Registration of Satellite Imagery Using Genetic Algorithm

Rakesh Singhai and Jyoti Singhai

Abstract— **Image Registration is the process of determining a transform that provides the most accurate match between two images. The search for matching transformation can be automated with the use of suitable metric, but it is difficult to determine local maxima with direct search methods. In this paper a simple and powerful search strategy based on genetic algorithm is proposed to register satellite images. This method applies mutual information (MI) to measure statistical dependence of information redundancy between the image intensities of corresponding voxels in both floating image and reference image. Partial Volume distribution interpolation (PV) is used to compute the MI criterion. Scope of the paper is limited to pair of images, which are misaligned by rigid transformation (i.e. rotation and/or translation). Performance of genetic algorithm based proposed approach is compared with existing search methods, which shows that the proposed approach overcomes the limitation of local maxima with the desired accuracy and speed.**

Index Terms— **Image Registration, Mutual Information, Interpolation, Genetic Algorithm**

I. Introduction

REGISTRATION is the determination of geometrical transform that aligns points of an object in one view with corresponding points of that object in another view. Registration of satellite images is often necessary for integrating information taken from different sensors, transponders, finding changes in images taken at different times, elevation or under different conditions for model based object recognition and inferring three-dimensional information from images in which either the camera on satellite or the objects in the scene have moved. Registration of satellite images require spatial (geometric) transformation mapping that establishes a spatial correspondence between all points in input gray level satellite image $S_i(x,y)$ and reference image $S_r(x,y)$. The main aim of image registration is to determine optimum transformation parameters that can best match the two images. The four components of image registration which contribute to the optimization are feature space, search space, search strategy and similarity metric [1]. Image registration uses similarity measure by finding an accurate match between an input image S_i and transformed versions of the reference image S_r. These similarity measures are either feature based or intensity based. In feature based similarity measure, the image is preprocessed to extract features such as edge and then geometric correspondence is established between these features. In this method, reliable edge detection or image segmentation is required. In intensity-based method, preprocessing is not required. Cross-correlation is the most common intensity based similarity metric used in image registration. Other intensity based objective functions are intensity correlation, mean square difference of image intensity values, mutual information (MI) etc. In this paper, mutual information is used as the similarity metric. Mutual information found to be robust for satellite image registration and in medical imagery [3][9][13].

In this paper, the mutual information between two satellite images is maximized by optimizing the parameters using Genetic algorithms (GA's). Genetic algorithms (GA's) [5][6] are mathematically motivated search techniques that try to emulate biological evolutionary processes to solve optimization problems. Instead of searching one point at a time, GA's use multiple search points. GA determines near-optimal solutions without going through an exhaustive search mechanism. Thus, GA can claim significant advantage of large reduction in search space and search time. In GA, search for function optimization starts from population of points in the function domain, instead of a single point as in direct search method. This characteristic suggests that GA is global search method. They can climb peaks in parallel, reducing the probability of finding local maxima, which is one of the drawbacks of traditional optimization methods.

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II. Optimization OF MI Using Genetic Algorithm

The commonly used method as search strategy is simple hill climbing search method. A simple hill climbing search method can give good performance, if the MI function of the parameter space is enough smooth. The best situation is that the MI value function is strictly monotonic, in that case, there are no local maxima, and a hill climbing search always works [2][4]. This requires the spatial dependence of image intensity values. If this is not satisfied, the existence of too many local maximums of the MI function values will mislead the process of finding the global maximum. In this paper, a genetic algorithm based search method is proposed to overcome this problem.

Figure 1 depicts the block diagram of the genetic evolution implemented in the proposed simulation. Let S be a solution space where all the elements have their associated fitness values. The straightforward way to find the element with the maximum fitness value is to search among all the elements and to compare their fitness values. However, the computational complexity will be very high if the space size is large. In order to reduce the computational complexity, an efficient search algorithm should be applied.

In most GA's based applications, random selection of elements from the solution space creates the initial population [8][14]. As shown in Figure 1, first block generates a population P consisting of elements and population size N. Each element in P is a chromosome, which is composed of a list of genes. The population will evolve into another population by performing some genetic operations. The chromosomes with higher fitness values will have more probability to be retained in the population of the next generation, and to propagate their offspring. On the other hand, the stronger chromosomes will replace weak chromosomes whose fitness values are small. Therefore, the quality of the chromosomes in the population will be better and better. After a suitable number of generations, the mature population will be expected to contain the elements with the global maximum value. In this application, the solution space S is a 32-bit binary data. In which the first 12 bits represent the rotation angle, next 10 bits represent X-translation and the last 10 bits represent Y-translation. The i^{th} chromosome C_i in the population is defined as $C_i = [b_{i1}\ b_{i2} \ldots\ldots\ldots\ldots b_{i32}]$.

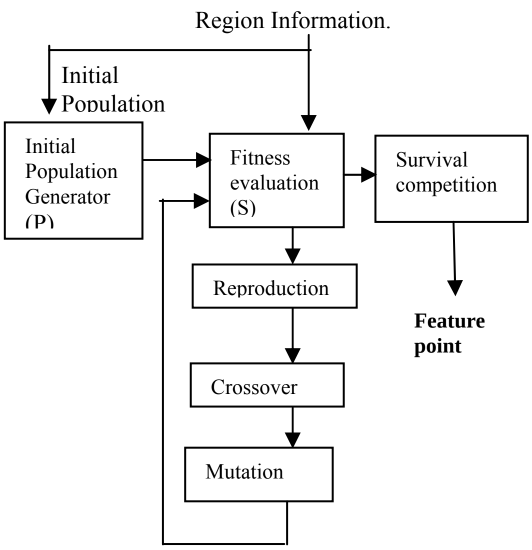

Figure 1 Block Diagram of the adopted Genetic Algorithm

The objective function in image registration is to maximize the mutual information between the reference and input images. This means that the fitness function is simply the mutual information between the transformed image and the reference image [10]. The correlation function between two images A and B to be registered with marginal probability distributions $P_A(a)$ and $P_B(b)$ and joint probability $P_{AB}(a,b)$ is given as

$$I(A,B) = \sum_{a,b} P_{AB}(a,b) \log \frac{P_{AB}(a,b)}{P_A(a) * P_B(b)}$$

MI of two images is maximal when these two images are perfectly aligned [11]. Therefore, image registration is achieved by adjusting relative position and orientation of images, until their mutual information is maximized.

For individual selection, we select highly fit individuals with higher mutual information values based on Partial Volume distribution interpolation [12]. Chromosomes with larger MI values in the current population have higher probability to be selected as seeds of the next generation. The reproduction method used in this work is similar to the weighted Roulette wheel method [6]. The relative weight of the fitness values for each chromosome i can be expressed as follows.

$$Fi = \frac{fi}{\sum_i fi}$$

where F_i is the weighted fitness of a chromosome i and f_i is the fitness of chromosome i. The Roulette selection assigns probability to each chromosome i, using the F_i value. The roulette wheel is partitioned into sectors as in Figure 2 corresponding to the weighting obtained from F_i. The spinning of the wheel begins by generating a random number. If the number falls into a portion that belongs to a specific individual, that individual is selected. When the interval of each chromosome has been determined, N real numbers, R_n , for n=0,1,…N-1, are randomly generated, where $0 \leq R_n < 1$

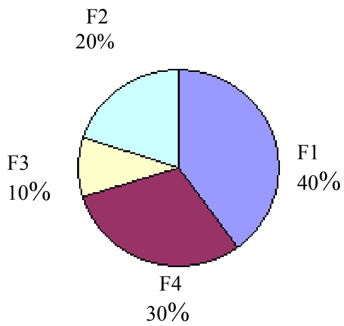

Figure 2 A Roulette wheel for chromosome selection

The chromosome C_i is then selected as a seed to generate the rival population. It is possible that one chromosome can be selected twice or more. Because real random numbers are generated, seeds could be selected and placed in the mating pool. The seeds will be processed by the genetic operations of crossover and mutation. As part of the reproduction, the crossover is a recombination operator for a pair of chromosomes. The crossover method used here is the so-called uniform crossover [7]. For every two seeds C_L and C_{N-1-L}, $0 \leq L \leq \frac{N-1}{2}$ selected from the mating pool, two new chromosomes are produced by performing uniform crossover operations as

$$M'i = (mi \cap Mx) \cup (mj \cap M'y)$$
$$M'j = (mi \cap M'x) \cup (mj \cap My)$$

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where M_i' and M_j' represent the new chromosomes, mi and mj are the original chromosomes selected from the mating pool, Mx and My are two randomly generated bit masks. $M'x$ and $M'y$ are the complements of Mx and My respectively. The simplest crossover is called a single-point crossover. Usually, the crossing point is randomly selected. For example in Figure 3, the genes in two 8-bit chromosomes A and B are exchanged at the cross point 2 from the left. This produces two new chromosomes C and D.

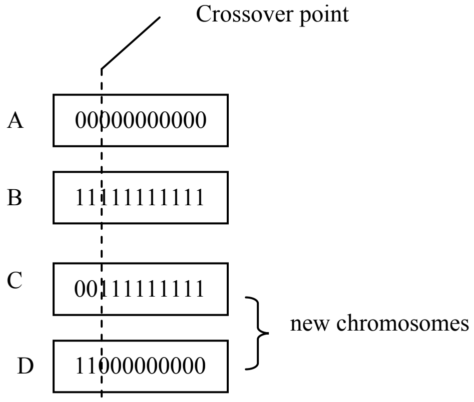

Figure 3 An example of a single-point crossover

New elements from the search space are explored by applying crossover operations. In the proposed algorithm, we have used many types of cross over are implemented to get better results and compare the performance such as simple, uniform, non-uniform, arithmetic , heuristic, single point and two point. After the crossover stage, each chromosome in the mating pool is processed and transferred into a candidate chromosome of the new generation.
Mutation is a random change of the gene. For example, an 8-bit chromosome '0000 0000' can be mutated at bit 4 to produce a new chromosome '0001 0000'. Mutation offers the opportunity to introduce new genetic material into a population. Mutation is useful for avoiding local optima problems. It occurs, after the crossover, only at a small percentage of the time.

In the proposed algorithm, various mutations like uniform, non-uniform, shift, swap, adjacent swap, binary, boundary mutations are used with the mutation rate of 0.01. Using the mutation rate of 0.01, each selected individual is mutated by randomly altering one bit in the chromosome string. The position of the bit to be altered is also randomly selected. The proposed GA-based algorithm stops when the solution has converged or a certain number of generations is reached. There are chromosomes in the mating pool after performing the genetic operations. Along with the original chromosomes in the current generation, chromosomes are selected from these chromosomes according to their fitness values .The chromosomes with larger fitness values will be picked up as the members of the population in the next generation, and go through the next iterations of the genetic evolution. Although the sorting operation is needed in the survival competition stage, the overhead is not high because the population size is usually not large in this case. This stage is added in the proposed algorithm to prevent the chromosomes from being destroyed by the new ones with poorer fitness values, because the new chromosomes generated from the original ones are not guaranteed to have larger fitness values in GA's. The chromosome with the maximum fitness value is selected from the current population as the possible solution. The other ones from a generation to the other generations might replace the possible solution. The iteration will be terminated if the solution is not updated for a predetermined period of iterations

III. EXPERIMENTAL EVALUATION

A. Spatial Dependence Of Image Intensity And Smoothness Of MI Function

Spatial dependence of image intensity values will result in the smoothness of MI values. The Figure 4 and 5 show the MI values corresponding to different rotation angles and translation. Figure 4(a) is the result based on NN interpolation, and Figure 4(b) on PV interpolation. It is clearly seen that at the center, which indicates no rotation, a max MI value is attained, and MI value shows some smoothness in the neighbour of the no rotation position.

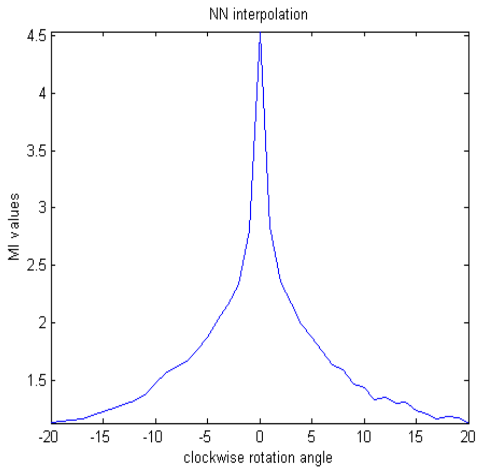

Figure 4(a) MI for NN interpolation

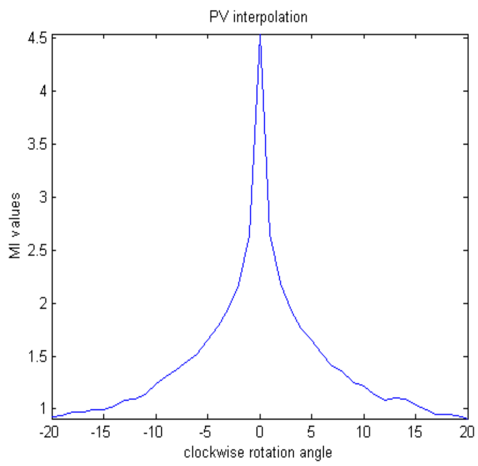

Figure 4(b) MI for PV interpolation

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Furthermore, the PV interpolation shows more smoothness than NN interpolation, which indicates more robustness of the algorithm. This is proven in the experimental results of searching.

B. Description Of Test Data Sets

Performance of proposed algorithm is evaluated on two data sets, namely a remote sensing imagery of Bhopal city and group of four satellite images. The 601 × 701 BPL.tif image is the image of Bhopal city, which is artificially translated and rotated to create data set for testing the algorithm. In these images translation parameters are varied in the horizontal direction by 0 to 100 pixels and rotation parameters are varied with angles ranging from 0 to 6^o. Reference image of Bhopal city is shown in Figure 5(a), while translated and rotated images are shown in Figure 5(b) to Figure 5(f). The second data set is group of four different image pairs of the same scene due to satellite rotation, in which one is reference and the other is the input image as shown in Figure 6(a) and 6(b). The reference and calculated transformation parameters are tabulated in Table II.

C. Algorithm Implementation

A series of experiments is conducted using synthatic images from the dataset 1 . The two search methods "simple hill climbing search" and "genetic algorithm search" are used to get registration parameters.
Search space used in simple hill climbing search method were Angle Range from *0* to *(pi/30=0.1047)*2,*i.e. the true solution lies at the center; Translation along *x* direction from *-10* to *10*, the true solution lies at the center; Translation along *y* direction from *-10* to *10*, the true solution lies at the center.
Search space used in Genetic Algorithm method is rigid transform. For this search space chromosome, encoding is tabulated in Table I.

D. Image Registration Accuracy

The registration accuracy for three types of search method i.e. using simple hill climbing search method, genetic search with 25 generations and genetic search with 200 generations are compared in terms of RMSE of the registered image with respect to the reference image. Table II represents the results of data set 1 which shows the average RMSE values for the above three methods. Table III represents the results of data set 2, which shows the average RMSE values for the same three search methods. In Table II and III, dX and dY are translation in x and y direction in pixel and dR is the rotation in degree.

E. Timing Performance

Table IV summarizes the total execution time of the image registration methods using three types of search methods. The genetic algorithms provide significant computational savings over the exhaustive search. The hill climbing search method provides the best accuracy, but fails when local maxima occur. Genetic search method is suitable for any range of data at the cost of speed. Table IV shows that as the number of generations in GA is increased the execution time also increases.

IV. Conclusion

In the proposed algorithm, registration of rigidly transformed satellite images is implemented with an optimization strategy i.e. genetic algorithm (GA). GA is applied to optimize search space and the results of proposed algorithm are compared with the conventional hill climbing search method. The experimental results show that mutual information criterion applies well to image registration. The mutual information criterion states that the images are geometrically aligned by the transformation for which *I(A,B)* is maximal. Partial Volume interpolation method improves the smoothness of the mutual information function and reduces the chances of local maxima, but it needs more time compared to nearest-neighbour scheme for each mutual information evaluation.

The results show that the average RMSE calculated for data set I with GA for 200 generations is 0.043, which is improved as compared to RMSE of 0.18 of hill climbing search method. Similarly, for second data set average RMSE value for y translation is reduced from 5.93 of hill climbing search to 1.65 of genetic search with 200 generations. Timing accuracy shows that genetic search gives good speed as 1.9160 seconds, which is comparable with 2.213 of hill climbing search. The GA with 25 generations takes 0.7190 seconds, which gives better speed, but at the cost of accuracy.

Genetic Algorithm (GA) is a good searching strategy to overcome the limitation of local maxima and is also suitable for the mutual information maximization process. It is based on crossover, mutation, and selection idea. However, the limitation of GA algorithm is decrease in its speed, if the numbers of generations are increased to improve the accuracy. Combination of traditional gradient based method and GA may give good performance.

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Table I: Search space for GA

Search space	Chromosome encoding		
Transform	Bit Length	Range	Scope
Rotation	12	± 2048	±20.48º
X Translation	10	±512	±5.12 pixels
Y Translation	10	± 512	± 5.12 pixels

Table II: RMSE performance for data set 1

Input Images	Ground Truth (transformation parameter)			Hill Climbing Search			GA (25 Generations)			GA (200 Generations)		
	dR	dX	dY	dR	dX	dY	dR	dX	dY	dR	dX	dY
BPL_a.tif	0	0	0	-0.12	0.12	-0.15	0.02	0.22	-0.32	0.05	-0.16	-0.47
BPL_b.tif	-10	0	0	-10	-0.21	-0.02	-9.69	0.13	-0.5	-10.	0.01	-0.02
BPL_c.tif	18	0	50	17.54	0.48	50.22	17.86	-0.14	51.01	18.02	0.06	50.1
BPL_d.tif	4	50	0	3.96	50.29	-0.48	4.17	49.67	0.09	3.97	49.99	0.02
BPL_e.tif	4	53	0	4.14	52.83	0.25	3.92	52.74	-0.9	3.99	52.50	0.05
BPL_f.tif	4	5	-2	3.96	5.23	-2.03	3.69	5.07	-1.88	4.09	4.50	-2
Avg. RMSE				0.18	0.381	.354	0.15	0.24	0.206	0.043	0.069	0.18

Table III: RMSE performance for data set 2

Input Images	Ground Truth			Hill Climbing Search			GA (25 Generations)			GA (200 Generations)		
	dR	dX	dY	dR	dX	dY	dR	dX	dY	dR	dX	dY
Sat_a1 & Sat_a2	0.5	16	5	1.1	12	10	0.81	16	4	0.6	14	6
Sat_b1 & Sat_b2	0.2	5	16	2.1	8	20	0.21	5	11	0.21	4	15
Average RMSE				.82	8.3	5.93	.478	2.56	2.80	0.42	1.31	1.65

Table IV: Total Execution Time

Input	Average Time(Sec.)		
	Hill climbing Search	GA (25 generations)	GA (200Generations)
Data Set 1	3.219	1.0231	2.224
Data Set 2	2.213	0.7190	1.9160

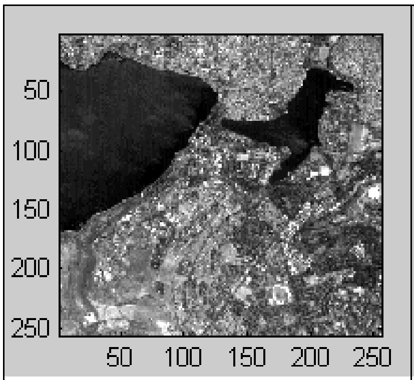

Figure 5(a) BPL_a.tif

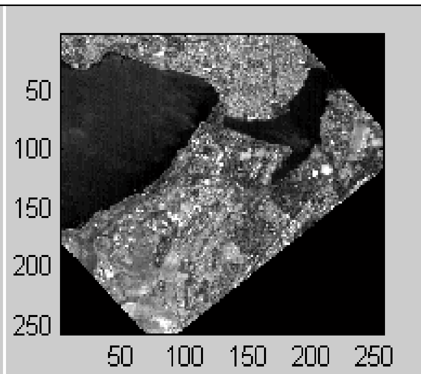

Figure 5(b) BPL_b.tif

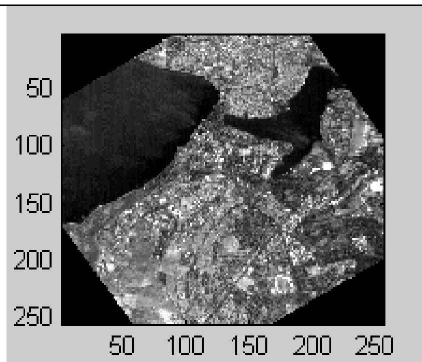

Figure 5(c) BPL_c.tif

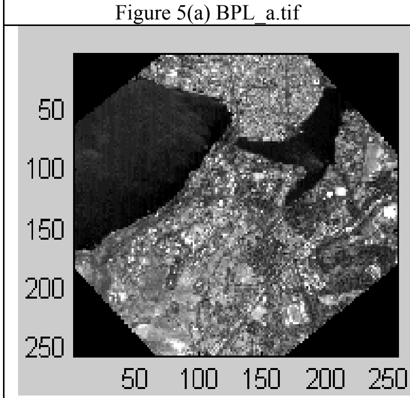

Figure 5(d) BPL_d.tif

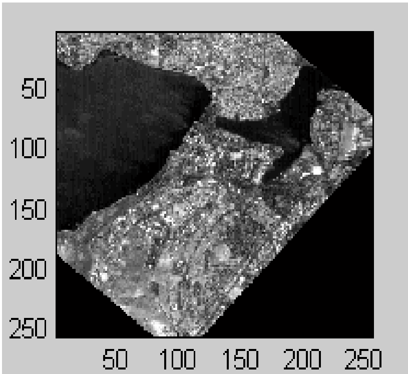

Figure 5(e) BPL_e.tif

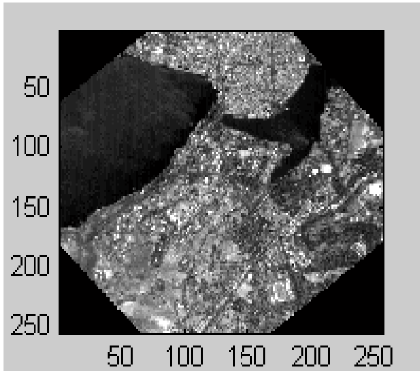

Figure 5(f) BPL_f.tif

Figure 5: Data set 1: Satellite Reference Image and translated/ rotated satellite images of Bhopal city, India


Figure 6(a1) Sat_a1.tif

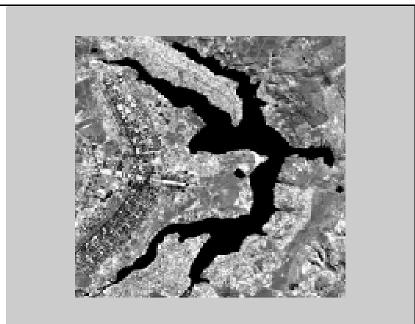
Figure 6(a2) Sat_a2.tif

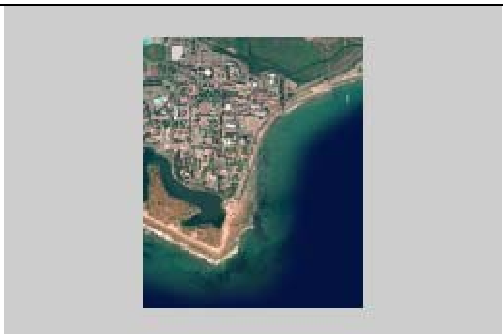
Figure 6(b1) Sat_b1.tif

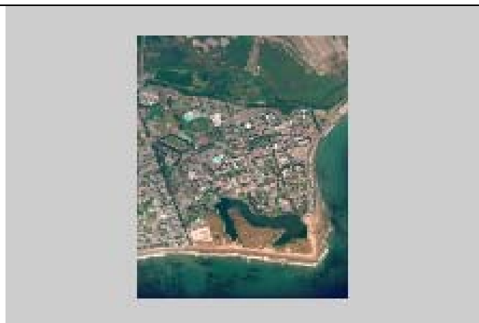
Figure 6(b2) Sat_b2.tif

Figure 6: Data set 2: Satellite Image pairs of the same scene due to satellite rotation

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