Multi-target Matching based on Niching Genetic Algorithm

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Abstract:
Multi-target matching is an active and challenging research topic. Many different approaches to the problem exist. Niching methods extend genetic algorithms and enable the genetic algorithm to be applied to the problems that require the location of multiple solutions in the search space. In this paper, we review and discuss various strategies of niching for optimization and apply them to multi-target matching. It has been shown that the methods are faster and the optimal solution is more precise for multi-target matching than traditional methods.

Key words:
Genetic Algorithm, Multi-target Matching, Niching methods

1 Introduction

Image matching is an important branch of pattern recognition, which is a problem of longstanding interest. Template matching is the technique for finding a given image, the template, in an observed noisy image. It finds a variety of applications in remote sensing, computer vision, pattern recognition , and target recognition etc.. Unfortunately, traditional image matching techniques tend to be costly. The two conflicting requirements of image matching are the time and accuracy. Accordingly, one can employ a fine search (brute force) or a coarse-fine search (efficient in time) method. In fine search strategy, matching starts at the top left corner of the search space and continues along each row and column moving the sub image by one pixel each time. The accuracy of matching algorithm using fine search is good but the computation time is large. In coarse-fine search strategy, matching is done by extracting sub images of equal size as that of the reference image at the start of search space on a coarse grid. An approximate match point is found at the end of this step. A full search is done in a local region surrounding this match point. A coarse-fine search strategy is efficient if the system allows a minor degradation in accuracy.

In recent years much works has been done with the aim of extending genetic algorithms (GAs) to make it possible to find more than one local optimum of a function and so to reduce the probability of missing the global optima. The techniques developed for this purpose are known as niche techniques. Besides the greater probability of the success of the algorithm and a significantly better performance on GA-hard problems, niche techniques provide the user with more information on the problem, which is very useful in a wide range of applications.

Real world optimization problems often present multiple optima in the feasible domain. In particular, it has been shown that multi-objective recognition or tracking problems are frequently multimodal. In this context, global optimization techniques such as evolution strategies, genetic algorithms or simulated annealing have been successfully applied to find a global optimum [3]. However, in case of multi-object matching optimization, it could be advantageous to identify multiple optimal profiles by locating global as well as local optima. For that purpose, niching methods extend genetic algorithms by promoting the formation of stable subpopulations in the neighborhood of optimal solutions. So, we present a new method that makes use of niching genetic algorithm to search the targets with template.

2 Niching Genetic Algorithm

Genetic Algorithms (GAs) are stochastic optimization methods based on the mechanics of natural evolution and natural genetics [5].They work with a population of individuals, each representing a feasible solution in the search space. A fitness score (namely the objective function) measures the adaptation of individuals in their environment. For each individual, the set of parameters are coded into a finite-length character string (chromosome). The convergence of the population to a global optimum of the space is obtained by applying sequentially three operators: selection, crossover and mutation. However, for simple genetic algorithms, all the individuals in the population converge to a single solution representing the global solution of the problem.

In the optimization of multimodal functions, a simple GA cannot maintain controlled competition among the competing schemata corresponding to different peaks and cause the population to converge to one alternative or other. Moreover, in dealing with multimodal function with peaks of unequal value, a simple converges to the best peak, whereas, in addition to wanting to know the best solution, one may be interested in knowing the location of other optima. To overcome these limitations a natural remedy is tried. In natural ecosystems, animals compete and survive in many ways (by grazing and hurting for example) and different species evolve to fill each role. A niche can be viewed as an organism task which permits species to survive in their environment. Species are defined as a collection of similar organisms with similar features. For each niche, the physical resources are finite and must be shared among the population of that niche. The subdivision of environmental resources and this reduction in competition help stable sub-population to form around different niches in the environment. By analogy, in multimodal GAs, a niche is commonly referred to as the location of each optimum in the search space, the fitness representing the resources of that niche. The organisms in a niche can be defined as similar individuals in terms of similarity metrics [5].

Niching methods have been developed to minimize the effect of genetic drift resulting from the selection operator in the traditional GA in order to allow the parallel investigation of many solutions in the population. An important number of niching GAs have been reported in the literature for example [5]-[7].Three general niching techniques: pre-selection, crowding and fitness sharing will be shown below in this paper.

2.1 Pre-selection Method

Pre-selection method creates niche surroundings like this: if the fitness of a child exceeds the fitness of parent, it is permitted that the child replaces the parent. Because of the similarity of structure of coding between the parent and the child, the replacement takes place only when the individuals are similar. So the method can maintain the variety effectively of the population and come into niching.

2.2 Crowding Methods

Crowding techniques insert new elements into the population by replacing similar elements. We report two interesting crowding schemes.

(1)Deterministic crowding (DC): Mahfoud improved standard crowding of De Jong by introducing competition between children and parents of identical niches [5]. After crossover and eventually mutation, each child replaces the nearest parent if he has a higher fitness. Thus, DC results in two sets of tournaments: (parent 1 against child 1 and parent 2 against child 2) or (parent 1 against child 2 and parent 2 against child 1). The set of tournaments that yields the closest competitions is held.

(2)Restricted Tournament Selection (RTS): RTS adapts tournament selection for multimodal optimization [6]. RTS initially selects two elements from the population to undergo crossover and mutation. After recombination, a random sample of w individuals is taken from the population. Following this way, each offspring competes with the closest sample elements. The winners are inserted into the population. This procedure is N/2 times repeated per generation.

2.3 Fitness Sharing

Fitness sharing modifies the search landscape by reducing the payoff in densely-populated regions. It derates each population element’s fitness by an amount nearly equal to the number of similar individuals in the population. Typically, the shared fitness $f_i^{'}$ of an individual i with fitness f_i is simply:

$$f_i^{'} = f_i \Big/ \sum_{j=1}^{N} sh(d_{ij})$$

With $sh(d_{ij}) = \begin{cases} 1-(d_{ij}/\sigma_s)^{\alpha} & if d_{ij} < \sigma_s \\ 0 & otherwise \end{cases}$

Where N denotes the population size and d_{ij} represents the distance between the individual i and individual j .The sharing function (sh) measures the similarity level between two population elements according to a threshold of dissimilarity σ_s (also the distance cutoff or the niche radius). α is a constant parameter which regulates the shape of the sharing function (typically $\alpha = 1$). The effect of this scheme is to encourage search in unexplored regions.

2.4 Other niching methods

To give a complete description of niching Gas, we also mention Sequential Niching, Ecological Gas reported in [5], Immune Systems which have been already applied to solve electromagnetic optimization problems [3] and clearing is a recent promising multimodal method which has been successfully applied to difficult mathematical problems [7].

Niching Gas can be classed into two different groups [3]: (1) the first one involves Gas characterized by an explicit neighborhood since they need an explicit distance cutoff to set the dissimilarity threshold (clearing and sharing for example). In that case, we need a priori to know how far the optima are. However, for real optimization problems, we have generally no information about the search space and the distribution of the optima until we begin the search. This can be an important drawback and cause these methods to fail if the minimum distance between two optima is not correctly estimated. (2) The second one consists of techniques for which the neighborhood is implicit (crowding schemes). In that case, the algorithm requires no information about the search space and can be easily applied to various problems without the previous restrictions.

3 Multi-target Matching based on Niching GAs

Now, the proposed niching methods are applied to finding the multi-target in an observed image with complex background. That is a real world problem. Because of the varying size of images, the search space is changed with different images. So the binary coding is not suitable and the individual of Niching GAs here is coded with real numbers that represents the position of sub-image. The first step of optimization is a design of niching method including distance criterion, objective function and operators. The next step is to apply the niching method to find multiple solutions. The final step is marking the targets using the results from the last step.

3.1 Distance Criterion

All niching Gas must differentiate similar individuals from dissimilar ones. The similarity metric can be based on either genotype or phenotype similarity. Genotypic similarity is directly linked to bit string representation (binary GAs) and is commonly referred to as the Hamming distance. Phenotypic similarity is related to real parameters of the search space. This can be the Metropolis or Euclidean distances for mathematical problems since all parameters have the same dimension. For real problem, we must use a normalized distance because parameters generally have various physics dimensions. We propose the following distance to characterize the similarity level between an individual x_1 and an individual x_2 in the domain,

$$d(x_1, x_2) = \max_{i=1\ldots n} \left| \frac{x_{1i} - x_{2i}}{x_{i\max} - x_{i\min}} \right|$$

Where n is the number of parameters (also the space dimension), x_{1i} and x_{2i} denote the i^{th} parameter of the individual x_1 and x_2 respectively, $x_{i\min}$ and $x_{i\max}$ are the extreme values of the i^{th} parameter. As it can be seen in (2), this distance represents the maximum deviation of normalized parameters taken in all directions of the space.

3.2 Objective Function

There are a number of criterions of image matching having been proposed. Particularly, the similarity measure between the template and the image being searched is a common criterion of matching. The objective function to be maximized can be expressed by (3),

$$C(u, v) = \frac{1}{\left(\sum_{(i,j)\in V} \left| f(i+u, j+v) - h(i,j) \right|\right) + 1}$$

Where f is an observed noisy image, h is a given image, the template, and V is the pixel data set of the observed image. Fig. 1 shows an example of (3). The best position is at the top left corner.

$$\begin{vmatrix} 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 8 \end{vmatrix} \quad \begin{vmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{vmatrix}$$

$$\begin{vmatrix} \underline{1/3} & 1/6 & 1/8 & \times & \times \\ 1/5 & 1/7 & 1/8 & \times & \times \\ 1/8 & 1/9 & 1/57 & \times & \times \\ \times & \times & \times & \times & \times \\ \times & \times & \times & \times & \times \end{vmatrix}$$

Fig.1. An example of evaluation with the criterion (3). the left is the image data. The center is the given template data. The right is the results of matching（the best one is underlined）.

3.3 Operators

In GA, although the binary-coded algorithm can be better explained by biological hereditism than the real-coded algorithm, there exist some problems in solving continuous optimization, such as Hamming cliff and overlong binary code etc.. The real-coded GA can overcome these problems, and possess high speed. In addition of those, the genetic operators of the real-coded GA operate at phenotypic level, so it is easy to introduce other algorithms to improve its searching. In real-coded GA, the mutation operator is a main operator, which introduces new search space and maintains the genetic diversity of a population, however the crossover operator only operators in the known search space. The select operator uses the roulette wheel method.

In pre-selection strategy of Niching GA, there are deterministic evaluations of new individuals to deciding whether replacing their parents in crossover and mutation operations. In crowding strategy, every new individual should compare with the crowding numbers. And in sharing strategy, the fitness of every new individual should recalculate with sharing function.

3.4 Flow Chart

The program of Niching GA framework is implemented as following:

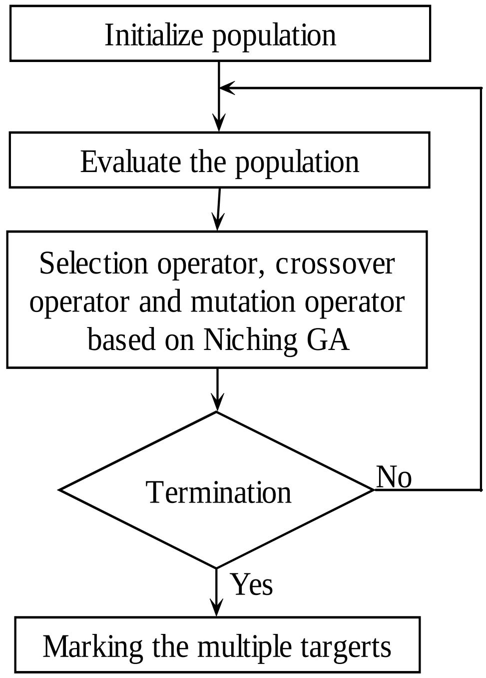

Fig.2. This flow chart show the process of niching genetic algorithms to finding the probability coordinates for image matching.

The step on selection operator, crossover operator and mutation operator based on Niching GA contents three methods such as pre-select method, crowding method and fitness sharing.

3.5 Experimental Results

For the experiments, test images are captured at a platform by camera (showed in Fig.3). The template image (a) comes from the other device. Obviously, (a) is different from the (b). The parameters of NGAs are set as following: the size of population is 50. The max generation is 300. The probabilities of crossover operation and mutation operation are 0.8 and 0.008. The termination criterion here includes setting the maximum of generation and diversity of the fitnesses of population.

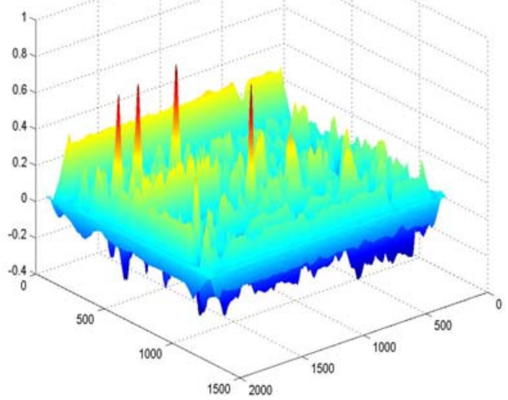

Fig.3. the 3D image of the normalized cross-correlation of the given image and the image captured by camera.

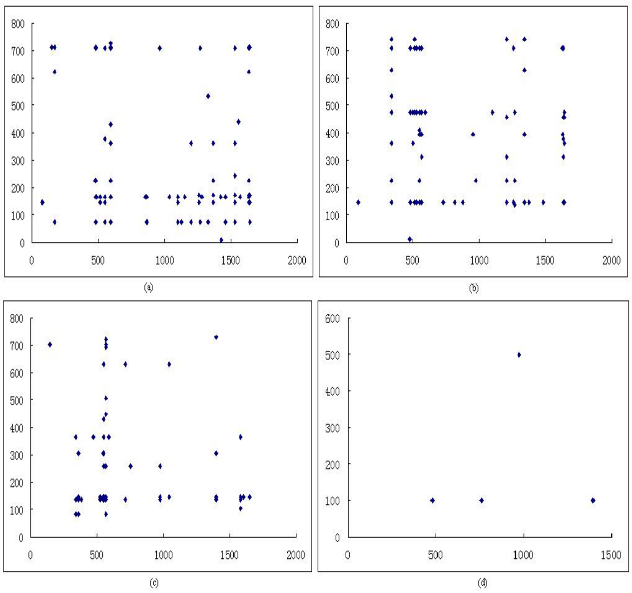

Fig.4. The process of convergence of the pre-selection method of NGA for normalized cross-correlation image matching. (a) The 10th generation of evolution (b) the 50th generation of evolution (c) the 100th generation of evolution (d) the 200th generation of evolution

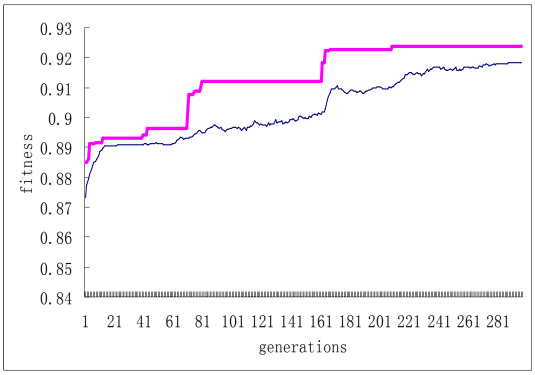

Fig.5. the fitness curves of average and the best individual of the pre-select method of NGA for grey-correlation image matching. The thick curve shows the best fitness of each generation. The thin curve shows the average fitness of each generation.

The performances of Niching GA with three kinds of methods are tested. Because of the results of the other methods (crowding and sharing) are similar to the Fig. 4 and Fig. 5, the paper here only gives the pre-selection method to show the process of evolution. Fig.4 shows that the scattered points trend to converging at the peaks. Fig. 5 shows that the population grows better as the generation increasing. So, the niching methods are suitable for searching the multi-target of image matching.

4 Conclusion

In this paper, three methods of Niching GA introduced into multi-target matching are proposed to identify and search multiple niches (the matching peaks) efficiently in a multimodal domain. It is found that Niching GA is robust optimization techniques which allow multiple solutions in multimodal domains to be found. They can be easily coupled with GAs with only a small increase of the computational time resulting from the computation of the distances between individuals. Nevertheless, this drawback is minor in relation to the advantages of these methods. The benefit of the detection of distinct optimal solutions is particularly interesting for multi-target matching optimization problems and inverse problems for which the uniqueness if the solution is not fulfilled.

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