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Image Registration of Printed Circuit Boards using Hybrid Genetic Algorithm

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Abstract— **In this paper, hybridization of hill-climbing (HC) and elitism (E) with a specially tailored Genetic Algorithm (GA) for image registration of Printed Circuit Boards (PCBs) placed arbitrarily on a conveyor belt during inspection is proposed to maximize the robustness of the existing framework. These hybrid methods are investigated individually and in combination for accuracy, reliability and performance. Experimental results highlight the potential of the hybrid GA (HGA) that consists of all methods in combination because of the most accurate findings and significantly more reliable than GA alone. However, there is a compensation on performance, though it converges efficiently in terms of number of generations.**

I. Introduction

The goal of the registration task is to find the transformation that best represents the relative transformation between two compared images. In inspection case, the objective is to find, in a huge search space of geometric transformations, an acceptable accurate solution in a reasonable time to provide better registered image for high quality product. So, [1] has used GA to estimate the rotation angle and displacement values at x-axis and y-axis of the inspected board image of PCB placed arbitrarily on a conveyor belt based on the reference board image, while detecting any physical defects on the inspected board. The GA framework has been tuned optimally to find the most accurate values of transformation with low computational time, that is suitable for efficient real-time inspection environment. [2] has also used GA to find misorientation parameter values of individual Integrated Circuits (ICs) on board to determine the ICs on PCB has no defects and has implemented the technique on a System-On-Chip (SOC) platform. In [3], the researchers have used GA to optimize the search solution space of multi-resolution wavelet decomposed images for remote sensing image registration.

Genetic search can adequately handle simple translations and rotations in image registration task, even in the presence of variation in contrast [4]. The advantage of GA has also been tested in a complex and noisy environment by [5] to search for the position and orientation of target image for object recognition.

Hybridization of GA and hill-climbing has been done on range image registration in [6]. They have proved that hill-climbing provides fast convergence and good performance in finding correct registrations compared to GA alone. Discussion on two ways of hybridizing GA with hill-climbing and elitism methods for global optimization has been presented in [7].

It is very unlikely that GA alone will outperform a specialized scheme tailored to a problem. Most successful applications of GAs have been hybrids [8]. Combination of hill-climbing and elitism usually performs better than either one alone. This happens because there is a possibility of incorporating domain knowledge, which gives it an advantage over a pure blind searcher (i.e GA).

Based on the performance of the first prototype with GA alone [1] and motivated by previous reviews, the hybrid method cooperating GA with hill-climbing and elitism is proposed in this paper to maximize the robustness of the search technique in order to provide better quality in registration of inspected PCB during inspection process.

In the following section, we explain how hill-climbing and elitism are implemented with the existing GA. Then, the experimental setup is described in detail followed by results on fitness and generation evaluation for reliability test for each investigated method. The performance of each method and accuracy of transformation parameter estimation by the best method are also presented in results and discussion section. Finally, we conclude the work based on the simulation findings.

II. Implementation

The proposed technique uses a perfect board as the reference image and the inspected board as the test image. In this work, GA is used to derive the transformation between test and reference images based on a simple GA strategy as presented in [9] during registration stage.

For this work, real integer coding has been implemented for this problem considering the range of transformation value that we are going to find. The rotation value ranged from 0 to 359 degrees while the displacement of x-axis and y-axis value is considered between -10 to 10 pixels. Every individual represents a combination of all transformation parameters which describes an image transformation. The domain of search for these parameters is large ($360\times21\times21$=158760) which is suitable for GA to explore.

The fitness function in this work is evaluated from total similarities values in each pixels between test image and reference image divided by total pixels in reference image assuming that both images are the same size. The fitness

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value may range from 0 to 1.0, when the ideal solution is found. The fitness value is defined as:

$$\text{if } f(x_a, y_a) == g(x_b, y_b), \text{ counter ++}$$

$$\therefore fitness = counter/(W \times H)$$

where $f(x_a, y_a)$ is pixel intensity of reference image, $g(x_b, y_b)$ is pixel intensity of test image, in condition of $x_a = x_b$, $y_a = y_b$ where x and y are pixel location at x-axis and y-axis. W and H are the width and height of the reference image respectively since both compared images are the same size.

Fixed global multi-thresholding operation is applied to both images to enhance the images and highlight the details before performing GA search. It is also essential to deal with variations in intensity of components on PCB images. For this application, the threshold value for the thresholding operation is chosen based on visual observations. The reference image will be transformed using random rotation and displacement values to create the initial population for GA. Every transformed reference image is compared with the test image to evaluate the fitness value and individuals with solution of rotation and x-y translations information are created. Center block matching with size of 40×40 pixels is used in this work to reduce the number of pixels compared and directly decrease computational time requirement with assumptions that this block of pixels are fault-free and safe from shading problem since lighting systems usually focus on the center of PCBs.

Iteratively, the whole population for the next generation is formed by selected individuals from the parents and offsprings in current generation. These individuals are ranked based on their fitness performance and the top fittest only are selected for a new population. The population will perform GA activities such as selection, mutation and crossover in every generation until the termination requirements are fulfilled. The GA search will be terminated if an individual with an acceptable approximate solution is found or maximum generation is reached.

A. Elitism implementation

At each iteration, the best 5 percent individuals of the previous generation are preserved. The remaining 95 percent are from the top ranked individuals after all the GA operations are performed. The preservation of the best 5 percent individuals are required in case there is no better individual found in the next generation.

B. Hill-climbing implementation

The concept of hill climbing algorithms is individual alleles are modified in such a way that the overall fitness is maximised. Hill climbing algorithms are typically very efficient at locating local maxima although this leads to their major deficiency; they tend to get stuck at local maxima rather than continuing to the proper global maxima.

In this implementation, a limit for the generation, l is set for every set of GA search. This limit is the number of times the same individual is recognized as the fittest individual. Hill-climbing will be performed if the limit is reached. The fittest individual of the current generation will be selected for this process where every transformation values (rotation, x and y displacement) will be incremented and decremented by a single unit sequentially. The modifications will be evaluated to examine the fitness value which may replace the current solution. The GA search will be terminated with the current solution unless a better individual is found during hill-climbing. If the search is continued, the hill-climbing process will be repeated when the limit is reached again.

III. Experiment setup

The study of these hybrid methods is conducted on a Linux-based PC and the image of the PCB is captured using a black and white CCD camera. The basic image processing functions such as global multi thresholding [10] and transformation is written in C-language using NetPBM image library [11].

First, the hybrid methods are investigated individually by combining GA with elitism (GA+E) and combining GA with hill-climbing (GA+HC). Finally, GA is combined with hill-climbing and elitism (GA+HC+E) and few adjustments has been done on few parameters in GA+HC+E known as hybrid GA (HGA). The adjustments on GA parameters are done based on independent experiments using various values.

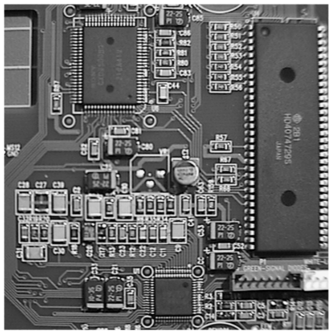
Parameters for all methods are configured according to the previous GA framework [12] where maximum generation is 200, selection is using Roulette-wheel method, crossover probability is 0.5 and mutation probability is 0.01. The first three methods (GA+E, GA+HC and GA+HC+E) have a population size of 18 while hybrid GA (HGA) has a population size of 50. The limit of generation, l is set to 20 for GA+HC and GA+HC+E cases while HGA has a limit of generation of 10. These settings and adjustments are made on observation of all methods performance which is aims to improve the robustness of the HGA.

Two reference images shown in Figure 1(a) - 1(b) and four test images shown in Figure 2(a) - 2(d) are used in the experiment. Test image 1 (T1) and 2 (T2) are artificially transformed images of the reference image shown in Figure 1(a) while test image 3 (T3) and 4 (T4) are artificially transformed images of reference image shown in Figure 1(b). Estimation of transformation parameters using each search method is repeated for 20 times for every test image.

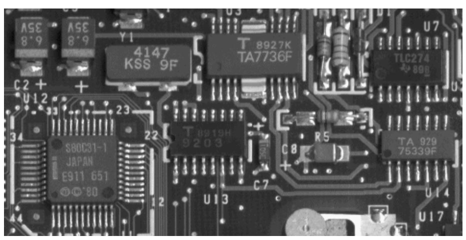
IV. Experimental results and discussion

A. Fitness and generation evaluation

Three types of hybrid methods have been simulated and the performance of each method has been compared with a standard GA search. The comparison is conducted based on the percentage of simulation that successfully gain a maximum fitness of more than 0.85 and the number of generation to converge. Higher maximum fitness gives better accuracy in estimating the transformation value. It is worth



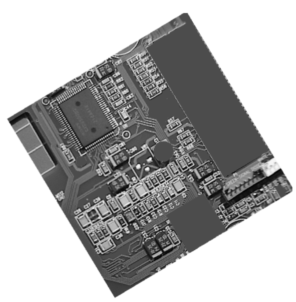
(a)



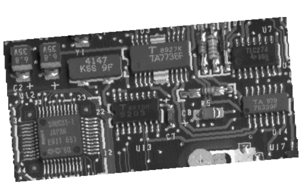
(b)

Figure 1: (a) - (b) Reference images

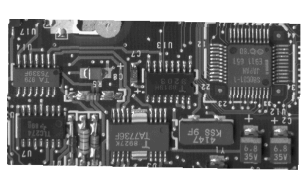
(a)



(b)



(c)



(d)

Figure 2: Test image: (a) T1, (b) T2 with artificial defects (multi components missing), (c) T3 and (d) T4. All test images are transformed with known values.

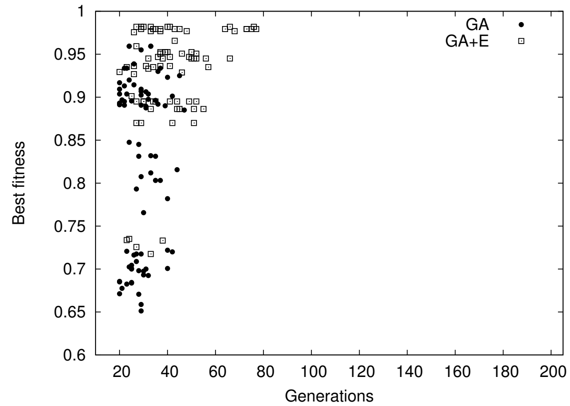


Figure 3: Generations vs optimum fitness for GA and GA+E for all test images.

noting that all scatter plots are purposely represented by two symbols to highlight the performance of each method, rather than considering the results from different test images.

Based on Figure 3, GA+E has outperformed GA considering only best fitness. About 93 percent of the total number of runs using GA+E has produced best fitness of more than 0.85, while GA was able to produce the same best fitness range in only 50 percent of the total simulation. However, GA+E requires more generations than GA to converge for these solutions. GA requires between 20 to 45 generations to converge while GA+E requires between 20 to 78 generations to yield a near correct estimation.

This “elitist” concept yielded improved convergence times without loss of population diversity. Preservation of 5 percent of already known potential individuals for the next population with new creations, provides new variants of individuals for next GA operations such as selection, mutation and crossover. These characteristics complement each other and make the GA search more robust. The variations of population have activated exploration activity for fitter individual which may become the final solution. However, there are few evaluations that require more generations to converge and this may be caused by the small size of population which is not enough to contribute for population diversity in the GA search.

The results from implementation of hill-climbing on GA (GA+HC) are slightly improved compared to GA as shown in Figure 4 when 63 percent of the total number of runs achieved maximum fitness of more than 0.85. The spread of termination for GA+HC is also longer compared to GA ranging from 20 to 200 generations.

By hybridizing with hill-climbing, the GA search has advantage to exploit the local maxima to extract more information at local level. This exploitation may lead to the fittest individual that possibly has the near exact transformation values. However, the possibilities of the search getting stuck in local maxima is still high when considering another 37 percent of the evaluations failed to

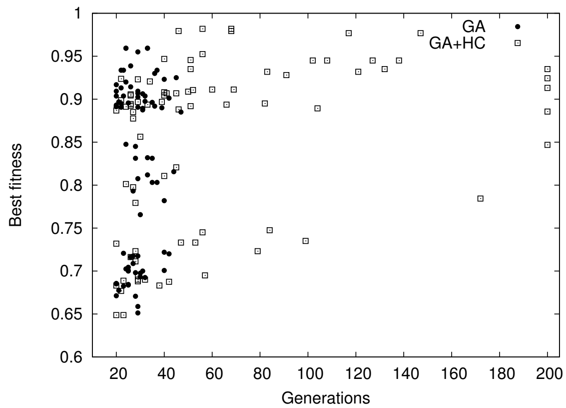


Figure 4: Generations vs optimum fitness for GA and GA+HC for all test images.

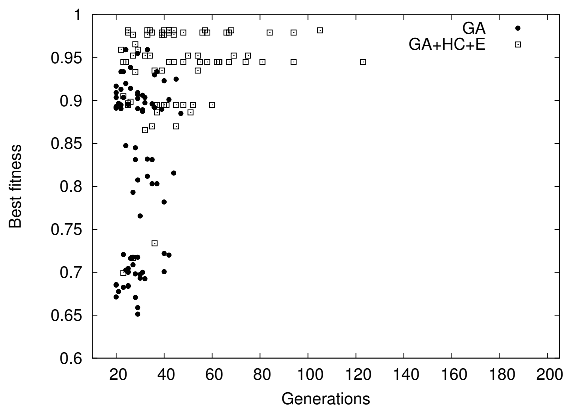


Figure 5: Generations vs optimum fitness for GA and GA+HC+E for all test images.

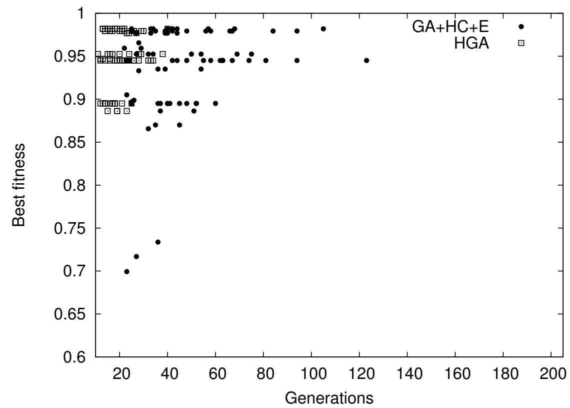


Figure 6: Generations vs optimum fitness for GA+HC+E and HGA for all test images.

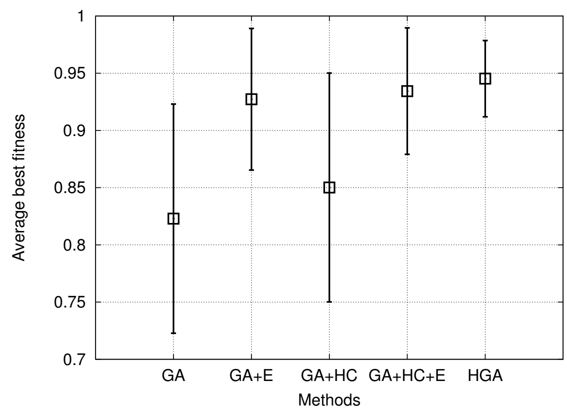


Figure 7: Average best fitness obtained from median value while errorbar shows the standard deviation of each method.

yield maximum fitness of more than 0.85. With regard to the number of generations, the method lacks in generation efficiency due to generation limit, l of 20 and small population size of 18. The expected reward of the GA will be greater at the beginning of the simulation and at some point when the population has almost converged, the expected reward of the HC will be greater.

GA+HC+E enhanced the GA's robustness when this method outperformed GA significantly as shown in Figure 5 because the method benefited from both specialities of hill-climbing and elitism when it successfully achieved an excellent results. GA+HC+E needs 22 to 120 generations to estimate the most accurate transformation values of all test images.

GA+HC+E has produced best fitness of more than 0.85 in 96 percent of the total number of runs. However about 4 percent of the simulation failed to reach more than 0.85 of maximum fitness that raise an issue with regard to reliability. This issue has been investigated and small population size is identified as one of the reasons. If the population size is too small, the GA search may not explore enough of the solution space to consistently find good solutions. Longer period of generation is caused by longer generation limit, l of 20. To overcome these issues, the parameters of GA+HC+E are tuned optimally to obtain more reliable results.

The enhanced GA+HC+E with population size of 50, known as HGA is more reliable than GA+HC+E. HGA is able to find individual with fitness of more than 0.85 in all 20 trials of each test image (as shown in Figure 6). It managed to converge with these excellent results efficiently in 10 to 38 generations. Based on this plot, it is obvious that the increment of population size and decrement of generation limit, l to 10 have boosted the robustness of HGA.

The best fitness found by these methods are not normally distributed. Hence, a Wilcox test has been performed on the methods pair by pair and all p-values from the test are less than 0.01 except pair of GA and GA+HC. The p-values smaller than 0.01 indicate there are significant differences in performance among the methods but GA and GA+HC produced nearly similar performance.

Figure 7 depicts the average best fitness found by every method using the median value and the standard deviations of best fitness found are shown by the errorbars. As discussed before, HGA outperformed other methods with highest average best fitness and smallest standard deviation, follows

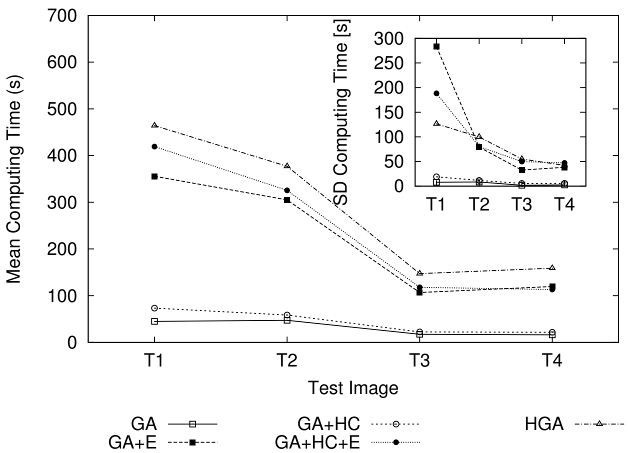


Figure 8: Mean of computing time for every test image and standard deviation of computing time for every test image (sub-figure).

by GA+HC+E, GA+E, GA+HC and GA. These statistical findings support that the HGA is the most robust method to register PCB images in this inspection framework.

From the presented findings, it is almost impossible to obtain a maximum fitness of 1.0 due to loss of pixel's information during image rotational operation. This deficiency may affect the accuracy of the results since this work is a reference-based method.

B. *Computational efficiency*

Each investigated hybrid methods have outperformed GA in maximum fitness findings, however these methods generally require more generation to find those results.

Figure 8 shows that GA computes the maximum fitness in the least mean time followed by GA+HC and GA+E. As predicted, GA+HC+E and HGA require the most computing time to find the finest estimations. However, HGA needs slightly more time than GA+HC+E in all test images due to the use of larger population size. It also shows that implementation of elitism costs more computational time due to evaluation of 95 percent new individuals in each generation.

As we can see in Figure 8, each method needs more mean time to compute the first and second test image (T1 and T2) and reduced drastically in third and forth test image (T3 and T4). This may be caused by the different size of T1 and T2 compared to T3 and T4.

Referring to the inset of Figure 8, the standard deviation of computing time for GA and GA+HC is negligible compared to GA+E, GA+HC+E and HGA. In general, the performance of GA+E, GA+HC+E and HGA depend on the complexity of the image transformation and the size of the images. Image T1 has the worst standard deviation of computing time compared to T2, T3 and T4 for GA+E, GA+HC+E and HGA cases.

C. *Registration accuracy*

For the inspection system to be reliable, it must reduce 'escape rates' (i.e. non-accepted cases reported as accepted) and 'false alarms' (i.e. accepted cases reported as non-accepted) as much as possible [13]. For that reason, HGA has been selected as the best hybrid method considering the consistency to find the target maximum fitness.

Table I: Rotation accuracy of HGA on all test images.

Image	Known [degree]	Mean [degree]	RMS [degree]
T1	329	329.0	0.00
T2	329	329.2	0.41
T3	354	356.1	2.79
T4	180	182.0	1.12

Table II: Displacement at x-axis accuracy of HGA on all test images.

Image	Known [pixel]	Mean [pixel]	RMS [pixel]
T1	0	2.0	0.00
T2	-6	-5.2	0.41
T3	5	3.0	0.00
T4	0	0.2	1.86

Table III: Displacement at y-axis accuracy of HGA on all test images.

Image	Known [pixel]	Mean [pixel]	RMS [pixel]
T1	0	3.0	0.00
T2	4	2.8	0.41
T3	5	2.0	0.00
T4	0	0.0	0.00

Based on Table I - III, the accuracy of each transformation parameters for all test images are presented. The first column denotes the known value of corresponding parameter, second column is the mean value estimated by the HGA for 20 evaluations and the last column is the root mean squared (RMS) error between truth and every estimation value from the simulation.

The inaccuracy of transformation parameters are about ± 2 degrees in rotation and ± 2 pixels in displacement at x-axis while displacement at y-axis may varies up to ± 3 pixels .

Generally, RMS error values are reasonable, ranging from 0 to 2.79. As we can see, the rotational parameter has slightly high errors especially in T3 when compared to other images. This may be caused by loss of pixel's information from rotation operation compared to displacement operation.

V. Conclusion

We have presented an improved novel technique using hybrid GA to register image of PCB that is placed arbitrarily on a conveyor belt during inspection. A specially tailored GA combined with all methods, HGA has outperformed individual hybrid methods (GA+E and GA+HC) in terms of reliability and accuracy. However, HGA needs more parameter tuning to reduce the computational time in order to be implemented in high volume production industry environments.

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