Tile Image Registration Based on Improved Adaptive Genetic Algorithm

LI Wei-qing
School of Engineering and Technology,
China University of Geosciences,
No.29, Xueyuan Rd., Haidian District,
Beijing, 100083, China

WANG Qun
School of information and Technology,
China University of Geosciences,
No.29, Xueyuan Rd., Haidian District,
Beijing, 100083, China

WANG Cheng-biao
School of Engineering and Technology,
China University of Geosciences,
No.29, Xueyuan Rd., Haidian District,
Beijing, 100083, China

CHEN Guang-she
Beijing Hongdizhanye Trading Com. Ltd.,
RM. 2504, 14 Build, Yongtai Residential,
Qinghe Town, Haidian District,
Beijing, 100085, China

Abstract - *An improved adaptive Genetic Algorithm was proposed, and the method was applied to the optimization process of tile image registration. This paper improved traditional Genetic Algorithm in three aspects. The probability of crossover and mutation was adjusted in a dynamic way according to the change of the fitness of individual during the evolutionary process and in different way when the evolution was in different phase. Random dislocation arithmetic crossover that non-allelic genes of the two father individual did crossover operation was introduced to prevent invalid crossover and to increase searching space and convergence speed so that global optimum was obtained even if some generations fell into premature convergence. Two-population immigrant strategy based on maximum entropy was applied to obtain diversification gene. The method was able to overcome the disadvantage of traditional adaptive Genetic Algorithm which tends to fall into a local optimum answer. The experiment showed the validity and feasibility of this algorithm.*

Keywords: Genetic Algorithm, Image registration, Mutual information, Maximum entropy, Random dislocation crossover operator

1 Introduction

Image processing and pattern recognition have been generally applied in online inspection of tile quality. A common practice is that tiles are divided several groups by comparing the image of sample tiles with ones of online tested tiles to differentiate kinds of fault such as chromatism, size, dirty point etc. The fact is that the position and direction of the online tested tiles are inevitably different and cause various errors which influence the effect of image processing and pattern recognition. Therefore, it is necessary to do a registration to the image of inspected tile with the image of sample tile as reference before features are extracted. This practice is generally called image registration [1] which make the point in the inspected tile image is identical to the corresponding point in the sample tile image through one or a series of image transformations generally including rigid-body transformation, affine transformations, projection transformations and non-linear transformations. It is expected that the same point has the same position in two images, but it is impossible. Therefore, it is required to find a method that makes the error so small that it can be acceptable in application.

2 Image registration

The methods for image registration usually include Fourier transformation, point mapping, elastic model and cross-correlation. The technology of image registration went through a development process from registration methods based on lightness or salient attributes (such as edge, curve, surface etc) to ones based on statistical feature. The later is characteristic of better robust, higher precision and less human intervention. Cross-correlation is a kind method of image registration based on statistical feature (such as pixel comparability) where image registration applies all of the pixels in the image and introduces the application of entropy and mutual information. This method has been applied in many domains because it can reach a high precision answer approaching accuracy of sub-pixel.

Some algorithms based on Cross-correlation have been applied widely such as Simplex, Powell and Simulated Annealing [2]. Every algorithm has its advantages and disadvantage. For instance, the computation of Simplex and Powell method is simple because their differential coefficient needn't be computed. However, Powell method may fall into a local optimum and convergence speed is so slow that it will consume exponential runtime in some conditions. Further more, these two methods are not able to solve complex problems. Simulated Annealing method is able to dap out the trap of local optimum. Nevertheless, it consumes more time and sometimes probably goes into error searching direction.

Genetic Algorithm (GA) based on revolution theory is a kind of effective searching and optimization method which has been applying in many domains. Its prominent advantage is that it has few limits to almost any problem which need optimized and its robust and implicit parallelism make it possible to effectively do global searching in the sense of probability. This method was applied in this paper because it is able to solve complicated problem with reasonable complexity of computation [3].

However, traditional Genetic Algorithm has some obvious disadvantages. For example, this algorithm will cause premature convergence when the ability of crossover operator to produce new chromosome slows down so that the diversity of population depresses during its evolutionary process. Another insufficiency is its slow convergence speed. There are many researches about these problems. Whitley [4] though that two most important factors influencing this problem are the diversity of population and the selection pressure. Overmuch selection pressure is the most important one. Though it can improve the convergence speed, it also speeds up the death of individual with low fitness. So, with the loss of diversity aggrandizing and searching space reducing, the result converges into local optimum. On the other hand, small selection pressure can increase the probability of obtaining global optimum, but it also reduces the searching efficiency so that the convergence speed is too slow to meet need. It is important to balance the relation between selection pressure and keeping diversity of population in order to obtain a good searching result.

In present, two methods were applied to adjust the selection pressure and to prevent premature convergence. One is to modify the selection operator, and the other is to do fitness scaling to fitness function. De Jong [5] put forward a method that the problem was solved by producing several kinds of selection operator's variant of roulette wheel selection. Whitley [4] brought about a kind of selection operator based on rank. Goldberg [6] put forward three kinds of fitness scaling. Michalewicz [7] put forward a modGA algorithm that the probability of premature convergence was reduced by cutting down the probability that individuals with high fitness bring the same offspring as themselves. Lately, Chang-Yong [8] introduced Entropy-Boltzmann selection operator to GA.

Some references showed other improvements in GA such as: GA based on fuzzy encoding [9], compact GA [10] by applying optimization selection, GA based on multi-agent [11] etc. Several references [12] [13] [14] showed that the ability of global searching was improved by mending genetic operator. Tow references [15] [16] put forward a method that the ability of local searching was improved by mending mutation operator. Another reference [2] showed a method that the ability of global searching was improved by applying Simulated Annealing algorithm. A method [17] [18] [19] [20] [21] [22] made GA converge into global optimum or secondary optimum by applying dynamic crossover and mutation probability to achieve the diversity of population. A reference [23] thought that crossover operator is the key factor to solve premature convergence problem. Every one of these methods solved some given problems, however, none of them can solve in nature the conflict between convergence speed and diversity of population.

This paper obtained a better result of tile image registration by the practice that registration measurement applied mutual information and searching strategy applied improved adaptive GA after some algorithms were analyzed.

3 Image registration base on maximum mutual information

3.1 Mutual information

Mutual information [24], a conception in Information Theory, describes statistics relativity between two random variables. It is a measurement that the information of one variable includes that of the other one and it can be expressed by their entropy:

$$I(A,B) = H(A) + H(B) - H(A,B) \qquad (1)$$

If given image is two dimension, H (A), H (B) and H (A, B) can be expressed as follows:

$$H(A) = -\sum_{m_A=1}^{M_A}\sum_{n_A=1}^{N_A} f(m_A,n_A)\log_2 f(m_A,n_A) \qquad (2)$$

$$H(B) = -\sum_{m_B=1}^{M_B}\sum_{n_B=1}^{N_B} f(m_B,n_B)\log_2 f(m_B,n_B) \qquad (3)$$

$$H(A,B) = -\sum_{m_B=1}^{M_B}\sum_{n_B=1}^{N_B} \mathrm{P_{AB}}\log_2 \mathrm{P_{AB}} \qquad (4)$$

$$\mathrm{P_{AB}} = f(m_A,n_A)f(m_\mathrm{B},n_\mathrm{B}) \qquad (5)$$

I (A, B) is the mutual information of the image A and B. H (A) (or H(B)) is the entropy of image A (or image B). They express bit's average value of every gray level of image A or image B. H (A, B) is the joint entropy of image A and B. $f(m_A,n_A)$ or $f(m_B,n_B)$

is gray probability function of image A or B. P_{AB} is joint probability of image A and B. n_A (or n_B) is gray level ordinal mumber in image A (or image B). N_A (or N_B) is the total gray level number of image A (or image B). m_A (or m_B) is pixel ordinal number in image A (or image B). M_A (or M_B) is the total pixels number of image A (or image B). The mutual information reaches the maximum when the position of the two images is uniform. The practice of this method is that one or a series of space transformation were searched based on the rule that the mutual information of the transformed image reaches maximum.

Because mutual information is sensitive to overlap region, Studholme [25] and Maes [26] respectively put forward normalized expressions of mutual information, which can reflect better the change of registration function.

$$I'(A,B)=\frac{H(A)+H(B)}{H(A,B)} \qquad (6)$$

$$\mathrm{I}''(A,B)=\frac{2I(A,B)}{H(A)+H(B)} \qquad (7)$$

3.2 Model of registration transformation

Registration result was mainly decided by feature spaces, similarity measurement, searching space and search strategy.

In registration, the first step is the selection of feature space which can be the easily recognized features or statistic feature. In this paper, planar coordinate systems were found to do rough registration, whose origin point was gravity center of gray. Firstly, one image was selected as a referent image R, and the other image was selected as a float image F. Then, the rigid transformation from planar coordinate of image F to that of image R can be express as follows:

$$\mathrm{P_R}-C_R=R_{xy}(\Phi_{xy})\cdot(\mathrm{P_F}-C_F)+t(t_x,t_y) \qquad (8)$$

P_F (or P_R) expresses planar coordinate matrix of image F (or image R). C_F or C_R is individually the geometry center of the two images. R_{xy} (Φ_{xy}) is a 2×2 rotation matrix. Φ_{xy} expresses the rotation angle around of point (x, y). $t(t_x, t_y)$ is translation vector. t_x or t_y individually expresses translation distance in the direction x or y axis.

Registration process is a multi-parameter optimization one whose aim is to obtain the optimum of the parameters of t_x, t_y, Φ_{xy} and space transformation which can make the mutual information maximum.

4 Improved adaptive GA

Traditional adaptive GA changes crossover probability P_c and mutation probability P_m in a dynamic way according to the change of the fitness of individual. In tile inspecting process, this practice was not all able to obtain wanted result because the algorithms sometimes fell into local optimum when the evolution generations reached a certain value and it was difficult to reproduce new individual. In order to dap out the trap of local optimum, this paper improved the GA by applying improved adaptive probability of crossover and mutation, random dislocation arithmetic crossover and two-population immigrant strategy based on maximum entropy to obtain the global optimum.

4.1 Improved adaptive probability of crossover and mutation

In tile registration process, the result tended to fall into a local optimum with Crossover probability P_c and mutation probability P_m according to traditional adaptive GA. The improved adaptive algorithm, which changed P_c and P_m in a dynamic way according to the change of the fitness of individual and in different way when the evolution was in different phase, solved this problem. P_c and P_m have great influence on the result of GA. This paper thought bigger crossover probability and smaller mutation one should be selected when (9) is true in order to speed up the convergence because, in this phase, the evolution is in prophase and the dispersion of the fitness is bigger. Otherwise, smaller crossover probability and bigger mutation one should be selected to enlarge the searching scope and prevent falling into local optimum other than global one because it is easy to appear premature convergence when, in this phrase, the evolution is in anaphase and the dispersion of the fitness of the population is changing into smaller value.

$$\frac{f_{\max}-f_{\mathrm{avg}}}{f_{\mathrm{avg}}}>k \qquad (9)$$

K is a constant. $f_{\max}$ is the maximum fitness of the population. f_{avg} is the average fitness of the population.

In this paper, the prophase value of P_c and P_m were selected as follows:

$$P_c=P_{c0}\times e^{(\frac{f_{\max}-f_{\mathrm{avg}}}{f_{\mathrm{avg}}}-k)/(\frac{f_{\max}-f_{\mathrm{avg}}}{f_{\mathrm{avg}}})} \qquad (10)$$

$$P_m=P_{m0}\times e^{-(\frac{f_{\max}-f_{\mathrm{avg}}}{f_{\mathrm{avg}}}-k)/(\frac{f_{\max}-f_{\mathrm{avg}}}{f_{\mathrm{avg}}})} \qquad (11)$$

P_{c0}和P_{m0} was respectively the initial value of P_c and P_m. This paper chose P_{c0} as o.3 and P_{m0} as 0.2.

The anaphase value of P_c and P_m were selected as follows:

$$P_c=P_{c0}\times e^{(\frac{f_{\max}-f_{\mathrm{avg}}}{f_{\mathrm{avg}}}-k)/k} \qquad (12)$$

$$P_m=P_{m0}\times e^{-(\frac{f_{\max}-f_{\mathrm{avg}}}{f_{\mathrm{avg}}}-k)/k} \qquad (13)$$

4.2 Random dislocation arithmetic crossover

Invalid crossover where children are the same as their parents is likely to appear when evolution enters into local optimum. This paper introduced random dislocation arithmetic crossover method that non-allelic genes crossover operation was applied to prevent invalid crossover. This method greatly increased searching space and convergence speed and obtained global optimum even if some generations fell into premature convergence. The result showed that this method is able to dap out local optimum.

4.3 Two-population immigrant strategy based on maximum entropy

This paper introduced two-population immigrant strategy based on maximum entropy to prevent falling into local optimum. There were two populations in this method. The first one is a master population and the second one is an additional population. In the process of crossover and mutation, the first population selected improved adaptive crossover and mutation probability, and the second population selected bigger mutation probability to guarantee global searching ability of evolution computation.

Two initial populations were produced based on maximum entropy. Whenever a new initial individual was randomly produced, the entropy of new population which was composed of the new and produced initial individual were computed, and only when the entropy is bigger than given threshold, did it qualify for joining into initial population in order to obtain diversification gene.

Immigrant operation was done to supply new individuals every certain number generation. Fitness should be computed before immigrant operation because only the individuals in the population with bigger average fitness did immigrate into the other one. If the average fitness of the second population was bigger, some excellent individuals in this population were immigrated into the first one and replaced some individuals in the first population whose fitness was smaller. Otherwise, some excellent individuals in the first population were immigrated into the second one and replaced some individuals who were similar with the immigrated individuals in the first population other than those whose fitnesses were smaller. Thus, the second population was able to keep diversity of individual and supplied diversity individuals for the first population, which is beneficial to answer's dapping out local optimum and reaching global one.

4.4 Steps of the algorithms

The steps of the improved adaptive genetic algorithm applied in this paper to image registration were as follows:

1) Firstly, every input parameter was initialized.

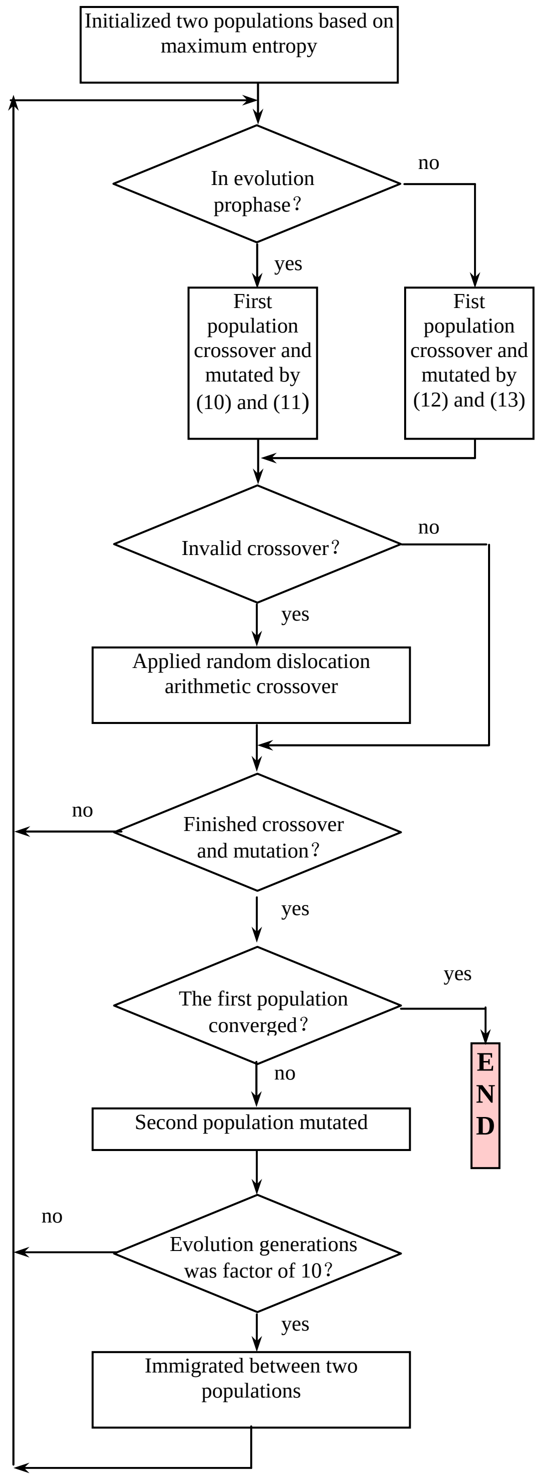


Fig 1: the flow chart of improved algorithm

Secondly, the three parameters （t_x， t_y, Φ_{xy} ） were encoded with float code in order. Thirdly, the fitness (usually is object function) of every individual was computed. The fitness of this paper was the value that the mutual information of the individual subtracts the minimum mutual Information of the individual in this generation.

$$f_i(A,B) = I_i(A,B) - Min(I_i(A,B)) \qquad (14)$$

$f_i(A,B)$ is the finess of tested image. I (A,B) is the mutual information of tested image and sample one.

2) The result of the first population was judged if the stop rule (15) was true or evolution generations reached the maximum given generation. An optimum was obtained if it was true. Otherwise, went to step 3).

$$I_i(A,B) - I_{i-1}(A,B) \le 0.001 \qquad (15)$$

In the evolution process of the first population, which phase it was in needs judged, prophase or anaphase? Bigger crossover probability and smaller mutation one were selected according to (10) and (11) when it was in prophase, and smaller crossover probability and bigger mutation one were selected according to (12) and (13) when it was in anaphase.

3) Roulette wheel selection was applied to select the individual, whose fitness was bigger, to crossover and judged if it was invalid crossover. If it was invalid crossover, random dislocation arithmetic crossover would be applied.

4) Mutation was done and evolution generation was judged. Two-population immigrant strategy based on maximum entropy would be done to exchange some individuals every ten generation.

5) Returned step 2).

Fig.1 showed the flow chart of improved algorithm.

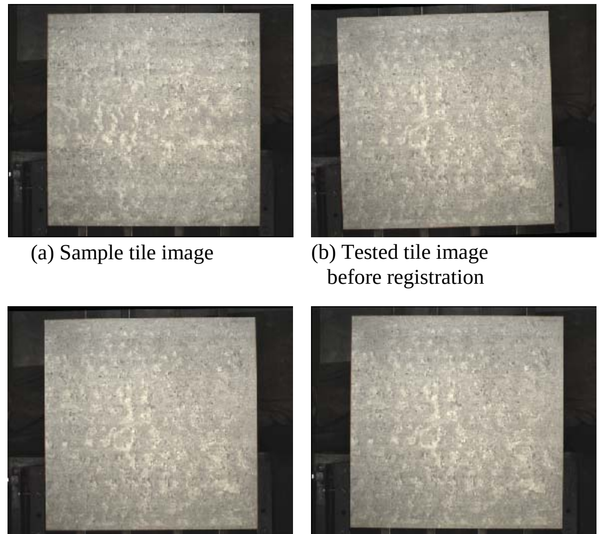
4.5 Results

Table 1 showed the data of some experiments. Every one of the 5 group data in table 1 was composed of the results of one sample tile image and 20 tested tile images. It shows that the result of improved adaptive GA is is much better than that of traditional adaptive GA.

Table 1 : Data comparing improved algorithm with traditional one

			normalized average mutual information after registration	
No.	Entropy of sample tile image	Average entropy of tested tile image	Traditional adaptive GA	Improved adaptive GA
1	3824．9	3517．3	0．79	0．97
2	3673．5	3210．6	0．72	0．93
3	3749．7	3497．9	0．75	0．95
4	3893．1	3649．2	0．81	0．98
5	3786．4	3582．7	0．69	0．91

Fig.2 showed that the result is the same as the result of table 1.



(a) Sample tile image

(b) Tested tile image before registration

(c) Tested tile image after registration with traditional adaptive GA

(d) Tested tile image after registration with improved adaptive GA

Fig.2 The tile image registration results

5 Discussion

By introducing complex adaptation process of natural biologic system and simulating evolution mechanism of biology to form artificial intelligence system, GA provided a universal frame to solve the optimization for complex problem. It is independent of provided domain, therefore, GA has been used successfully in many domains such as: function optimization, optimal grouping, Job shop Scheduling Problem, auto-control, robot intelligent control, image processing and pattern recognition, artificial life, genetic programming and machine learning.

With the development of imaging technology, the improvement of image resolution rate and the augment of image data, it is very significant to apply high-performance registration method based on GA because GA is characteristic of inherent parallelism. However, traditional GA tends to fall into local optimum. This paper introduced improved adaptive probability of crossover and mutation, random dislocation arithmetic crossover and two-population immigrant strategy based on maximum entropy, which are able to overcome the premature convergence and obtain global optimum.

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References

[1] ChristianH,etal,Overview of image matching technique, WWW_DGR_PHOT,1998.10

[2] Mahfoud S W and Goldgerg D E. A genetic algorithm for parallel simulated annealing [J]. Parallel Problem Solving from Nature 2, North Holland, 1992, 301 ~ 310

[3] Wang X P, Cao L M. Genetic Algorithms - Theory, Application and Software Realization. Xi'an, China: Xi'an Jiaotong University Press, 2002 (in Chinese)

[4] Whitley D. The genitor algorithm and selection pressure: why rank-based allocation reproduction trials is best [A}. In: Schaffer J, ed. Proceedings of 3rd International Conference on Genetic Algorithm. Los Altos: Morgan Kaufmann Publishers, 1989

[5] De Jong KA. An analysis of the behavior of a class of genetic adaptive system [D}. University of Michigan, 1975

[6] Goldberg D E. Genetic algorithms in search, optimization and machine learning [M}. Addison-Wesley Publishing Company, 1988

[7] Michalewicz. Genetic Algorithm + Data Structures = Evolution Programs, ed Rev edition [M}. Springer-Verlag, 1996

[8] Chang-Yong Lee. Entropy-Boltzmann selection in the genetic algorithms. System, Man and Cybernetics [J}. Part B, IEEE Transactions on, 2003. 13:138-149

[9] kumar S S, Irwin G W. Fuzzy Coding of Genetic Algorithms. IEEE Trans on Evolutionary Computation, 2003 7(4): 344-355

[10] Wook A C, Ramakrishna R S. Elitism-Based Compact Genetic Algorithms. IEEE Trans on Evolutionary Computation, 2003, 7(4): 367-385

[11] Zhong W, Liu T. Xue M, Jiao L. A Multi-agent Genetic Algorithms for Global Numerical Optimization. IEEE Trans on Systems, Man, and Cybernetics-Part B: Cybernetics, 2004,34(2): 1128-1141

[12] Schaffer D, Eshelman L J, Offutt D. Spurious Correlations and Premature Convergence in Genetic Algorithms. In: Rawlin G J E, ed. Foundations of Genetic Algorithms-1. San Mateo: Morgan Kaufmann, 1991, 102-114

[13] De Jong K A, Spears W M. A Formal Analysis of the Role of Multi-Point Crossover in Genetic Algorithms. Annals of Mathematics and Artificial Intelligence, 1992, 5(1): 1-26

[14] Qi X, Palmieri F. The Diversification Role of Crossover in Genetic Algorithms. In: Proc of the 5th International Conference on Genetic Algorithms. Urbana-Champaign, USA, 1993, 132-137

[15] Oliver L M. A study of permutation crossover operators on the traveling salesman problem [C]. Proc. of 2th International Conference on Genetic Algorithms, 1987, 224 ~ 230

[16] Lee. S and D. Lson. A gradient algorithms for chance constrained nonlinear programming [J}. European Journal of Operational Research, 1977,11(1):343 ~ 369

[17] Bessaou M, Siarry P. A Genetic Algorithm with Real-Value Coding to Optimize Multimodal Continuous Functions. Structure Multidiscipline Optimization, 2001,23(1): 63-74

[18] Libelli S M, Alba P. Adaptive Mutation in Genetic Algorithms. Soft Computing, 2000, 4(2): 76-80

[19] Yang J M, Kao C Y. Integrating Adaptive Mutations and Family Competition into Genetic Algorithms as Function Optimizer. Soft Computing, 2000, 4(2): 89-102

[20] 19 、 Li T H, Lucasius C B, Kateman G. Optimization of Calibration Data with the Dynamic Genetic Algorithms. Analytic Chimica Acta, 1992, 268: 123-134

[21] Schraudolph N N, belew R K. Dynamic Parameter Encoding for Genetic Algorithms, Machine Learning, 1992, 9:9-21

[22] Lee M A, Takagi H. Dynamic Control of Genetic Algorithms Using Fuzzy Logic Techniques. In: Proc of the 5th International Conference on Genetic Algorithms. Urbana-Champaign, USA, 1993, 76-83

[23] Booker L. Improving Search in Genetic Algorithm. In: Davis L, ed. Genetic Algorithms and Simulated Annealing. Los Altos: Morgan Kaufmann Publishers, 1987, 61-73

[24] Shannon C E. A Mathematical Theory of Communication, Bell System Tech. [J],1948,27:379-423,623-656.

[25] C.Studholme, D.L.G.Hill, D.J.Hawkes, An overlap invariant entropy measure of 3D medical image alignment [J]. Pattern Recognition, 1999, 32(1):71-86.

[26] F.Maes,A.Collignon,D.Vandermeulen,et al. Multimodality image registration by maximization of mutual information[J].IEEE Transactions on Medical Imaging,1997,16(2):187-198.