논문 2009-1-11

재능 유전인자를 갖는 네스티드 유전자 알고리듬을 이용한 새로운 다중 초점 이미지 융합 기법

A Novel Multi-focus Image Fusion Scheme using Nested Genetic Algorithms with “Gifted Genes”

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요 약 본 논문에서 이미지 선명도 함수의 최적화에 의해 융합 법칙이 유도되는 새로운 이미지 융합 접근법을 제안한다. 선명도 함수에 비교하여 소스 이미지로부터 최적 블록을 통계적으로 선택하기 위하여 유전자 알고리듬이 사용되었다. 변이 연산에 의해 만들어진 유전인자들의 포격을 통해서 찾아진 재능 유전 인자를 갖는 새로운 네스티드 유전자 알고리듬을 설계하였고 구현하였다. 알고리듬의 수렴은 해석적으로, 실험적으로 그리고 통계적으로 3개의 테스트 함수를 사용하여 표준 GA와 비교하였다. 결과의 GA는 변수와 집단 크기에 불변이며, 최소 20 개체이면 시험에 충분하다는 것을 알 수 있었다. 융합 응용에서 모집단내의 각 개체는 입력 블록을 나타내는 유한한 이산 값을 갖는 개체이다. 이미지 융합 실험에 제안한 기법의 성능은 출력 품질 척도로 상호 정보량(MI)으로 특징지워진다. 제안한 방법은 C=2 입력 이미지에 대해 테스트되었다. 제안한 방법의 실험 결과는 현재의 다중 초점 이미지 융합 기법에 대한 실제적이고 매력적인 대안이 됨을 보여준다.

Abstract We propose in this paper a novel approach to image fusion in which the fusion rule is guided by optimizing an image clarity function. A Genetic Algorithm is used to stochastically select, comparative to the clarity function, the optimum block from among the source images. A novel nested Genetic Algorithm with gifted individuals found through bombardment of genes by the mutation operator is designed and implemented. Convergence of the algorithm is analytically and empirically examined and statistically compared (MANOVA) with the canonical GA using 3 test functions commonly used in the GA literature. The resulting GA is invariant to parameters and population size, and a minimal size of 20 individuals is found to be sufficient in the tests. In the fusion application, each individual in the population is a finite sequence of discrete values that represent input blocks. Performance of the proposed technique applied to image fusion experiments, is characterized in terms of Mutual Information (MI) as the output quality measure. The method is tested with C=2 input images. The results of the proposed scheme indicate a practical and attractive alternative to current multi-focus image fusion techniques.

Key Words : Image Fusion, Multi-focus, Genetic Algorithm, Nested Genetic Algorithm, Gifted Genes, GA Convergence.

Ⅰ. INTRODUCTION

There are many reasons to fuse images of the same scene, and over the years these operations have provided useful ways of enhancing contexts in order to warrant subsequent analyses. In [1] for instance, infra red and visible images are fused to see associations between objects that are only sensible in one of the

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접수일자 2008.12.29, 수정완료일자 2009.1.31

spectral bands.

While advances in hardware sensor designs may have provided significant improvements in image acquisition and scene imagery, the need for post-processing techniques remains because of the constant presence of “noise” in anytarget environment. For example, high-sensitive ISO ratings, which are common in today’s “point-and-shoot” CCD cameras often result in crisp and sharp results but in prolonged exposure introduces grain-like noise artifacts.

In some cases, images may have been acquired out-of-focus and the real-time scenario prevents the human observer from recapturing the scene. For instance, under security and surveillance situations, post-processing a region-of-interest may be needed in a time-critical situation in order for the human observer to make a decision. Hence, improving the would-be image by physically interfering with the scene or removing occlusions may not be practical and possible.

For face recognition, fusion techniques may be employed to “cancel” out the noise in each of the source face images in order to produce a composite face image that is clearer and richer in feature. This will aid the recognition algorithm since the face is more defined. In [2], interestingly, a single face image is fused with its own features. The goal is to improve the context of the face data and increase the information that will be provided to the recognition system.

In this paper, we propose a novel approach to image fusion using evolutionary operators. The fusion rule is stochastic in that the system randomly picks from among the corresponding input blocks those which will compose the fused image. The motivation stems from factual bases, and empirical results suggesting that image clarity measures behave as monotonic functions of the degree of blurring. Therefore, image fusion can be viewed as an optimization task to find the block combinations that maximize these clarity measures.

The novelty of the proposed scheme is twofold. First, the method proposed is the first image fusion technique to apply Genetic Algorithms (GA). Second, the scheme is the first among GA-driven optimization techniques to innovatively use nested GAs – an outer GA, and an inner smaller GA. The main goal is to achieve a simple convergence model that provides prediction of the number of generations required to evolve into the global solution.

The main contributions of this paper are: a Genetic Algorithm framework under which image fusion systems can be built; and a proposed experimental hybridization scheme that uses two GAs, one nested with the other. Section 2 provides an overview of image fusion problem followed by a brief survey of literature. Section 3 discusses details of the GA-based image fusion scheme following introduction of relevant Genetic Algorithm concepts, and analytical treatments of its dynamic behavior. Results of the proposed method are presented and described in Section 4, and Section 5 is the concluding part.

Ⅱ. BACKGROUND OF IMAGE FUSION

The basic requirement to image fusion is for the fused image to be "visually pleasing" [3]. The result of fusion should preserve all relevant information of the input images, eliminating redundancy and noise [4]. Image Pyramids are among the pioneering representations of image data for fusion systems. An image pyramid is a set of lowpass or bandpass copies of an image, each copy representing pattern information of a varying scale. Falling under this class of fusion methods are: Laplacian pyramid, Ratio of Low Pass Pyramid, Contrast Pyramid, Filter-Subtract-decimate (FSD) Pyramid, Morphological Pyramid, and Gradient Pyramid. These methods are only efficient for specific types of applications and are limited performance [5].

An alternative to the pyramid schemes are Discrete Wavelet Transforms (DWT), but due to subsampling, results of DWT fusion are shift-variant and this characteristic often leads to misalignment among source images. On the other hand, the over-complete signal representation [4] obtained from the undecimated form of the dyadic filter tree results into an increase in computation requirements and high redundancy in the output information, making subsequent processing also expensive [6].

P. Hill, et. al. [7] tackled the shift-variation problem of DWT, and the redundancy issue with Shift Invariant DWT (SIDWT) by proposing the use of Dual Tree Complex Wavelet Transform (DT-DWT). The DT-CWT is a reduction from the over-complete nature of SIDWT but also suffers from an increase in memory and computational cost. The magnitudes of complex wavelet coefficients of both images are combined based on Maximum Selection (MS) fusion rule, before the inverse transform is produced.

The method of Z. Zhang and R. Blum [8] is also an example of the use of Discrete Wavelet Transforms (DWT). In this case, however, the proposed scheme applies region-based fusion depending on the activity level of a region. The activity level of each region is the average of the absolute value of the high frequency band wavelet coefficients. Some heuristics are applied to the regions in both images and a binary decision map is created whose pixel P(i,j) is "1" if the wavelet coefficients from the first image are to be taken as the output image, and "0" if, otherwise.

S. Li, et. al. [9] applied a Radial Basis Function Network (RBFN) in the fusion scheme. Their idea was to treat every decision in fusing any two MxN image blocks as a simple classification problem. In the training stage, the NN is presented with sets of image features (Spatial Frequency(SF), Visibility, Edge(VE)) along with corresponding a priori "decisions". Thus, a generalization is achieved from the known collection of image sets, clarity measures, and associated decisions. S. Li and his colleagues reported that both RBFN and PNN are superior to DWT terms of RMSE, and Mutual Information (MI).

Pulse-coupled neural networks (PCNN) are proposed in [10, 11] taking total pulse of its pixel as input to the MS (maximum selection) fusion rule.

As implied earlier in this section, other than the intermediate representation of the input images such as those discussed, a key issue in the design of image fusion systems is the choice of fusion rule ϕ. Maximum Selection(MS) schemes imply picks the block (or coefficient, in the case of pixel-based techniques) in each subband with the largest magnitude. This rule takes into account the fact that salient features in an image are usually represented by rapidly-varying intensities. Generally, the main disadvantage of this rule, especially for conventional DWT-based fusion is its high sensitivity to noise and the formation of ringing artifacts and blurring effects in the fused image.

Generally, the fusion method proposed in this paper is more akin to MS, than to the WA scheme. However, the main difference lies in the process of selecting the best image for the current block being formed in the fused image. Specifically, a GA is used to stochastically choose those blocks for which the clarity function achieves optimum measure.

Ⅲ. GENETIC ALGORITHM and IMAGE FUSION

1. The Canonical Genetic Algorithm

Genetic Algorithm was based on natural biological principles governing cells of all living organisms, including humans. Organisms are made up of cells, each consisting of the same set of chromosomes, which are strings of DNA that serve as a model for the whole organism.

In GA optimization, a chromosome or individual is composed of strings of DNA called genes, each of which encodes a particular part of the solution, for example, the (j,k)th block of fused image Z. Many studies on GA optimization focus on optimization such as scheduling problems. Often, many resources of a specific type are available, see [13-16] for examples.

In searching for the solution, a population of N individuals is evolved at every iteration step (generation or epoch). First, an initial population is created or initialized which constitutes random permutations of L binary digits (or some finite alphabets when binary encoding is not used). At generation t=0, the initial individuals are subjected to crossover and mutation under some predefined probabilities P_c, and P_m, respectively. A fitness evaluation is then conducted on the each new individual X_i using some objective function $f(X_i)$ like SF or RMSE in the case of image fusion. Next, each individual X_i is ranked based on its fitness measure, and assigned survival probability proportional to its fitness in the population, or more concisely

$$P(X_i) = \frac{f(X_i)}{\sum_{i=1}^{N} f(X_i)} \tag{1}$$

where N is the population size, and $P(X_i)$ is individual X_i's probability of surviving to the next generation. This process can be summarized as follows:

i. Create an initial population.
ii. Randomly select pairs of individuals (parents) and with probability P_c (usually 0.7 to 0.9) perform crossover to obtain children (new individuals).
iii. With probability P_m (usually 0.01) perform mutation.
iv. Determine the fitness and $f(X_i)$ of each individual and calculate survival probability $P(X_i)$.
v. Perform selection.
vi. Go back to (ii.) until some stopping criterion is met.

2. Image Fusion As an Optimization Problem

Image fusion can be viewed as a form of an optimization problem. Given C registered input images, the goal of the system is to produce an output image $Z(k,l)$ which is essentially a combination of blocks from the inputs, such that the resulting image clarity measure $f(Z(k,l))$ is at maximum or minimum. For instance, the fused image can be maximized in terms of SF (Spatial Frequency, as in [9], or minimized in terms of the RMSE (Root Mean Squared Error).

We define the C input images $I_1(p,q)$, $I_2(p,q)$ ... $I_C(p,q)$ of P x Q blocks each. A region-based fusion system operates with each b x b distinct block B in $I_i(p,q)$ for all i in [1, C] as $B_{ikl}(b,b)$, where k=1···; l=1···. The system may then produce an output image Z defined as:

$$Z(k,l) = \sum_{p=1}^{P}\sum_{q=1}^{Q} B_{ikl}\delta(k-p)\delta(l-q) \tag{2}$$

subject to $\underset{i}{\arg}\max f(B_{ikl})$ for I=1,...,C where δ(k) is the Kronecker delta function and $f(\bullet)$ is a general image clarity function.

Note that $f(\bullet)$ in the expression denotes the total measure of image clarity that incorporates the constraints.

As introduced in Section 2, the choice of the optimal B(b,b) is conventionally approached by invoking a simple rule ϕ, one of which is the maximum selection (MS) scheme. In this method, a

particular $B_{ikl}(b,b)$ that yields maximum value for f(.) in Eq. (2) from among the C corresponding blocks is chosen as a block in the output Z. The rule is applied either directly at the image pixels (spatial level) or at its wavelet transform coefficients, depending on the image representation domain (e.g. frequency or spatial). Thus, in the MS scheme, the (k-th, l-th) block of Z, for i= 1,..,C is expressed as:

$$Z(k,l) = \underset{i}{\arg}\max f(B_{ikl}) \tag{3}$$

On the other hand, the Weighted Average (WA) scheme [17] reconstructs a region in Z as a weighted average between the coefficients of the input blocks.

The reconstructed region' coefficient is calculated from the normalized correlation between the input images' subbands over the relevant local regions. And finally, Window Based Verification (WBV) scheme [18] uses a majority filter that chooses an input block $B_{ikl}(b,b)$ if most of the blocks in the neighborhood of $Z(k,l)$ are taken from input image I_i.

Both the WA and WBV can also be readily applied to spatial levels of input images by directly operating on the image blocks as represented by some image features, instead of its wavelet coefficients.

MS and the fusion rules above imply a result that is optimal relative to the clarity measure "perceived" by $f(\bullet)$. However, a limitation arises when 2 or more image features are used as measure in an attempt to closely mimic a more HVS sensitive result. For instance, aside from calculating the spatial frequency [3], edge quantities and visibility metrics must be considered along with other characteristics that are associated with image quality. In this case, the use of such relational operators among the input blocks is no longer plausible. For one, it is obvious that the distribution of image blocks under these measures will be multi-dimensional in nature as opposed to the simpler case with single metric. Thus, with more than two image clarity functions, the quantities representing each input image block will be a point in some D-dimensional metrics-space and there might be complex, overlapping, non-linear boundaries between the distributions. Hence, the identification of the optimum block might not be accurately made through simple relational comparisons alone.

3. Hybrid Genetic Algorithms

The main difficulty in using GA is its lack of simple and concrete convergence proof. This can be attributed to the complex nature of the population dynamics and the randomness of the procedure (i.e. it is very unlikely for one pared-optimal solution to be the outcome of running a GA twice). Particularly, epitasis refers to the complex interactions among GA operators such as crossover and mutation that are difficult to model due to random individual behaviors in this highly-dynamic system. Many have attempted to use tools such as Markov chains and Schemas in modeling these complex systems to characterize convergence, parameter calibrations, population sizing, and other issues. Many, however, have resorted into hybridization [19] in order to encapsulate the GA into another search technique that is more tractable, well-established, and has simpler analytical properties. Such techniques include Simulated Annealing, Random Walk, Lamarckian Learning, Gradient ascent/descent, among others.

For example, in [19] is a hybrid GA that runs inside a simulated annealing algorithm. The GA has a Boltzmann acceptance function, and an annealing schedule to guarantee convergence. The method was applied to solve the classical 30-city Traveling Salesman Problem (TSP). Mutation rate is constant at 1.0 which means that all individuals are mutated. One unique feature of this scheme is its varying mutation amplitude, that is, the length of substring that is mutated changes proportionally to the system temperature T (simulated annealing parameter).

4. Nested GA and Gifted Genes

While many have ventured into hybridizing GA with such methods as gradient-descent, ant colony, and simulated annealing, to the best of our knowledge, no one have tried a scheme of having a smaller modified (inner) GA running within a bigger "other" (outer) GA. The outer GA, conceived in this way, is designed to work as a simple genetic algorithm, most probably a canonical one.

On the other hand, the smaller GA is simply composed of the 2 best individuals in a current generation of the outer GA. It is desired that the smaller GA execute in so small an amount of time so as to have a negligible effect on the overall time complexity of the whole algorithm.

The idea is to tweak the bits or genes of these two individuals (or parents) by repeatedly bombarding them with mutation operator (i.e. unusually high P_m), without conducting any crossover, so as to produce an individual that is far better in fitness. We will call this new individual the “gifted child” or one that has “gifted genes” This process has to be accomplished before the next generation is started, that is, before going back to step (ii). in Section 3.1 above.

One advantage this scheme can offer is that, with a very small population, the dynamics can be reduced significantly and analytical properties should be equally simpler. By using only mutation, we are taking advantage of this operator to provide higher sampling rate of the hyperplanes and schemas. Also, expensive processing tasks normally consumed in implementing crossover and selection such as ranking, O(n) fitness calculations, calculation of crossover points, and the like are eliminated. With only 2 individuals in the population, processing time is significantly reduced in the small GA thereby making our desire (and assumption) obtainable and valid.

The gifted individual found by the smaller GA will then be inserted into the population pool of the outer GA. The outer GA can then simply take the “gifted individual” found in the aggressive smaller GA as the baseline for its own search. Thus, the search for the gifted genes can be considered a form of local hill-climbing.

We define a scaling function ω that controls how much more fit the “gifted individual” has to be compared to its parents. It will become clear that ω is comparable to the rate of descent in gradient-descent techniques. We will allow this function to monotonically decrease per generation. Thus, we can visualize the effect that this smaller GA has on the outer GA, that is, as a hill-climbing (or rolling) scheme that “forces” the outer GA to have converge to the solution in a rate driven by the inner A. The revised GA is summarized as follows:

OUTER GA (CANONICAL)

i. Create an initial population.
ii. Randomly select pairs of individuals (parents) and with probability Pc = 0.8, perform one-point crossover to obtain children (new individuals).
iii. With probability Pm = 0.01, perform mutation.
iv. Determine the fitness and $P(X_i)$ of each individual.

INNER GA (SMALL)

a. Take the 2 best X_is as an initial population.
b. Do not perform any crossover.
c. Set elite count to 1, making sure that the best individual in the 2, gets a 100% chance to survive.
d. With high probability pm = 1.0, perform mutation.
e. Go back to (b.) until a gifted individual xi is found so that

$$f(X_i) \le f(X_{best}) - \omega f(X_{best}) \tag{4}$$

where X_{best} is the best individual between the 2 in (a.)

f. Insert xi into the population pool of the outer GA and update the population fitness values.

v. Perform Stochastic Universal Sampling (SUS) selection
vi. Go back to (ii.) until some stopping criterion is met.

It turns out that a simple exponential decay function has good properties for ω. In particular, if

$$\omega = e^{(-\lambda t)} \tag{5}$$

where t is the generation time index, then the outer GA will be “forced”to exhibit, an exponentially decaying (note that we are minimizing) quantity, that is, the best population fitness. The upper bound therefore of the convergence time is an exponential decay time complexity. Through the exponentially decaying ω, we are also able to satisfy a desirable searching property: wider steps in the global search, which makes the objective function vanish more quickly; and smaller steps as it settles at the local basin where the global best is located.

5. Image Fusion via Nested GA with Gifted Genes Chromosome Encoding

Central to any genetic algorithm design is the structure that encodes the candidate solutions. In the case of the problem at hand, we are referring to the layout of chromosomes or individuals that will comprise the population. These chromosomes encode the actual output image at any generation or epoch. It is therefore important that transforming (mapping) between these encoded values, and the actual image output be simple and straightforward. Figure 1 below illustrates the format of individuals proposed in this paper. The length of the chromosome, discussed next, is equal to the number of columns in the blocked image.

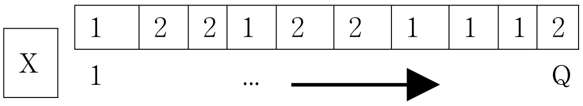


Figure 1. An individual (X) representing a sequence of image blocks in the output image.

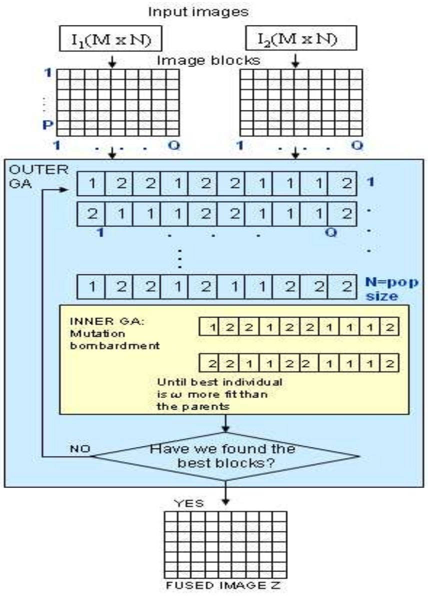


Figure 2. The Image Fusion scheme proposed.

Figure 2 shows the overall fusion scheme proposed. First, the input images are divided into P x Q blocks of b x b pixels. Thus, the size of each chromosome is P x Q of binary strings. To simplify the process, we operate on each 1 x Q row of blocks for the output image (row-by-row), instead of the whole matrix of blocks simultaneously (batch). Thus, for each 1 x Q row of blocks, N individuals were used and evolved up to T generations in the outer GA. This process is repeated for P times, one for each row of blocks.

For N input images of P x Q blocks each, there are NQ distinct individuals possible for each row of blocks. Note that without taking each row one by one, the number of distinct individuals or solutions in the search space is N PxQ. Thus, with 256x256 image inputs, blocks of size 8x8 (b=8), and N=2 inputs, there are 2^{32} = 4,294,967,296 solutions for the row-by-row method, a significant search space reduction from 2^{1024} = 1.8 x 10^{308} points in the hyperspace for the batch method!

가. Objective Function, Fitness Evaluation, and Output Quality Measures

Theoretically, we can minimize any image function such as the Root Mean Squared Error (RMSE) defined as:

$$SE=\sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(R(i,j)-Z(i,j))^2} \qquad (6)$$

where R is the reference (ground truth) image, Z is the fused image, each of size MxN pixels. Or, we may maximize measures such as EOL (Energy Of image Laplacian), SF (Spatial Frequency), and MI (Mutual Information) whose equations are given below:

$$EOL_{ikl}=\sum_{x=1}^{b}\sum_{y=1}^{b}\left(\sum_{u=-1}^{1}\sum_{v=-1}^{1}B_{ikl}(x+u,y+v)K(u+2,v+2)\right)^2 \qquad (7)$$

where K is the 3x3 mask $\begin{bmatrix}-1 & -4 & -1\\ -4 & 20 & -4\\ -1 & -4 & -1\end{bmatrix}$

$$SF = \sqrt{RF^2 + CF^2} \tag{8}$$

where

$$RF = \sqrt{\frac{1}{b^2}\sum_{i=1}^{b}\sum_{j=2}^{b}(B(i,j)-B(i,j-1))^2}$$

and $$CF = \sqrt{\frac{1}{b^2}\sum_{j=1}^{b}\sum_{i=2}^{b}(B(i,j)-B(i-1,j))^2}$$

$$MI = H(R) + H(Z) - H(R,Z) \tag{9}$$

where *H(I)* is the entropy of an image I, and *H(U,V)* is the joint entropy of images U and V. Image Entropy *H(I)* is given by

$$H(I) = -\sum_{i=0}^{L} p(i)\log p(i) \tag{10}$$

where L = 255 in a grayscale image, and *p(i)* is the probability estimate of gray level *i* in the image.

However, in this paper, we make use of MI and RMSE as qualitative metrics of the fusion results. In the results that follow, the fusion scheme proposed is implemented for minimizing RMSE, and for maximizing SF. RMSE is minimized in the objective function because its is related to the error in the fused image compared to the reference. Spatial frequency on the other hand, is maximized because salient features in an image are known to have higher spatial frequencies. The MI between fused image and reference image is associated to the amount of additional information that the former provides. Thus, it is desired that MI of the fused image be as high as possible.

나. Convergence Analysis, Population Size, and Parameter Settings

Ignoring crossover and mutation first, that is, when only selection is used, a hyperplane in the solution space is sampled or represented in the next generation's population pool based on the fitness of individuals belonging to the schema [21] for the hyperplane. Thus, taking M_t to be the number of individuals sampling a particular schema H at generation t

$$M_{t+1}(H) = M_t(H)\frac{f_t(H)}{\overline{f_t}} \tag{11}$$

where $f_t(H)$ is the average fitness of the individuals representing H in the population, and $\overline{f_t}$ is the average fitness of all individuals.

To account for the effects of crossover and mutation, the schema theorem is expressed as [22]:

$$M_{t+1}(H) \geq M_t(H)\frac{f_t(H)}{\overline{f_t}}\left(1 - P_c\frac{\delta(H)}{l-1} - P_m O(H)\right) \tag{12}$$

where P_c is the crossover probability, P_m is the mutation probability, *l* is the length of individual strings, δ is the defining length of schema *H*, and O(*H*) is a function that counts the order of the schema.

In a canonical GA, as analytically stated in the schema theorem [21], the 2 negative terms at the right of the inequality in (Eq. 12) is considered as the amount of sampling loss due to disruptions caused by crossover and sampling gains due to preservation of schemas by mutation operators, respectively. A loss occurs when a potential schema H is lost in the population. Thus, in our proposed scheme, the assumptions (and desire) made for the inner GA (that it converge to an individual ω-magnitude fitter) is theoretically sound since, by eliminating disruptive crossover, the loss terms in (Eq. 12) vanishes.

We can then expect potential schemas to be represented in the population without getting lost in the evolution. To achieve this, we rely on the effect of bombarding the gifted genes with mutation.

Once the inner GA has returned an individual xi, which by our definition in (Eq. 4) is ω-magnitude better than the best individual in the outer GA at generation t, we are immediately assured of a new individual sampling a potentially diverse schema or region in the hyperspace. This assurance is supported with Rudolph' [23] analytical proof.

Therefore the convergence of our method, is invariant to the population size (a minimal baseline size of 20 individuals is used in the experiments with the results shown in this section) and depends only on the best individual in the initial population at $t = 0$. Specifically, if X^* is the a priori known global best and X^*_{it} is the best individual (most likely the X_{best} returned by the inner GA,) at arbitrary time t, then we seek X^*_{it} to be as close to X^* as possible so that $f(X^*_{\mathrm{it}}) \approx f(X^*)$. Thus, following our definitions in (Eq. 4-5), we can estimate the (upper bound) number of generations needed to converge into the global solution. Assuming we have found X^* at generation t, we know that $f(X^*)$ is related to the best individual at t=0 by,

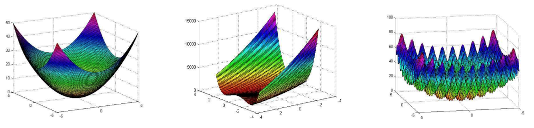
$$f(X^*) = e^{-\lambda t} f(X^*_{i0}) \tag{13}$$

Taking natural logarithms on both sides and rearranging

$$t \approx -\frac{\ln f(X^*) - \ln f(X^*_{i0})}{\lambda} \tag{14}$$

which gives us the upperbound for t in terms of the best fitness value in the initial population (generation t=0), the known global optimum value, and the decay constant λ. The λ parameter can be considered similar with the step parameter η in gradient-descent. It controls the amount of improvement in fitness that the inner GA must provide at a particular generation t. A higher λ means that the inner GA is required to find much fitter individuals, than smaller λ. In our experiment, a value of 0.1 for the λ parameter is chosen empirically. With this exponentially decaying fitness (when minimizing), the convergence exhibits the desirable asymptotic form.

Shown in Figure 3 below are test functions used to characterize the convergence of the proposed method. These functions are well known test functions in the GA and optimization literature commonly used to benchmark algorithms. The first one, is DeJong' first function which has the minimum at point (0,0). The second, known as DeJong's 2nd function has a slight saddle shape which is normally where gradient-based techniques fail. The minimum value for this case is at point (1, 1). The last test function, Rastrigin', is the most difficult of the three, with minimum at point (0,0). It has many valleys and ridges that can deceive localized searches (deception is an important issue in the optimization and GA literature). With a gradient descent method, the search can easily get trapped in any of the local minima.



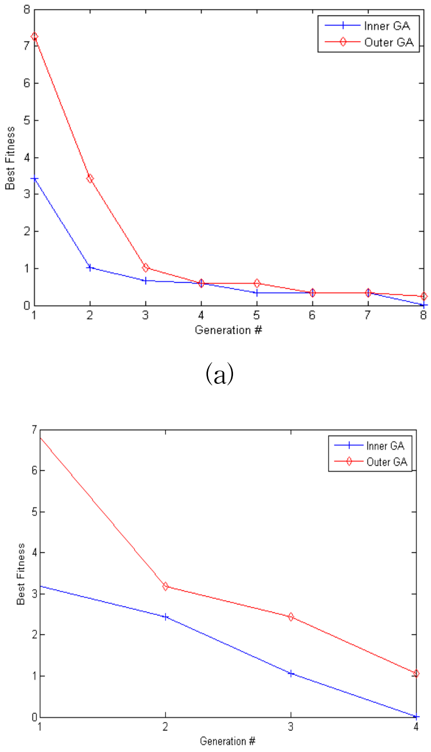
(a) (b) (c)

Figure 3. Surface plots of test functions used: (a) DeJong's 1st function (b) DeJong's 2nd function; and (c) Rastrigin's function.

Ⅳ. RESULTS

1. Effect of Inner GA in Convergence of Outer GA

Figure 4 below demonstrates the effect of the inner GA on the convergence of the outer GA in the nested algorithm proposed. Notice that the outer GA (shown in red) in both trials (a) and (b) below, is initialized (generation t = 1) with a population that has a best fitness somewhere around value 7. The inner GA (shown in blue) “"drags”" the fitness of the outer GA lower as for example in generation 2 in (a) and (b). The best fitness in the population of the outer GA is simply the “"gifted”" individual xi returned by the inner GA at generation 1, or referring back to Section 3.4, the individual xi in step (iv.) of the outer GA, step (f.) of the inner GA described therein.



(a)

(b)

Figure 4. The forceful effect of the inner GA imposed on the outer GA shown here for two trials (a) and (b).

2. Comparative Results of Canonical GA and Nested GA with the Test Functions

Summarized in Table 1 below are the results for tests on convergence of the canonical GA (CGA) and nested GA (NGA) over the test functions described in Figure 3.

Table 1. Fitness and Convergence of Nested GA (NGA), and Canonical GA (CGA) in the 3 test functions

Test Function	GA Type	Mean		Std Deviation	
		Convergence	Fitness	Convergence	Fitness
DeJong1	CGA	17.80	0.00	12.06	0.00
	NGA	13.04	0.00	4.71	0.00
DeJong2	CGA	56.00	0.21	31.86	0.57
	NGA	22.32	0.08	4.03	0.11
Rastrigin	CGA	27.24	2.20	7.19	2.06
	NGA	26.58	1.34	6.95	1.09

It is undeniable in the case of Dejong′ 1st and 2nd functions that the proposed method is superior to the canonical genetic algorithm. In these 2 test functions, the NGA consistently exhibited lower means and standard deviations showing that the two methods are significantly different in both the shape of the underlying population distribution and center density. However, in the test with Rastrigin's functions the difference between the two methods' performance is not clearly discernible. The 2-dimensional measure observations (fitness and convergence) seem to have come from the same population of measured fitness and convergence pairs. To quantify and reinforce any claim that we have for the proposed method, we conducted a 2-dimensional single-factor Analysis of Variance (MANOVA). But before doing so, we have to make sure that the assumption on equal variances between the samples (CGA and NGA) is satisfied. Figure 5 shows the result of this test indicating that MANOVA can be performed. In the right portion of the figure is the summary for the Levene's test which results in p-value = 0.589, greater than 0.05 significance level. The null hypothesis tested is that the variances are equal. With a p-value of this amount, we cannot reject such a hypothesis and we conclude that the variances are indeed equal. This is also apparent in the graphical display of the 95% Bonferroni Confidence Intervals for the standard deviations.

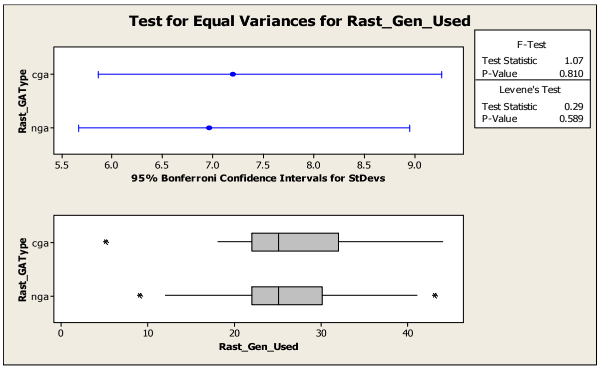
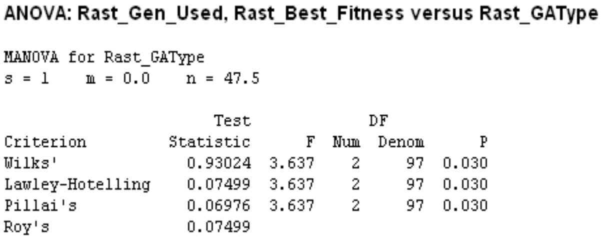


Figure 5. Result of the Test for Equal Variance with the measured quantities for CGA and NGA involving Rastrigin's test function.

Finally, the MANOVA result (see Fig. 6) below indicates a significant difference between the two methods. The null hypothesis in this case is that the effect of GAType (whether NGA or CGA) is not significant on the amount of (fitness, convergence) pair observed, that is, they have equal means for both GAs and the observed values came from only one population (GAType). The p-value for the GA Type factor is 0.03 in all (Hotelling, etc) tests. Because this value is less than the significance level of 0.05, we reject the reject the null hypothesis in favor of the alternative, and conclude that the effect of GAType on the measured 2-dimensional values (Gen Used and Fitness) is significant. In other words, a significant amount of variation in the measured convergence and fitness under the Rastrigin test function is associated with the variation in the algorithms used.



```
ANOVA: Rast_Gen_Used, Rast_Best_Fitness versus Rast_GAType

MANOVA for Rast_GAType
s = 1    m = 0.0    n = 47.5

                       Test           DF
Criterion         Statistic      F  Num  Denom      P
Wilks'              0.93024  3.637    2     97  0.030
Lawley-Hotelling    0.07499  3.637    2     97  0.030
Pillai's            0.06976  3.637    2     97  0.030
Roy's               0.07499
```

Figure 6. Result of the MANOVA on 2-dimensional measured values (Generations Used and Fitness) versus GA Type for the Rastrigin test function.

3. Image Fusion Results

The figures shown next are sample outputs of the fusion implementations. Blurred regions in the input images are shown enclosed with red borders. In figure 7 are images from running the nested GA with a fitness function designed to minimize RMSE.

Aside from the improved visual clarity of the fused image, the quantitative measures on MI and RMSE indicate improvements. Figure 8 is the result for maximization of spatial frequency (SF).

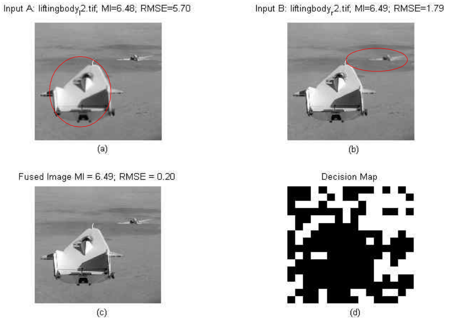


Figure 7. Results of the fusion scheme using the Nested GA: (a) input image A; (b) input image B; (c) fused image Z; (d) genetic decision map.

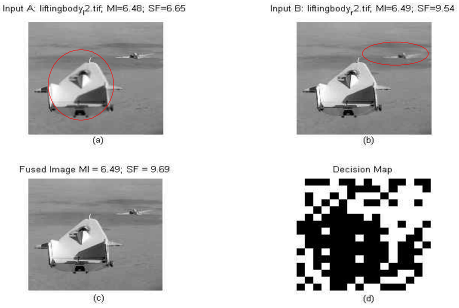


Figure 8. Results of the fusion scheme using the Nested GA: (a) input image A; (b) input image B; (c) fused image Z; (d) genetic decision map.

Ⅴ. CONCLUSION

In this paper, we presented a novel approach to image fusion that employs evolutionary operators in finding the optimal combination of image blocks from input images. Individuals (chromosomes) are sequences of indices to blocks in input images. The novelty of the proposed scheme arises from two aspects. First, this is the image fusion scheme that employs Genetic Algorithm. Second, the Genetic Algorithm is a hybridization technique that uses a small inner GA nested inside a running bigger canonical GA.

We utilized an exponentially decaying scaling function ω forcing the inner GA to arrive at a gifted individual which is fitter than best individual in the outer GA by ω-magnitude. It is shown that the inner

GA is able to influence and affect significantly the convergence of the whole algorithm. The resulting GA is invariant to parameters and population size, and a minimum *l* size of 20 individuals is found to have good results. It is statistically found out that the proposed nested GA is superior to canonical lGA in terms of convergence and optimal solutions found.

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※ Acknowledgment
This paper has been supported by the 2008 Hannam University Research Fund (2008A025).

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