A 2D Rigid Point Registration for Satellite Imaging Using Genetic Algorithms

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Abstract. Image registration is an important step for a great variety of applications such as remote sensing, medical imaging, and multi-sensor fusion-based target recognition. 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 images for high quality products. In the broad area of global optimization methods, Genetic Algorithms form a widely accepted trade-off between global and local search strategies. They are well-investigated and have proven their applicability in many fields. In this paper, we present an efficient 2D point based rigid image registration method integrating the advantage of the robustness of GAs in finding the best transformation between two images. The algorithm is applied for registering SPOT images and the results show the effectiveness of this approach.

Keywords: Image registration, point registration, feature points, satellite images, Genetic Algorithms.

1   Introduction

The process of image registration can be formulated as a problem of optimizing a function that quantifies the match between the original and the transformed image. Several image features have been used for the matching process, depending on the modalities used, the specific application and the implementation of the transformation. The registration process can be divided into three main categories: point-based, surface-based and volume-based methods. *Point-based* registration involves the determination of the co-ordinates of corresponding points in different images and the estimation of geometrical transformation using these corresponding points. Then, the task of registration is to place the data into a common reference frame by estimating the transformations between the datasets. What makes the problem difficult is that correspondences between the point sets are unknown a-priori. A popular approach to solving the problem is the class of algorithms based on the Iterated Closest Point (ICP).

The ICP algorithm described by Besl and McKay [1] is well known for aligning 3D object models. Originally ICP starts with two data sets (mostly points) and an

initial guess for their rigid body motion. Then the transformation is refined by repeatedly generating pairs of corresponding points of the sets and minimizing an error metric. ICP algorithms are mostly applied to 2D or 3D point sets [2]. ICP is attractive because of its simplicity and its performance. Although the initial estimate does need to be reasonably good, the algorithm converges relatively quickly. This algorithm is composed of two basic procedures. The first one is to find matching points, and the second one is to estimate the transformations iteratively for these points until some stop distance criteria is satisfied. Another approach to the registration of images consists in determining a set of matches through a search process instead of the classical approach based on distances. This approach consists in finding a solution close to the global minimum in a reasonable time. This can be done by means of a Genetic Algorithm (GA).

In recent years, GAs have been intensively investigated and applied to many optimization problems [3]. GAs are especially appropriate for the optimization in large search spaces, which are unsuitable for exhaustive search procedures. GAs do a trade-off between the exploration of the search space and the exploitation of the best solutions found so far. A number of authors have used GAs for full-view image matching in various forms. Jacq and Roux [4] use GAs for registration of 3D medical images. Brunnström and Stoddard [5] used a GA to find an initial guess for the free-form matching problem that is finding the translation and the rotation between an object and a model surface. In contrast to the 2D–3D registration, numerous methods exist to precisely register 3D data by iterative algorithms like the Iterative Closest Point and its variants [6].

In this paper, a novel approach is developed based on the application of GAs for registration of two data sets from satellite images. The remainder of the paper is organized as follows: the second topic gives an overview of genetic algorithms and their basics. The third topic describes the registration strategy used in this work. The feature point extraction algorithm based on the NSCT method is given in the fourth topic. The simulation results are presented in the fifth topic, and in the last we finalize with a conclusion.

2   Genetic Algorithms Overview

The GA is a well-known efficient global optimization algorithm, introduced by Holland [7] in 1975, that utilizes the concept of biological structure to natural selection and survival of the fittest. Due to the fact that the method requires no previous experience on the problem, it is applied on various problems whereof some characteristics are mentioned in [8].

The general principle of a genetic algorithm is to subject a population of individuals to an evolutionary process, encoded as chromosomes, which represent some possible solutions to a searching problem. During evolution, an aptitude value is assigned to each individual obtained from a specifically defined function for the problem to be solved. This function, called aptitude or fitness function, should be designed in such a way that it favors the most apt or adequate individuals as the

solution to the problem. The aptitude assigned to each individual is taken into account in the selection of the parents who will take part in the reproduction process. Here there is an exchange of genetic material or content of a pair of selected individuals to generate two new individuals or two new possible solutions to the problem that, according to a replacement mechanism, are incorporated into the population. The new descended individuals are also subjected to a mutation process which is a random perturbation of its genetic material in order to offer variability and also to enrich the exploration of the possible solutions to the problem. These are represented as chromosomes. Finally, after having completed a certain number of cycles of aptitude assignation, reproduction, mutation, and replacement (called generations), the individual with better aptitude is chosen as the best solution to the problem. The GA cycle is shown in the following figure.
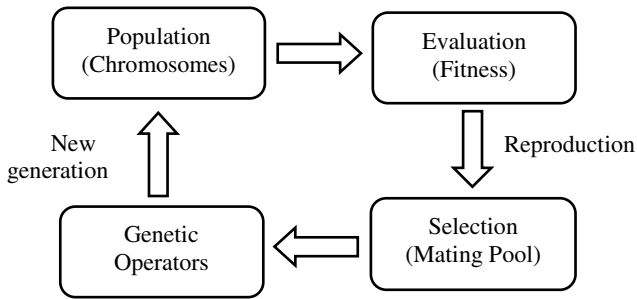
Fig. 1. A GA scheme

3   Registration Strategy

For the GAs to be successful, how to formulate the chromosome and fitness function is very important. The GAs will have better convergence behavior if the fitness function is generally continuous and the chromosome with the optimal fitness value corresponds to the target solution. In the following, formulations of the chromosomes and the fitness function for point registration are described.

3.1   Similarity Metric

One of the most important components of any image registration method is the similarity metric. This is considered as a function F that measures the goodness of a given registration solution, that is, of a registration transformation f.

A genetic algorithm uses a fitness function to determine the performance of each artificially created chromosome; therefore the fitness function should measure the registration quality of each chromosome. A GA should try to find a chromosome with the minimum Euclidean distance between each correspondence pair [9].

Assume that the given two data sets to be matched are $P = \{p_1, p_2, \ldots, p_m\}$ and $Q = \{q_1, q_2, \ldots, q_n\}$ where m is not necessarily equal to n.

If the registration parameters are given, then for any point p_i in P, we can use the following criterion to determine its possible correspondent q_i in Q:

$$q_i = argmin\|q-(Rp_i+T)\|\cdot \tag{1}$$

Thus the objective is to minimize the Euclidean distance between the transformed point Rp_i+T and q in the Q. A suitable transform means the distance error between P and Q is minimized. Therefore, the *fitness function* of GA to be *minimized* is described in the following equation

$$F = median \|p_i - q_i\|. \tag{2}$$

We assume that the type of transformation is rigid. Then, for the data point in the model image with coordinates x, y and intensity value I, its image is x', y', and I', and then they are related by the mapping:

$$Pt = R*p_i+T. \tag{3}$$

Where, R is the rotation matrix and T is a translation vector in both x and y directions.

3.2   Chromosome Encoding

The geometric transformation between two models can be defined by three parameters, defined as a chromosome. Each parameter corresponds to one of the genes in the chromosome.

Using a bit encoding scheme for the chromosome string, the rotational transform (R), x-axis translational transform (X), and y-axis translational transform (Y) are encoded. An 8-bit field is used to represent the possible relative rotation of the input image to the reference image. Likewise, 6 bits are used to express the translation in the x-axis and 6 more for the y-axis. Thus, the total length of the chromosome is 20 bits.

All representations are signed magnitude, using one bit for the sign and the rest of the bits to represent the magnitude of the rotation or translation. Thus, the relative rotation has a range of ± 128 degrees, while relative translation in the x (or y) direction has a range of ± 32 pixels. Every individual represents a combination of all transformation parameters which describe an image transformation.

4   Feature Points Extraction

The purpose of the feature extraction is to derive features that describe image characteristics that are relevant in a co-registration process and which can be used to select a subset of regions and choose an appropriate method for each. The feature extraction approach used in this paper exploits a nonsubsampled directional multi-resolution image representation to capture significant image features across spatial and directional resolutions.

Recently, Cunha et al. [10] proposed the non-subsampled contourlet transform (NSCT) which is a shift-invariant version of the contourlet transform and

multidirectional expansion that has a fast implementation. The NSCT eliminates the downsamplers and the upsamplers during the decomposition and the reconstruction of the image. Instead, it is built ahead the nonsubsampled pyramids filter banks which provide multiscale decomposition and the nonsubsampled directional filter banks which provide directional decomposition.

The proposed feature extraction method is described in the following algorithm [11]:

Step 1: Compute the NSCT coefficients of both images for N levels and L directional subbands.

Step 2: Compute the difference between each directional subband at one level and the corresponding one at another level. L difference subbands will be obtained at the end.

Step 3: At each pixel location, compute the maximum magnitude of all obtained difference subbands. These points are called "maxima of the NSCT coefficients".

Step 4: A hard thresholding procedure is then applied on the NSCT maxima image in order to eliminate non significant feature points. A point is recorded if NSCT maxima > Th,

Where Th = c (σ + μ), c is a parameter whose value is defined by the user, and σ and μ are the standard deviation and mean of the NSCT maxima image, respectively.

Step 5: Take a block neighborhood of size w×w and find one local maximum in each neighbourhood, this will eliminate maxima that are very close to each other. The locations of the obtained thresholded NSCT maxima are taken as the extracted feature points.

After the feature points are detected from the images to be registered, a correspondence mechanism between these two feature points sets must be established in order to refine the control points. The objective is that each feature point in the reference image is paired with its correspondent in the sensed image. In this work, correlation based similarity measure is used to establish the correspondence between the two feature point sets.

5   Simulation Results

The parameters of GAs used in this test are: The population size in each generation is restricted to 100 individuals with a crossover probability of 0.75 and a mutation probability of 0.05. GA meets the criterion within 200 generations. To improve the performance of GAs, we have used two techniques named elitism and fitness sharing. Elitism consists of preserving the best individuals at each generation and fitness sharing to keeps the population diversity.

We have applied our algorithm on SPOT satellite images. The transformed image to be corrected is rotated by 7 degrees and displaced by 13 and 9 pixels in X and Y directions from the center of the reference image. The sensed (reference) image is warped using bilinear transformation.

Evaluation of the fitness function described above requires a search on the closest point from a data set given an input data point. The corresponding searching time will be very long and becomes a major obstacle in utilizing the GA approach for practical applications. Therefore, in the first experiment and in order to limit the point set representing the image, we choose a window of size 40*40 pixels from the center of both images in order to have about 1600 points at each model.

Figures 2 and 3 illustrate the performance of GAs process during the run. In figure 2, we see the evolution of the best fitness value at each generation. This value which is median (dist) is minimized from generation to another until found the optimal fitness value which corresponds to the optimal solution. Figure 3 depicts the evolution of the parameters (R,X,Y) during the generations. The red dashed lines show the initial parameters and blue lines show the optimal parameters found during the run the GAs. We see that the optimal parameters values are closer to the initial parameters.

The results of the parameters transformation found with this technique of GAs based point registration noted by 'GAs proposed' is compared with other registration methods as the ICP algorithm (noted ICP) and the intensity registration based method (noted GAs intensity) for which the objective is it to maximize the correlation coefficient of the two images.

The analytical results are depicted in table 1. The results found with 'GAs proposed' are similar to those of ICP. However, the results of the GAs intensity method are slightly different particularly for the X translation. So, we can say that the point registration is more robust and accurate than those of intensity methods.

Table 1. Analytical results of the parameters found with different methods

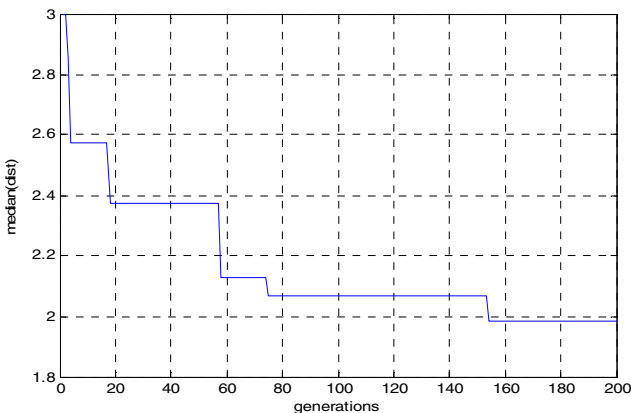| Methods	Rotation R	Translation X	Translation Y
ICP	-7	-13	-8
GAs intensity	-7	-10	-8
GAs proposed	-7	-13	-8

Fig. 2. Evolution of the best fitness during the run of GAs
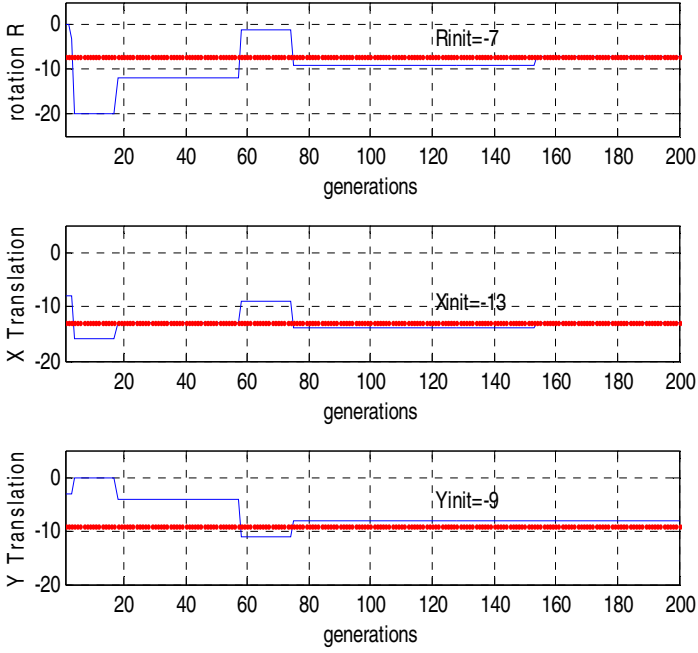
Fig. 3. Evolution of the parameters transform during the generations

In the case of important sizes where the data sets are very large and time consuming is very important, we have suggested to employ the NSCT method for extraction of the feature points as cited in section IV (the second experiment). The NSCT decomposition of images was performed with the following parameters: N=4 levels and L=4 sub-bands at each level; c=1 and the block neighborhood is of size w = 32. An example of interest points extracted using the NSCT method is shown in figure 4 for both images of size 512*512 pixels.
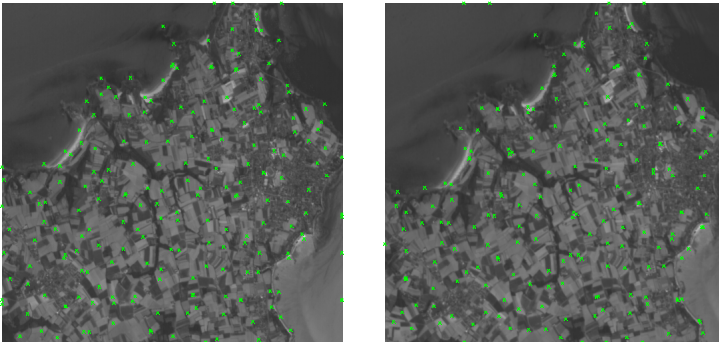

Fig. 4. Feature points extraction using the NSCT method of the reference image at the left and the transformed image at the right

After selecting the corresponding feature points with the NSCT method, we apply the GAs process for registration of the corresponding point sets pair. The registered image obtained is shown in the following figure.
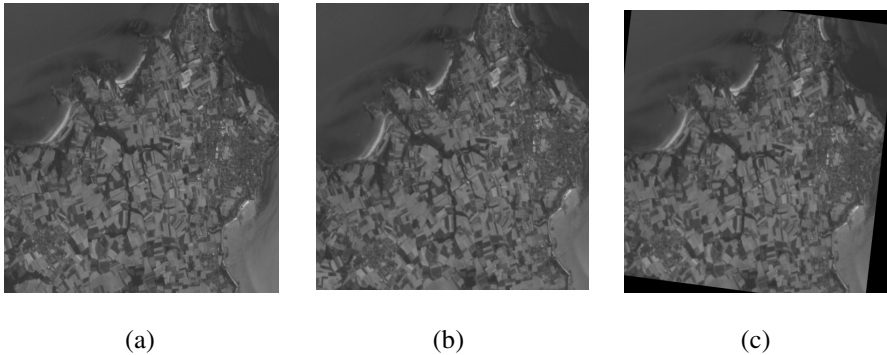

| (a) | (b) | (c) |

Fig. 5. Image registration results: (a) reference image which corresponds to model M, (b) transformed image which corresponds to model P to be registered, and (c) the resulting image registered with the GAs process

6   Conclusion

Point set registration is among the most fundamental problems in vision research. It is widely used in areas such as range data fusion, medical image alignment, object localization, tracking, object recognition, just to name a few. The goal of the registration task is to find the transformation that best represents the relative transformation between two sets data. In this paper, we present an efficient point based rigid 2D image registration method. The registration optimization problem is solved by the Genetic algorithms method.

GAs represent an intelligent exploitation of a random search used to solve optimization problems. In this work, GAs have been used to estimate the rotation angle and displacement values at x-axis and y-axis. We have considered an image registration algorithm based on the alignment of a set of feature points. Our interest in this problem stems from its application in remote sensing, and in particular in the alignment of satellite images. We have presented a novel approach of a 2D point registration based on the GAs for which the results have proven its accuracy compared to the intensity based methods.

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