EVALUATION OF OPTIMIZATION METHODS FOR MEDICAL IMAGE REGISTRATION

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ABSTRACT

In modern medicine, digital subtraction angiography is a powerful technique for the visualization of blood vessels in a sequence of X-ray images. A serious problem encountered in this technique is misregistration of images due to patient motion. In this paper, we present two different image registration methods applied to the angiographic images. The coordinate mapping that relates the two images is found using an optimalization procedure. This work compares the two optimalization methods (Simulated Annealing , Control Random Search) combined with two similarity criterions (Mutual information, Angle criterion). The optimalization methods are tested on manually deformed CT images of a leg.

1. INTRODUCTION

The aim of registration is to find the spatial mapping that will bring the moving image into alignment with the fixed image. It can be treated as an optimization problem formalized as finding the optimal parameter vector α_0 of spatial transform T_α,

$$\alpha_0 = \arg\min C\big(f(\bar{x}), g(T_\alpha(\bar{x}))\big) \tag{1}$$

where f is the fixed (reference) image and g is the floating image to be registered, which is transformed by T_α to coordinates of the fixed image. The registration quality is evaluated by the global similarity criterion C [2].

In this paper, two different optimization methods are compared with respect to speed, accuracy and robustness. We use affine geometrical transform, where the nearest-neighbor interpolation is used. In general, an affine transform is composed of linear transformations (rotation, scaling or shear) and translation (Fig. 1.).

The remainder of this paper is organized as follows. The definition of optimalization methods is provided in Section 2. Section 3 contains description of used criterial function. The experimental results of these registration methods are described in Section 4. This paper concludes in Section 5.

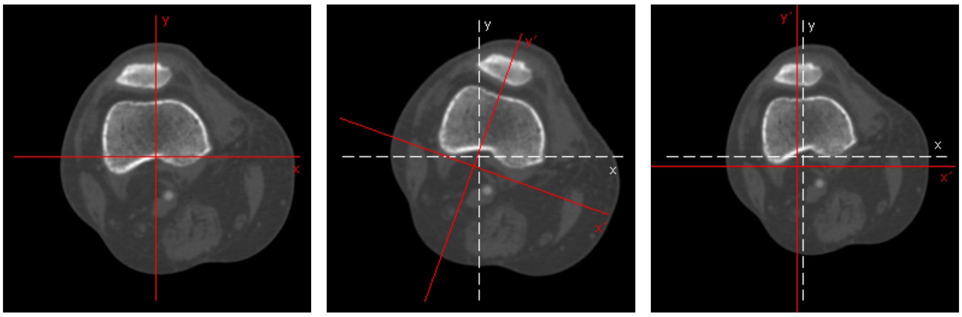

Fig.1. Schedules of affine transformation

2. OPTIMIZATION METHODS

In this section, the basic concept of using optimalization methods - Simulated annealing (SA) and Controlled random search (CRS), is briefly introduced.

2.1. SIMULATED ANNEALING

Inspired from the principles of the metallurgic annealing, Kirkpatrick proposed an optimization method named simulated annealing. The energy of a material can be viewed as a cost function of the optimization problem. The different states of this material can be considered as solutions of the cost function. The general structure of the simulated annealing algorithm is the following [2]:

```
Initialization (X actual solution,T actual)
while (stop criterion non satisfied)
    do
        while (quasi equilibrium not reached at actual temperature);
        do
          generate a neighbor solution X';
          if (acceptation (cost(X), cost (X'), Tactual);
          then
            update X;
        end-while
    anneal (Tactual);
end-while
```

Initially the temperature is very high i.e. all the solutions of the search space are acceptable. The simulated processes by generating and accepting a neighbor solution until quasi equilibrium reached. Annealing will follow until satisfying a stop criterion. Being probabilistic, the simulated annealing process can accept a solution that is worst than the actual solution. With this acceptation strategy, simulated annealing avoids the trap of local optima. Calculating an "admission" probability makes accepting a neighbor solution.

2.2. CONTROL RANDOM SEARCH

Controlled random search (CRS) is a kind of contraction process where an initial sample set of points is iteratively contracted by replacing the worst point with a better one. For generating a new trial point we use the non - deterministic rule named heuristic. We determined four heuristic which alternating during the course of search. The CRS algorithm can be written in pseudo-code as follows [3].

```
generate P (population of N points in D at random);
find xmax (the point in P with the highest function value);
repeat
   generate a new trial point y ∈ D by using a heuristic;
   if f(y) < f(xmax) then
      xmax := y;
      find new xmax;
   endif
until stopping condition;
```

where D is the dimension of searching parameters and f(y) is the criterial value of the generated set of parameters.

3. CRITERIAL OF SIMMILARITY

3.1. MUTUAL INFORMATION

The MI, originating from the information theory, is a measure of statistical dependency between two data sets and it is particularly suitable for registration of images from different modalities. MI between two random variables X and Y is given by (2):

$$MI(X,Y) = H(Y) - H(Y/X) = H(X) + H(Y) - H(X,Y) \tag{2}$$

where H is the entropy function of the image intensities. The method is based on the maximization of MI [4].

3.2. ANGLE CRITERION

The angle criteria is the criteria based on the criterion of correlation coefficient and represent the difference angle between the image vector x and y. This criterion is naturally normalized to the range <-1,1> and can therefore be used for estimating the absolute degree of similarity [1].

$$C_A(\bar{x},\bar{y}) = \frac{\bar{x}\,\bar{y}}{|\bar{x}|\cdot|\bar{y}|} = \frac{\sum_{i=1}^{N} x_i y_i}{\sqrt{\sum_{i=1}^{N} x_i^2 \cdot \sum_{i=1}^{N} y_i^2}} \tag{3}$$

4. EXPERIMENTAL RESULT

In this paper, we present the results for a CT slice, where the deformation with many different parameters was implemented. To compare the accuracy of implemented methods, we define the *average displacement distance* (ADD) (4).

$$ADD(\bar{x},\bar{y}) = \frac{1}{|N|}\sum_{i=1}^{N}\|x_i - y_i\| \tag{4}$$

We compared the images visually. The computational time of the optimization methods are in the Tab. 1 as the ADD values. The fields *´similarity´* describe value of the similarity function of the best vector of parameters.

mean	CRS - Angle	CRS - MI	SA - Angle	SA - MI
Time [s]	12,6	24,48	1,89	2,59
ADD	0,5952	0,7503	1,7629	2,7077
Similarity	0,0025	-2,45	0,0087	-2,39

In the sence of accuracy the best results gives the method CRS combined with the Angle similarity criterion. In the table 1, you can see, the CRS method takes much more time required for calculation than the SA method. It is caused by the type of searching the final point, where the CRS method allowes for the more points on the beginning. For the similarity criterion, the computation time is longer for MI (because of the histogram computation).

For the comparison we use a subtraction between the registered and reference images (Fig. 2.). Based on the visual evaluation, the CRS method seems to be more precise than the SA and the angle similarity criterion better than MI criterion.

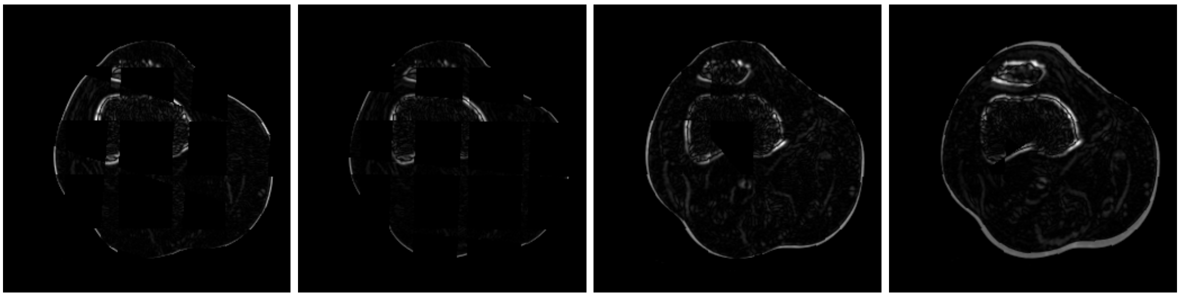

*Fig.2. Results (*range modified to 0-1*) based on different methods (CRS-A, CRS-MI, SA-A, SA-MI)*

5. EXPERIMENTAL RESULT

This work contains the evaluation of the Control Random Search and the Simulated Annealing methods. The experiment shows that the Control Random Search method is more suitable for the image regitration. It is caused by the definition of the initial points in a whole dimension. On this account, this method is able to find the global extreme more precisely than the method SA. On the other hand the SA method requires less computation time. This results are derived from the manualy deformated images.

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