and $\vec{C}$ are the coefficient vectors represented as Equations (10) and (11) respectively [19].

$$\vec{A} = 2 \cdot k \cdot \vec{p}_1 - k \quad (10)$$

$$\vec{C} = 2 \cdot \vec{p}_2 \quad (11)$$

where $k = 2 - t \left(\frac{t}{T_{max}} \right)$ is decreased from 2 to 0

linearly through the number of iterations, T_{max} is total number of iterations and $\vec{p}_1, \vec{p}_2$ are two random vectors between [0, 1]. The alpha is responsible for directed the fishing pattern of the wolves. Beta and Delta are also involved in

fishing. Thus, the first three best solutions are chosen to be the hunting wolves, and their current positions can update all wolves' positions. The formulas in this regard are as follows:

$$\begin{cases} \vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}| \\ \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}| \\ \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \end{cases} \quad (12)$$

where $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\delta$ are the states of leaders alpha, beta and delta, respectively. $\vec{C}_1, \vec{C}_2$ and $\vec{C}_3$ are the random vector. After calculating the difference vectors $\vec{D}_\alpha, \vec{D}_\beta$, and $\vec{D}_\delta$ the updated states for $(t+1)$ the iteration can be calculated by:

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \vec{D}_\delta \end{cases} \quad (13)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (14)$$

where $\vec{A}_1, \vec{A}_2$ and $\vec{A}_3$ are the random vectors.

The GWO algorithm is summarized as follow:

Algorithm 2: GWO algorithm

1. **Initialize** the randomly generated population of wolves
2. **Evaluate** the fitness of each wolf
3. **Select** the fittest wolf alpha and second and third best wolves beta and delta form the population of wolves
4. **Initialize** the algorithm parameters $\vec{A}$ and $\vec{C}$
5. **Initialize** the iteration count $t=0$
6. **While** $t < T_{max}$
7. **For** each wolf
8. **Update** the position using equations 8-11:

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$
9. **End for**
10. **Evaluate** the fitness of wolves
11. **Update** the leaders alpha, beta and delta of the wolf pack
12. $t = t + 1$
13. **End while**
14. **Return** the fittest wolf alpha

4. Simulation results

Several simulations were performed to compare the algorithm SCA and GWO, to show the most effective algorithm in optimization. The results were obtained using MATLAB 2019 on a computer with an Intel CORE i3 processor.

4.1. Test Images

The test images are obtained from the PCB DSLR dataset available in [20]. The dataset contains 748 images of PCBs from a recycling facility, captured under representative conditions using a professional DSLR camera. Figure 2 shows three samples from the used dataset.

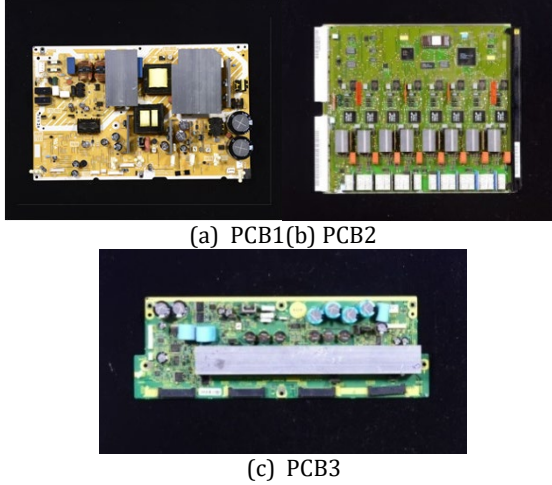


Fig.2 : Test images

4.2. Evaluation criterion

To assess the performance of the two methods GWO and SCA, the mean squared error (MSE), and structural similarity metric (SSIM) [21] are used as quantitative assessment metrics to compare various registration algorithms. They are defined as:

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (I_g(i, j) - I_{s_reg}(i, j))^2 \quad (15)$$

$I_g(i, j)$ and $I_{s_reg}(i, j)$ are the pixel values of the ground truth image and the registered image, respectively. The image size is $M \times N$.

$$SSIM(I_g, I_{s_reg}) = \frac{(2\mu_g\mu_{s_reg} + (k_1L)^2)(2\sigma_{gs_reg} + (k_2L)^2)}{(\mu_g^2 + \mu_{s_reg}^2 + (k_1L)^2)(\sigma_g^2 + \sigma_{s_reg}^2 + (k_2L)^2)} \quad (16)$$

Where $\mu_g, \mu_{s_reg}, \sigma_g, \sigma_{s_reg}$, are the local means, standard deviations, and cross-covariance for images I_g, I_{s_reg} . k_1, k_2 are parameters with small values and L is the maximum pixel value [21]. The higher SSIM value and the less MSE value indicate better registration results.

4.3. Accuracy

A test image and reference image will be converted into gray image first, and then the transformation matrix is calculated to transform the test image into the same orientation and

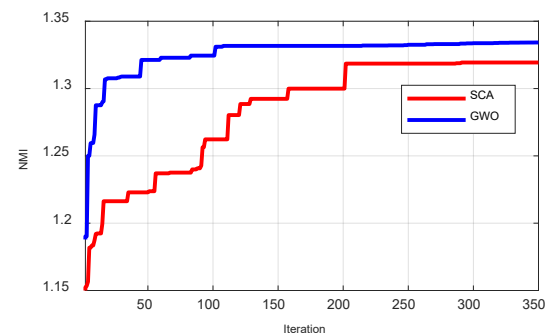
position as the reference image. In the experiment, the floating (test) image is obtained by applying a translation $(t_x, t_y) = (-5, -5)$ and, a rotation of $\theta = 5^\circ$ to the ground truth image. Bio-inspired algorithms SCA and GWO have been used to register these three images with similar population size of 40. Both algorithms are sufficiently iterated to ensure the convergence. After some trials, the number of iterations was fixed to 350.

After applying the SCA and GWO algorithms, the results were recorded and compared to determine the best algorithm. From the results obtained after applying the two algorithms to the PCB images that appear in Table 1, we found that the GWA algorithm is more accurate compared to the SCA algorithm, we can show that the transformation parameters obtained by the GWO algorithm are more accurate than those obtained using the SCA. The SSIM and the NMI values for the GWO are higher. This proves that the two images are well aligned. Furthermore, the GWO algorithm is faster than the SC algorithm.

TABLE 1 : Registration results for SCA and GWO

	PCB 1		PCB 2		PCB 3	
	SCA	GWO	SCA	GWO	SCA	GWO
$-t_x$	5.771	5.550	5.315	5.506	5.422	5.549
$-t_y$	6.612	6.626	6.140	6.620	6.726	6.584
$-\theta$	5.048	4.997	5.091	4.998	5.054	4.998
SSIM	0.977	0.980	0.969	0.970	0.969	0.973
NMI	1.319	1.334	1.284	1.322	1.279	1.292
MSE $\times 10^{-4}$	72	31	33	40	91	9
Time	586.9	540.6	611.8	587.4	596.	597.9

The convergence curves using the three images are shown in figure (3). As we can see, the GWO algorithm is faster and more accurate compared to the SCA algorithm. The Figures 4, 5, and 6 show the visual results of the registration process using the SCA and the GWO algorithm. The absolute error image and the SSIM map justify the efficiency of the GWO algorithm.



(a) PCB 1

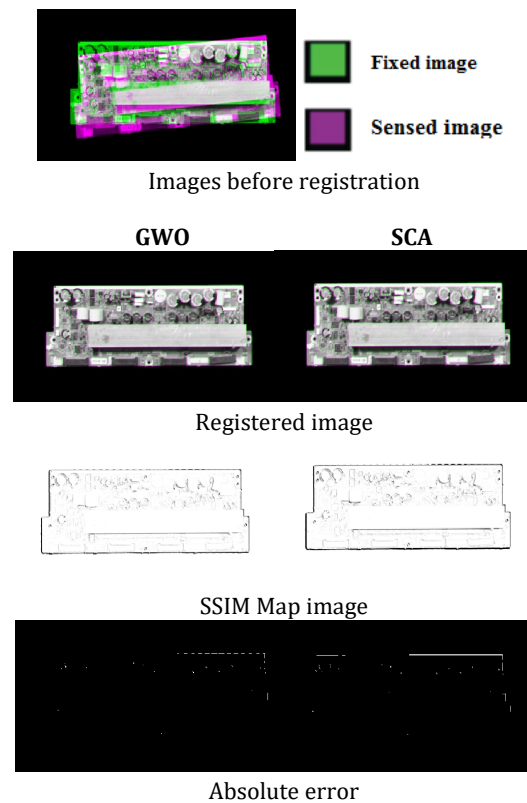
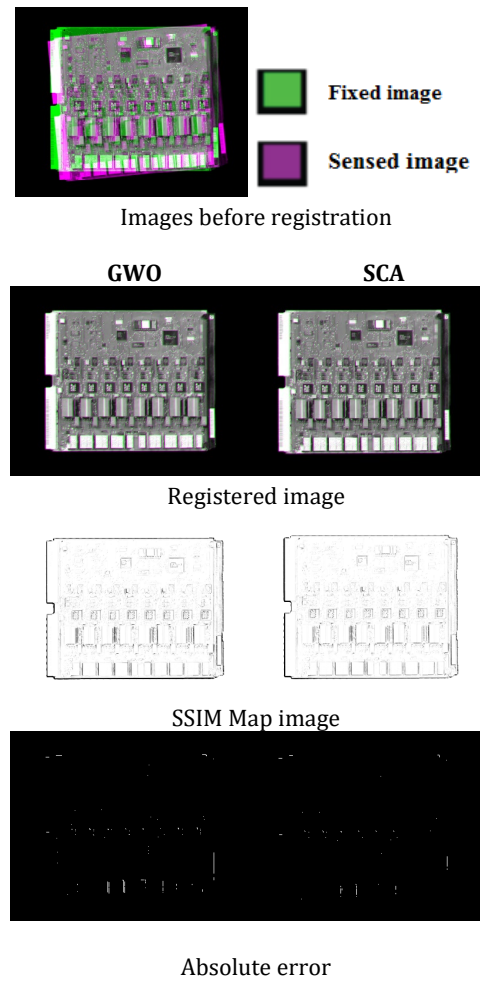
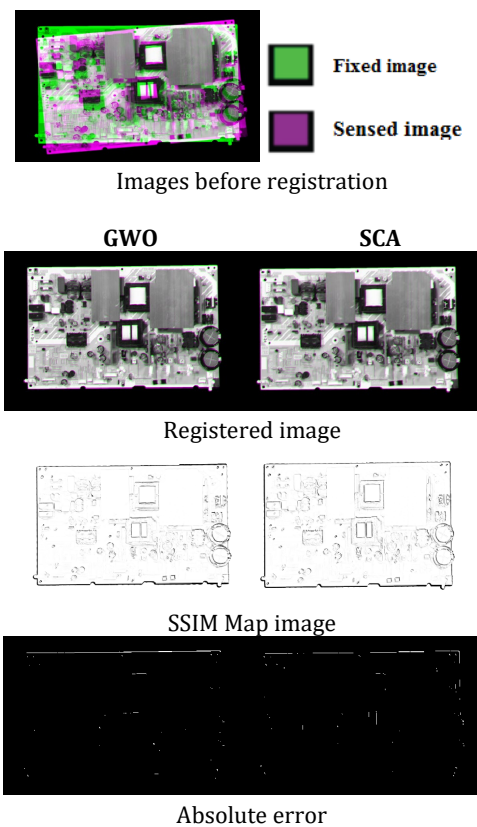
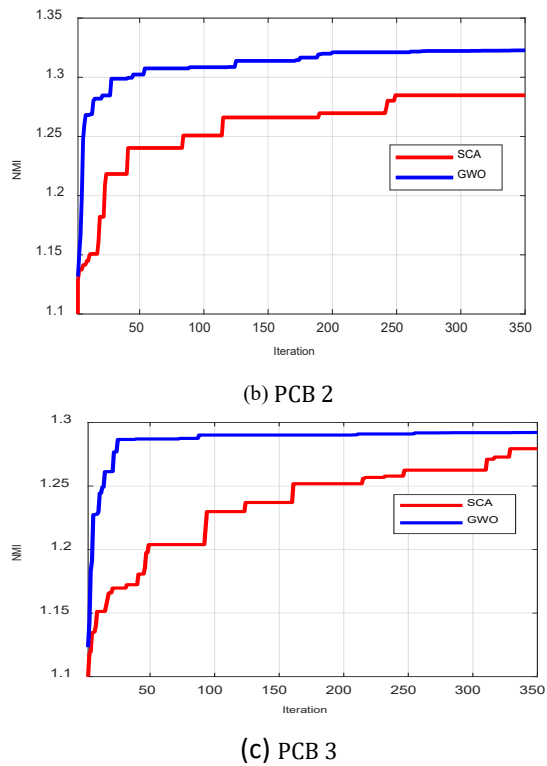


Fig.6 : Visual results for PCB 3

5. Conclusion

Printed circuit board (PCB) is the fundamental carrier in electronic devices on which a great number of elements are placed. The quality of the PCB will directly impact the performance of electronic devices. So registration is indispensable in reference comparison based method. During the last decades, a large number of image registration methods have been described in the literature. Unfortunately, there is no one method that works very well for Printed circuit board images registration. To improve the performance of image registration, two new methods sine cosine and grey wolf optimizer algorithms based on normalized mutual information are proposed in this paper. From the obtained results we have found that the GWO algorithm is faster and more accurate compared to the SCA algorithm for PCB image registration.

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