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Genetic Algorithm v/s Share Genetic Algorithm with Roulette Wheel Selection method for Registration of Multimodal Images.

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Abstract –

In this paper, we discuss the impact of optimization using genetic algorithm and share genetic algorithm on multimodal image registration by considering Mutual information concept . We obtain the global maxima of similarity measure between multi modal medical images i.e CT (Computer Tomography) and MRI (Magnetic resonant Images) .We also computed the performance of image registration by using Simple Genetic Algorithms and Shared Genetic Algorithms with respect to accuracy and time.

Image registration[1] is the process of overlaying one or more image to a reference image of the same scene taken at different time, from different view point and/or different sensor. The objective of the registration process is to obtain the spatial transformation of an input image to a reference image by which similarity measure is optimized between the two images, so as to obtain maximum information from the registered image. A Similarity measure called Mutual information [2] compares the statistical dependency between images. Image registration can be regarded as optimization problem where there is a goal to maximize the similarity measure. There is a requirement for finding the global maxima of similarity measure. This work focuses on image registration of two medical images of having different modality i.e. image acquired with different sensor e.g. .C T images, MRI images [2]. In this work, we perform a comparative study of the image registration process on the multimodal medial images by using different genetic algorithms relative to the performance as accuracy and time.

Keywords- Image registration, Genetic algorithm, Mutual information, Affine transformation.

I. INTRODUCTION

Image registration (IR) is defined as the search for the best mapping used to align two or more images of the same scene [1]. It has been applied in a number of research areas, including medical imaging analysis [3], computer vision and pattern recognition [4]. Image registration is the process of overlaying one or more image to a reference image of the same scene taken at different time, from different view point and/or different sensor[10]. This paper addresses the image registration problem applying genetic algorithms[6]. The image registration's objective is the definition of a mapping that best match two set of points or images. In this work the point matching problem was addressed employing a method based on nearest-neighbor. The mapping was handled by affine transformations.

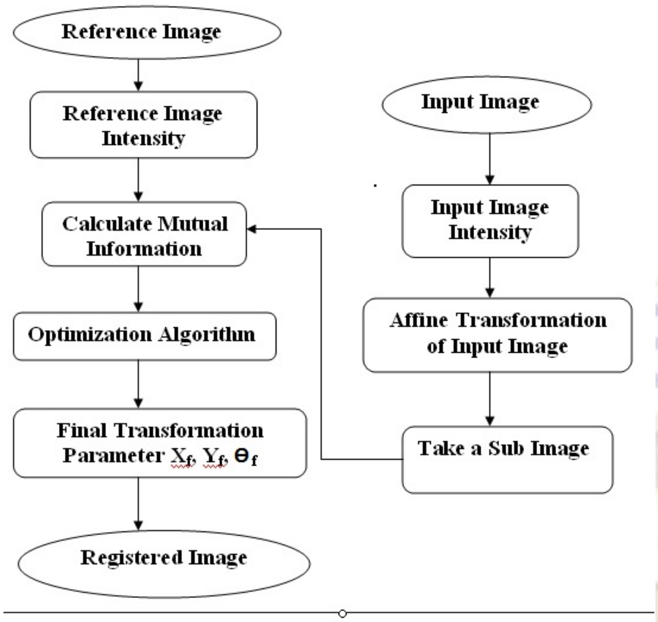
A. Image Registration process

The registration process involves finding a single transformation imposed on the input image by which it can align with the reference image. It can be viewed as different combination of choice for the following four components. [5].

(1) Feature space
(2) Search space
(3) Similarity measure
(4) Search strategy

The Feature space extracts the information in the images that will be used for matching[14]. The Search space is the class of transformation that is capable of aligning the images. The Similarity measure gives an indication of the similarity between two compared image regions[15]. The Search strategy decide how to choose the next transformation from the search space, to be tested in the search to spatial transformation[9]. Pixel-based algorithms work directly with the (totality of) pixel values of the images being registered. Preprocessing is often used to suppress the adverse effects of noise and differences in acquisition or to increase or uniform pixel resolution. The main advantage of this approach is a more global vision of the algorithm which increases its robustness.

There are many image registration methods and they can be classified into many ways. Mutual information (MI) based technique is the most popular technique, because MI does not rely on the intensity values directly to measure correspondence between different images, but on their relative occurrence in each of the images separately and co-occurrence in both images combined [17].



Flow Graph of Image Registration using mutual information

II. GENETIC ALGORITHM

The operations of the genetic algorithm are very simple. It maintains a population x1...n = {x1, x2 ….. xni}of n individual chromosomes xi (which may consist of a vector of parameters). These individuals are candidate solutions to some objective function F(xi) that is to be optimized to solve the given problem. The individuals are represented in the form of ‘chromosomes’, which are strings defined over some alphabet set that encode the properties of the individuals. More formally, using an alphabet set A = {0, 1, ----- k- 1}, we define a chromosome C = {c1, ... , c`i} of length l’ as a member of the set $S = A^{l`}$, i.e., chromosomes are strings of l symbols from A. Each position of the chromosome is called a gene, the value of a gene is called an allele, the chromosomal encoding of a solution is called the genotype, and the encoded properties themselves are called the phenotype of the individual. In the GA, typically a binary encoding is used, i.e., the alphabet is A = {0,1}. The GA employs three operators namely selection, crossover, and mutation. Being meta-heuristic GA require several decision to be made during implementation for encoding, selection, crossover and mutation.[11,15]

A. Floating Point Encoding

In this representation, each chromosomal string is represented as a vector of floating point numbers, of the same length as the solution vector .Each element is forced to be within the desired range, and operators are carefully designed to preserve this requirement. The required precision in this approach depends on the problem being solved and it is better than binary representation. Floating point representation is capable of representing large domains, where as in increase in domain size decrease the precision in fixed binary length representation.

B. Roulette wheel Selection

The best selection strategy for picking the parents to be the base for new offspring chromosomes is often problem specific. All strategies should however reflect the basic idea that a higher fitness means a higher likelihood of being selected. In selection the offspring producing individuals are chosen. The first step is fitness assignment. Each individual in the selection pool receives a reproduction probability depending on the own objective value and the objective value of all other individuals in the selection pool. This fitness is used for the actual selection step afterwards. For implementing the roulette wheel selection the individuals are mapped to contiguous segments of a line, such that each individual's segment is equal in size to its fitness. A random number is generated and the individual whose segment spans the random number is selected. The process is repeated until the desired number of individuals is obtained (called mating population).

C. Crossover

When parents have been selected according to the used selection strategy, crossover are performed on the parents to breed new chromosomes. The aim of the crossover procedure is to combine traits from the selected chromosomes to form a new chromosome. How crossover actually is done depends on the encoding used. Binary encoded chromosomes are usually crossed over by replacing a randomly chosen section of one chromosome with the corresponding content of the other (One Point Crossover). Alternatively, each bit position uses the bit at the corresponding position of a randomly chosen parent. Binary chromosomes can also be subject to some arithmetic operation to perform crossover. The performance of GA greatly depends on the ability of the crossover operator to combine solutions into a solution more probable of being successful than a randomly selected solution[15]

D. Mutation

Mutation is performed to introduce slight variations to allow for the exploration of states not generated through crossover. Suitable mutation rates are problem dependent, but are usually low as compare to the crossover rate. Mutation is critical to the performance of the genetic algorithm, as the crossover operator by itself requires large populations and is ineffective. It alters one or more gene values in a chromosome from its initial state. This can result in entirely new gene values being added to the gene pool. With these new gene values, the genetic algorithm may be able to arrive at better solution than was previously possible. Mutation is an important part of the genetic search as help helps to prevent the population from stagnating at any local optima. Mutation occurs during evolution according to a user-definable mutation probability This mutation operator

can only be used for integer and float genes. Let us consider a chromosome $X^i=[X_1, X_2, \ldots, Xm]$ and assume that X_k' is the element selected for this mutation from the set of genes in the chromosome and the resultant chromosome is $X^{t+1}=[X_1, X_2, \ldots, X_k' \ldots, X_m]$ where k is in the range[1,n] .
Here, $X_k' = X_k + \Delta(t, X_k^U - X_k)$ if the random digit is 0
$= X_k - \Delta(t, X_k - X_k^L)$ if the random digit is 1
The function $\Delta(t, Y)$ returns a value in the range [0,y] such that the probability of $\Delta(t, Y)$ being close to 0 increases as t increases. This property causes this operator initially, (when t is small) to search the space uniformly, and very locally at later stages. The function $\Delta(t, Y) = Y(1 - r^{(1-t/T)b})$ is used to determine the element to be selected . Here, r is a random number from[0,1],T is the maximal generation number, and b is a system parameter determining the degree of non-uniformity.

E. Stopping Criteria

Common to most stochastic optimization algorithms, we have no clear way of knowing when to stop the search and accept the currently best solution as the optimal or near-optimal solution.[13] In GA, we usually fix the number of generations to evolve, or end when the algorithm lack to make progress, which is defined e.g. in terms of G number of non-improving generations.

III . SHARE GENETIC ALGORITHM

The Simple-GA is able to explore effectively a multimodal search space. However it tends to find one single optimum, thus it can still be trapped in local optima. This problem is the result of genetic drift (Jong, 1975), which is the tendency of a genetic algorithm to select a population with similar chromosomes, thus to converge towards one solution. One strategy to overcome this problem consists in maintaining population diversity, so that different sub-populations are able to explore different portions of the search space, in order to identify and converge towards different multiple optima.

IV. METHODOLOGY & EXPERIMENTAL SETUP

We test the image registration of the 3 pair of medical images using the simple and share genetic algorithm with roulette - wheel selection method and after all showing the accuracy in figure. To illustrate the performance of our algorithm, we consider two type of medical images CT images and MRI images of the same patient .We take these images from the medical image database MEDIPIX. We get results of the two (simple and share GA) algorithms for the three images such as amount of translation along the x-axis and y-axis and rotation angle required to achieve the registration from the experiment. Maximum mutual information (MMI), the error and the time elapsed is also noted. We experiment it with termination criteria of 50 generation with arithmetic crossover and mutation rate of .01.

The experiment is done in MATLAB 7.5.The registration process is implemented for the multimodal images (image of different sensor). The class of transformation [7] that is assumes to be capable of aligning the input image with the reference image. We use affine transformation as the search space. This transformation is useful when registering images taken from a distant platform of a flat scene. We use translation, rotation and scaling as the transformation parameter[6,7]. After the linear transformation and rotational transformation the transformed point may not be on the exact pixel of the image for this it requires interpolation. Nearest neighbor and bilinear interpolation are the popular interpolation methods. We use bilinear interpolation as it produces smoother output image . For the interpolation bilinear method use 2x2 neighbourhood and nearest neighbour uses only nearest neighbour.

Registration of multimodal images is very difficult task, but often necessary to solve, especially in medical imaging[8]. Multimodal images of the same scene represent measurements of different properties of the objects in that scene. Although the image intensities corresponding to the same object may be very different between different modalities, in general they are not independent observations as the underlying physical reality, i.e., the objects or tissues, are the same. The intensity values in different images of the same scene at image positions that correspond to the same location in physical space are not independent quantities, but are statistically related measurements[8]. Knowledge of the outcome of one measurement provides some information about the underlying physical reality from which it was obtained and, therefore, reduces the uncertainty about the outcome expected from other measurements of that same reality.

In this work we use following optimization algorithms as search strategy:
(i)Simple Genetic Algorithm
(ii)Shared Genetic algorithm.
The implementation issues for GA and SGA are as follows:

A. Encoding Scheme

The geometric parameter between the data sets of the two images are translation on the x-axis(X_f), translation on the y-axis(Y_f) and the rotation (Θ_f).We define three geometric parameter as a chromosome [11,12] . Due to real-value nature of these parameter we choose the encoding technique of the chromosomes as floating-point encoding.It is fast relative to the binary coding and is also capable of representing large domains, where as in increase in domain size decrease the precision in fixed binary length representation.[15]

B. Selection

In this work we implement Roulette wheel selection method.

Roulette-wheel selection:- This is motivated by the fact that it is a commonly used selection scheme that is relatively easy to implement and understand. The strategy is also appealing due to its close resemblance with nature's own selection strategy.

C. Mutation

We use uniform mutation as the mutation operator which is one of the mutation operator for the floating-point coded chromosome.

D. Stopping criteria

We use fixed number of generation as the stopping criteria .We tested the algorithm for different number of generation. Accuracy of the image registration is calculated using the formula:

V. ERROR IN REGISTRATION

Error of the image registration is calculated using the formula: $err = \frac{\sum_{i=1}^{l}\sum_{j=1}^{m}(R(i,j)-S(i,j))}{lm}$

Where R(i,j) is the reference image and S(i,j) is the match sub image in the search space lxm. Matching is termed as mis registration if the err at the best match point exceeds the specific threshold.

VI RESULTS

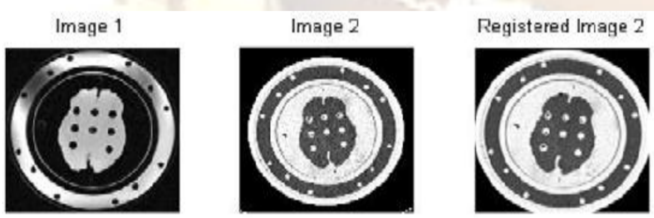


Fig. 1.1

Fig 1.2

Fig 1.3

Fig 1.1, 1.2 and 1.3 shows registration of three pairs of medical images using Genetic Algorithm with Roulette Wheel selection. Image1 is the reference image, Image2 is the input image and Registered image is the output image after registration Table1 shows the result of the algorithm GAr(Genetic Algorithm with Roulette wheel selection) for the three images showing amount of translation along the x-axis and y-axis and rotation angle required to achieve the registration.

Index	Translation On X-axis (X_f)	Translation On Y-axis (Y_f)	Rotation Angle (Θ_f)
Fig 1.1	51.0752	48.8278	-10.2901
Fig 1.2	16.7525	8.4617	-7.6914
Fig 1.3	16.3042	8.2494	-8.7529

Table 1 Result of the algorithm GAr

Fig 2.1, 2.2 and 2.3 shows registration of three pairs of medical images using Share Genetic Algorithm with Roulette Wheel selection. Image1 is the reference image, Image2 is the input image and Registered image is the output image after registration .

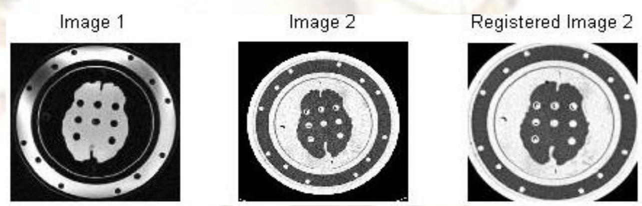


Fig. 2.1

Fig. 2.2

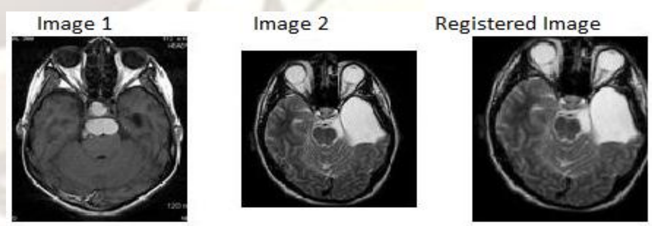


Fig. 2.3

Table2 shows the result of the algorithm SGAr(Share Genetic Algorithm with Roulette wheel selection) for the three images showing amount of translation along the x-axis and y-axis and rotation angle required to achieve the registration.

Index	Translation On X-axis (X_f)	Translation On Y-axis (Y_f)	Rotation Angle (Θ_f)
Fig 2.1	50.5196	47.4520	-10.2255
Fig 2.2	15.0336	7.6475	-11.7626
Fig 2.3	12.7481	8.6518	-6.7858

Table 2 Result of the algorithm SGAr

Table 3 shows Maximum mutual information (MMI), the error and the time elapsed corresponding to two algorithms GA and SGA with roulette wheel selection for three image pairs.

Image	**Ref. image size**	**Input image size**	**Algo.**	**MMI**	**Error**	**Time elapsed in sec.**
1	**230X 230**	**512X 512**	**Gar**	**1.1285**	**58.51**	**462.52**
			SGAr	**1.1385**	**58.47**	**453.74**
2	**130X 130**	**130X 130**	**Gar**	**0.8241**	**11.31**	**117.64**
			SGAr	**0.8225**	**11.34**	**122.03**
3	**110X 130**	**130X 129**	**Gar**	**0.8420**	**3.04**	**59.21**
			SGAr	**0.8585**	**2.22**	**55.95**

Table 3. Performance in terms of time, accuracy & MMI(Maximum mutual information)

Fig. 3.1, 3.2 and 3.3 shows the MMI(Maximum Mutual Information) value of corresponding Algorithms for Image Pair 1, 2 and 3 respectively

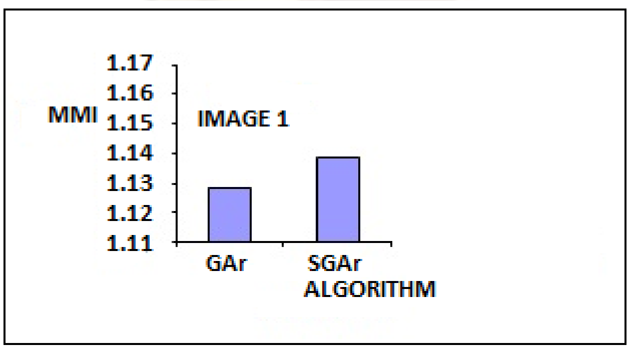


Fig 3.1

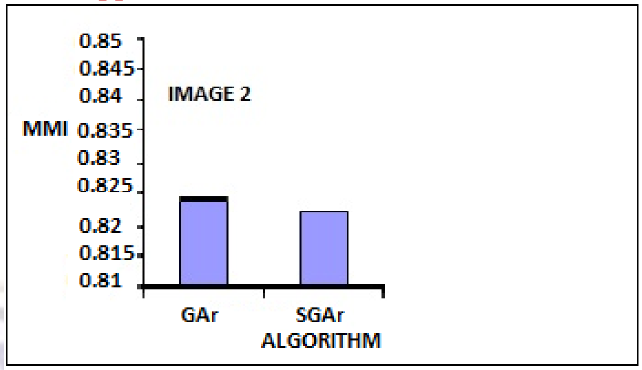


Fig. 3.2

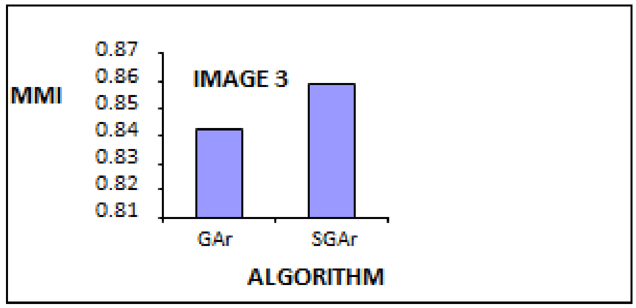


Fig 3.3

VII. CONCLUSION

In this work, we have implemented two genetic algorithms i.e. simple genetic algorithm and share genetic algorithm each both with roulette wheel selection method for registering multi modal images. We conclude from the results of our experiment as follows:

Both of the algorithms, simple genetic algorithm and share genetic algorithm are feasible alternative in performing image registration.

Genetic algorithm can be trapped in local minimum but share genetic algorithm solves this problem by maintaining diversity of solutions(chromosomes).

The selection method in the genetic algorithm highly affects the result.

We observed that Roulette-wheel is less time consuming, but share genetic algorithm is highly sensitive to calibration parameter. Therefore some time it does not give better performance.

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