A Genetic Quantum Hybridization for Multi-Sensors Image Registration.

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Abstract – **In this article, we propose a genetic quantum algorithm (GQA) for multi sensors image registration. Image registration is the most important step in image data fusion process. The image data fusion aims to integrate different but complementary scene characteristics to obtain more meaningful information about the scene under identification. This work is the fruit of a multidisciplinary rapprochement including quantum physics, computer science and genetics. We have used the mutual information as a measure of similarity between images. Some principles of quantum physics have been used to enhance the performance of genetic algorithms. A set of new operators called genetic quantum operators is defined as extension of classical genetic operators by integrating some quantum concepts such as quantum bit, states superposition and quantum measure. Also, some results of the application of this algorithm on test images have been provided.**

I. INTRODUCTION

Image registration is a key stage in the image fusion process. It aims to find the best geometric transformation that allows the superimposition of the common parts of two images. This problem is a much known combinatorial optimization problem. Many methods have been proposed for solving the image registration problem. Among these methods we can mention artificial neural networks, simulated annealing, taboo search, ant's colonies and genetic algorithm's [1] that we have extended by some quantum concepts to construct our Genetic Quantum Algorithm for the image registration.

Genetic algorithms (GAs) constitute one approximated approach that has proved its ability for solving combinatorial optimization problems. GAs uses the biological Darwinian principle to optimize a number of initial solutions encoded in structures called chromosomes.

Another search field called Quantum Computing (QC) has appeared and induced intense researches during the last decade. This evolution that takes its origins from the quantum physics principles reduces amazingly the algorithms complexity. This is offered by the possibility of parallel computing. Such possibility of parallel computing can be exploited to solve combinatorial optimization problems which use a great set of data. So quantum computing allows the possibility of designing very powerful algorithms. However, these algorithms may not be well exploited before developing of powerful quantum machines. Awaiting the construction of such machines, the idea of simulating quantum algorithms on classical computers or to combine them to other conventional methods has appeared [2]. In this optic, we are interested in studying the genetic quantum hybridization and its contribution in solving combinatorial optimization problems. Researches in the field of combination between evolutionary algorithms and quantum computing have started at the end of 90's. The purpose of this combination is to enhance the profit of each one of these two approaches by mutually inspiring each from the other.

In this paper we introduce a genetic quantum algorithm for a rigid-body Image Registration which is the fundamental step in the image fusion process.

Consequently, the rest of the paper is organized as follows. The section II gives some concepts about genetic algorithms, image data fusion and quantum computing. The proposed approach is described in the section III. The section IV illustrates some experimental results. Finally, a conclusion and some perspectives are drawn.

II. BASIC CONCEPTS

A. Genetic algorithms

Genetic algorithms derive from the Darwinian evolution theory. They were introduced in 1975 by John Holland and his team as a highly parallel search algorithm. Later, they have been mainly used as optimization device. [1, 5-9]

According to the evolution theory, within a population, only the individuals well adapted to their environment can survive and transmit some of their characters to their descendants. In genetic algorithms, this principle is traduced into the problem of finding the best individuals represented by chromosomes. So, each chromosome encodes a possible solution for the given problem and, starting from a population of chromosomes, the evolution process performs a parallel search through the solutions' space. The fitness is measured by a function related to the objective function of the problem to be solved.

Basically, a genetic algorithm consists of three fundamental operations: selection, crossover, and mutation. The selection evaluates each individual and keeps only the fittest ones among them. The others are removed from the current population. The crossover recombines two individuals to have new ones. The mutation operator induces small changes in chromosomes in order to maintain a good diversity during the optimization process.

B. Image registration

Image registration is the process of aligning two or more images of the same scene. Typically, one image, called the base image, is considered the reference to which the other images, called input images, are compared. The object of image registration is to bring the input image into registration with the base image by applying a spatial transformation to the input image. A spatial transformation maps locations in one image to new locations in another image. Image registration is often used as a preliminary step in other image processing applications. For example, we can use image registration to align satellite images of the earth's surface or images created by different medical diagnostic modalities (MRI and SPECT). After registration, we can compare features in the images to see how a river has migrated, how an area is flooded, or to see if a tumor is visible in an MRI or SPECT image.

Principally, registration approaches can be distinguished into landmark-based and Intensity-based schemes. Landmark-based schemes first extract landmarks (e.g., points, curves, surfaces) from images and then compute a transformation based on these features. With intensity-based schemes, the image intensities are directly exploited to compute the transformation [1, 4, 13-17].

- *Rigid and Non-Rigid image registration*

Generally, to align images, transformations can be divided into rigid and non-rigid transformations. The rigid methods can be used to cope with rotation and translation differences between the aligned images. Specific problems arise due to differences in image sensing for different studies, so elastic or non-rigid methods are required to cope with local differences between the images.

The elastic (Non-rigid) transformations are based on models from elasticity theory and describe local deformations. The central idea behind elastic registration is to consider images as continuous bodies and to model the geometric differences between images such that they have been caused by elastic deformation.

- *Intensity based methods for image registration*

Registration techniques are very numerous, and are generally classified according to the kind of features they use in the images to deform them. On one hand, intensity-based algorithms use the intensity of the images. On the other hand, geometric algorithms use geometric features segmented from the images, such as object boundaries.

Intensity-based approaches for elastic registration directly exploit the image intensities. The main advantage of these schemes is that an explicit segmentation of the images is not required.

C. Entropy based measures and mutual information

The entropy is a statistic defined by Shannon in 1948 that summarizes the randomness of a given random variable. The more random a variable is, the larger entropy it will have.

Given a random variable represented by a probability distribution X, i.e. a set of couples (x_i, p_i) where p_i is the probability of occurrence of the value x_i. The entropy of X is given by:

$$H(x) = -E_x[\log(X)] = -\sum p_i \log p_i \quad (1)$$

Intuitively, entropy measures the average information provided by a given distribution. When dealing with two random variables represented by two probability distributions X and Y, we are interested by answering the question: "How likely the two distributions are functionally dependant?" In total dependence case, a measurement of one distribution removes any randomness about the other. As a consequence, quantifying the independence is equivalent to quantifying the randomness. The joint entropy is given by [1, 4]:

$$H(X,Y) = -\sum\sum p(x,y)\log p(x,y) \quad (2)$$

In the case of total independence between X and Y, the joint distribution is the product of marginal distributions.

$$P(X,Y)=P(X).P(Y) \quad (3)$$

In terms of entropy, this leads to:

$$H(X,Y)=H(X)+H(Y) \quad (4)$$

The mutual information is a measure of the reduction on the entropy of Y given X and is then given by:

$$MI(X,Y)=H(X)+H(Y)-H(X,Y) \quad (5)$$

The mutual information is maximized when the two variables are totally dependant [1] [4].

D. Quantum computing

In early 80, Richard Feynman observed that certain quantum mechanical effects cannot be simulated efficiently on a computer. His observation led to speculation that computation in general could be done more efficiently if it used this quantum effects. This speculation proved justified in 1994 when Peter Shor described a polynomial time quantum algorithm for factoring numbers.

In quantum systems, the computational space increases exponentially with the size of the system which enables exponential parallelism. This parallelism could lead to exponentially faster quantum algorithms than possible classically [3].

1) Quantum bit (qubit)

The qubit is the elementary information unit. Unlike the classic bit, the qubit does not represent only the value 0 or 1 but a superposition of the two. Its state can be given by [2-4, 10-12]:

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle. \quad (6)$$

where $|0\rangle$ and $|1\rangle$ represent the classical bit values 0 and 1 respectively; α and β are complex numbers such that

$$|\alpha|^2 + |\beta|^2 = 1. \qquad (7)$$

If a superposition is measured with respect to the basis $\{|0\rangle, |1\rangle\}$, the probability that the measured value is $|0\rangle$ is $|\alpha|^2$ and the probability that the measured value is $|1\rangle$ is $|\beta|^2$ [2-4, 10-12].

2) Multiple qubits

In classical computing, the possible states of a system of n bits form a vector space of n dimensions, i.e. we have 2^n possible states. However, in a quantum system of n qubits the resulting state space has 2^n dimensions. It is this exponential growth of the state space with the number of particles that suggests a possible exponential speed-up of computation on quantum computers over classical computers. The basis of the state space of a quantum system of n qubits is: $\{|00...0\rangle, |00...1\rangle ... |11...1\rangle\}$

3) Measurement

The measurement of a single qubit projects the quantum state onto one of the basis states associated with the measuring device. The result of a measurement is probabilistic and the process of measurement changes the state to that measured. Multi-qubit measurement can be treated as a series of single-qubit measurements in the standard basis.

4) Quantum gates

The dynamics of a quantum system are governed by Schr.dinger's equation. The transformations must preserve orthogonality. For a complex vector space, linear transformations that preserve orthogonality are unitary transformations, defined as follows. Any linear transformation on a complex vector space can be described by a matrix. A matrix M is unitary if M.M'=I. Any unitary transformation of a quantum state space is a legitimate quantum transformation and vice-versa. Rotations are, for example, unitary transformations. One important consequence of the fact that quantum transformations are unitary is that they are reversible. Thus quantum gates, which can be represented by unitary matrices, must be reversible. It has been shown that all classical computations can be done reversibly.

III. THE GENETIC QUANTUM ALGORITHM FOR IMAGE REGISTRATION

Having two images I_1 and I_2 obtained from either similar or different sensors, the proposed algorithm allows the estimating of the geometric transformation which superposes the two images.

As in genetic algorithms, initial solutions are encoded in **N** chromosomes representing the initial population. The difference in our algorithm is that each chromosome does not encode only one solution but all the possible solutions by putting them within a superposition.

The geometric transformation that aligns the image I_2 to I_1 is rigid-body, i.e. a combination of a rotation, a translation and a scale change. A chromosome encodes the four parameters, which are the rotation angle θ, and the translation parameters dx and dy, and the scale factor s.

Having such parameters, the position of each pixel in the resulting image (x_2, y_2) can be calculated from the original position (x_1, y_1) as follows:

$$\begin{pmatrix} x_2 \\ y_2 \end{pmatrix} = \begin{pmatrix} t_x \\ t_y \end{pmatrix} + s \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x_1 \\ y_1 \end{pmatrix} \qquad (8)$$

Each parameter is encoded using a binary representation. A bit in a chromosome does not represent only the value 0 or 1 but a superposition of the two. In this way, all the possible solutions are represented in a chromosome and only one solution among them can be measured at each time according to the probabilities $|\alpha_i|^2$ and $|\beta_i|^2$. A chromosome is then represented by:

$$\left(\begin{array}{c|c|c|c} \alpha_1 & \alpha_2 & \cdots & \alpha_m \\ \beta_1 & \beta_2 & \cdots & \beta_m \end{array} \right)$$

Where each column represents a single qubit. In our algorithm α_i and β_i are real values only.

Initially we generate randomly 3 chromosomes. Each one is composed of N=32 qubits, 8 qubits for each parameter:

$-127 \leq dx \leq +127$;
$-127 \leq dy \leq +127$;
$0.5 \leq s \leq 2$ $(0.5 + (0/255) \leq s \leq 0.5 + (255/255))$;
$0 \leq \theta \leq 2\pi$ (the interval is subdivided into $2^8 = 256$ different values)

dx and *dy* are the 2D translation parameters and belong to the interval , *s* is the Scale Factor and θ is the rotation angle.

During the whole process we keep in memory the global best solution. The algorithm consists on applying cyclically 4 quantum genetic operations:

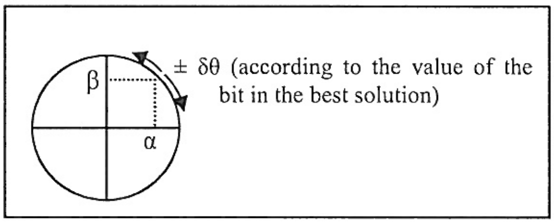

Fig 1. Quantum interference

The first operation is a quantum interference which allows a shift of each qubit in the direction of the corresponding bit value in the best solution. That is performed by applying a unitary quantum operator which achieves a rotation whose angle is function of α_i , β_i and the value of the corresponding bit in the best solution.

δθ is chosen equal to π/120. The following table gives the value of the rotation angle in function of α, β and the bit's value in the best solution.

The second operation is a crossover performed between each pair of chromosomes at a random position. Here is an example of a crossover between two chromosomes.

Table1. Lookup table of the rotation angle

A	β	Reference bit value	Angle
> 0	> 0	1	+δθ
> 0	> 0	0	-δθ
> 0	< 0	1	-δθ
> 0	< 0	0	+δθ
< 0	> 0	1	-δθ
< 0	> 0	0	+δθ
< 0	< 0	1	+δθ
< 0	< 0	0	-δθ

a = [**0.9887 0.4132** | *0.7955 0.8733 0.7676* ; **0.0224 0.8293** | *0.3672 0.2373 0.4108*]

b = [*0.3757 0.3368* | **0.7394 0.1644 0.4073** ; *0.8588 0.8866* | **0.4534 0.9730 0.8341**]

⇩

c = [**0.9887 0.4132 0.7394 0.1644 0.4073** ; **0.0224 0.8293 0.4534 0.9730 0.8341**]

d = [*0.3757 0.3368 0.7955 0.8733 0.7676* ; *0.8588 0.8866 0.3672 0.2373 0.4108*]

Fig 2. Quantum crossover

At each iteration, we obtain from the 3 initial chromosomes 6 new ones. The population becomes composed of 9 chromosomes.

The third operation consists on a quantum mutation which will perform for some qubits, according to a probability, a permutation between their values α_i and β_i. That will invert the probabilities of having the values 0 and 1 by a measurement. An example is given here:

0.2383	0.1079	**0.5057**	0.8337
0.9712	0.9942	**0.8627**	0.5522
		↓	
0.2383	0.1079	**0.8627**	0.8337
0.9712	0.9942	**0.5057**	0.5522

Fig 3. Quantum mutation

Finally, we perform a selection of 3 chromosomes among the 9 chromosomes. For this, we apply first a measurement on each chromosome to have from it one solution among all those present in superposition. But unlike pure quantum systems, the measurement here does not destroy the states' superposition. Since our algorithm operates on conventional computer and does not require the presence of a quantum machine, it is possible and in our interest to keep all the possible solutions in the superposition for the next iterations. For each measurement result, we extract the transformation parameters and use them to transform the second image and have a calculated image. To evaluate the quality of a solution, we compute the mutual information between the first image (reference image) and the calculated image. Greater the mutual information is, better the solution will be considered. Afterwards, we select the 2 chromosomes from which derive the 2 best results and we select also randomly one chromosome from the others (to maintain a good diversity). So we have all in all 3 chromosomes which form the new population. The global best solution is then updated if a better one is found and the whole process is repeated until we have an acceptable solution.

IV. EXPERIMENT AND RESULTS

We have applied this algorithm on many pairs of multi-sensors images. This section represents some obtained results of this algorithm application for registering images.

The following figures show at the above (of each figure) respectively the reference image and the mutual information evolution diagram. The image to be aligned and the result of the rigid-body transformation are given in the other part of figures.

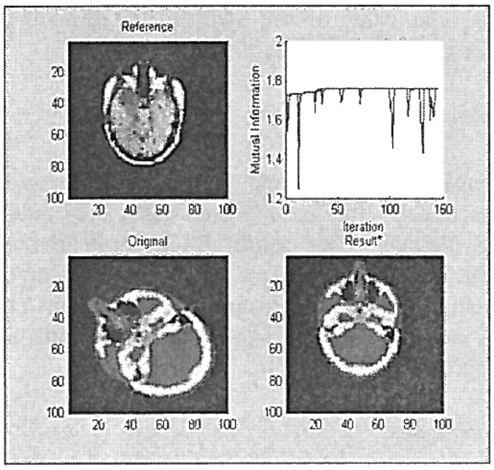

Fig 4 . Rigid-Body registration with a positive rotation and a scale decreasing.

Initial mutual information: 1.4390
Transformation parameters: tx: 8.0000 ty: 11.0000
s: 0.8471 θ : 0.9774 rad
Final mutual information: 1.7555

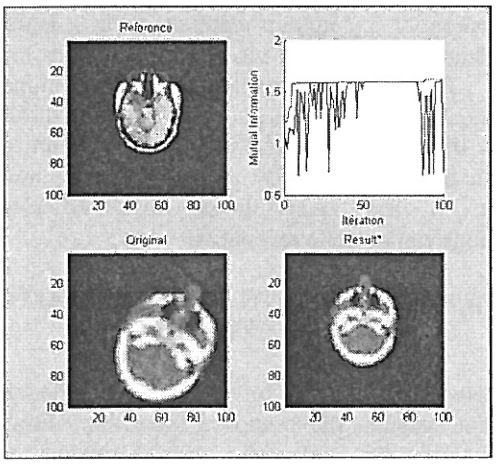

Fig 5 . Rigid-Body registration with a negative rotation and a scale decreasing.

Initial mutual information: 1.0958
Transformation parameters: tx: 15.0000 ty: 10.0000
s: 0.7118 θ: -0.4363 rad
Final mutual information: 1.6209

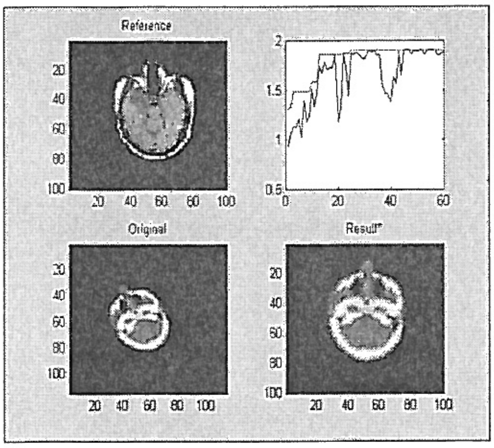

Fig 6 . Rigid-Body registration with a positive rotation and a scale increasing.

Initial mutual information: 1.4576
Transformation parameters: tx : 11.0000 ty : 2.0000
s : 1.2471 θ : 0.5061 rad
Final mutual information: 1.9032

We have also applied this algorithm for registering mono modal images and we have obtained good results.

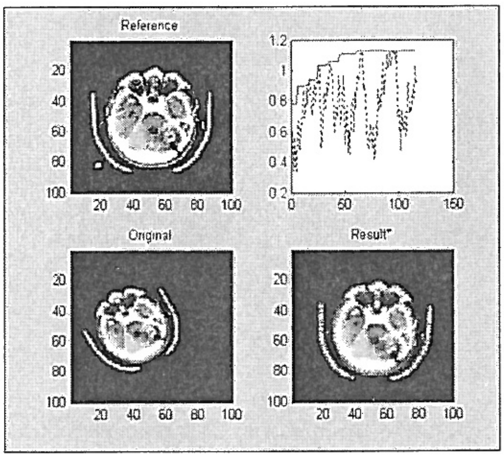

Fig 7. application on a mono modal images

The following figure represents the global best solution (on the whole process) and the local best solution (on each generation). Also this diagram shows the impact of the interference on the local solutions.

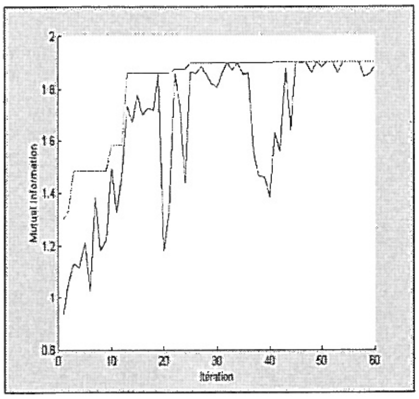

Fig 8. Global best (with red line) solution and local best solution (with blue line).

V. CONCLUSION

In this article we have presented a genetic quantum algorithm for multi sensors image registration. This GQA is based on the maximization of the mutual information between the reference and result images. The use of the mutual information allows the registration of images coming from different sensors. That will provide the possibility of data fusion. According to the obtained results, this algorithm assures convergence and offers very good solutions. We have used the algorithm for optimizing a rigid-body registration parameters but we may extend it for affine transformations.

This algorithm, compared to genetic algorithms, provides the advantage of giving a greater diversity by using quantum coding of solutions, i.e. all the solutions exist within each chromosome and what change are the probabilities to have one of them as a result of a measurement. Therefore, the size of the population does not need to be great. So, we have chosen to have only 3 chromosomes at the origin of each generation. Another advantage is that the interference provides in someway a guide for the population individuals and reinforces therefore the algorithm convergence. The proposed GQA has the advantage of using a small population size and the number of necessary iterations to have acceptable solution is significantly smaller (generally about 100 iterations). The obtained results lead us to think to extend it to other important optimization problems.

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