Annales UMCS Informatica AI 1 (2003) 149-156

Annales UMCS
Informatica
Lublin-Polonia
Sectio AI

http://www.annales.umcs.lublin.pl/

Registration of CT and MRI brain images

Karol Kuczyński*, Paweł Mikołajczak

Laboratory of Information Technology, Maria Curie-Skłodowska University,
Pl. M.Curie-Skłodowskiej 1, 20-031 Lublin, Poland

Abstract

The purpose of a registration process is to find a geometric transformation, that relates corresponding voxels in two different 3D images of the same object. We present an algorithm based on maximization of mutual information and its medical applications.

1. Introduction

Non invasive medical techniques, like stereotactic radiosurgery (Fig. 1), are becoming more and more commonly applied. In many cases a diagnose is based mainly on image data. Since an accuracy of a diagnose and a treatment planning (Fig. 2) is of a critical importance, there is a high demand for image processing techniques in order to make a profound use of the data acquired.

Figure 1: A patient being prepared for a stereotactic radiosurgery treatment

* Corresponding author: ***e-mail address:*** karolk@tytan.umcz.lublin.pl

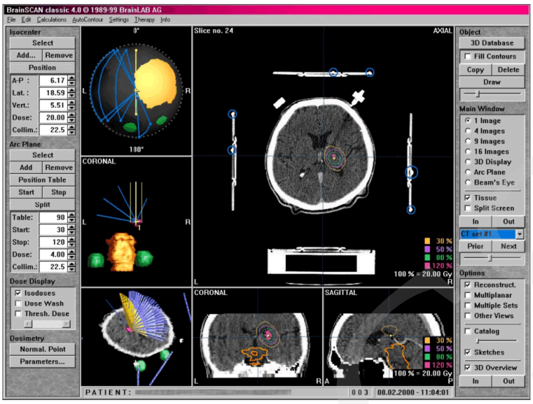

Fig. 2. Stereotactic radiosurgery treatment planning with the BrainLAB system

2. Medical imaging

There is a rich variety of available medical imaging techniques (CT, MRI, PET, SPECT, USG, …). They provide information about different physical properties of tissues. Since this information is often of a complementary nature, it is frequently desired to use integrated data from different modality images.

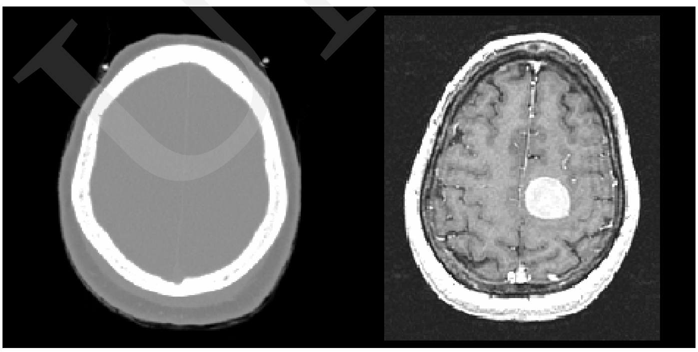

Fig. 3. Examples of CT and MRI brain images

In the case of brain imaging it is common to acquire both CT and MRI scans (Fig. 3). CT provides very precise anatomical information, especially about bones. Voxel intensities are proportional to the radiation absorption of the underlying tissues, which is particularly useful in radiation therapy planning. MRI is less accurate, but soft tissues (including tumours) delineation is significantly enhanced.

3. The purpose and methods of registration

The task of multi modal image data integration is not trivial due to unlike patient’s spatial orientation, datasets’ resolutions and voxel intensity profiles.

The goal of registration (matching, alignment) process is, given two images of the same object, to find a spatial transformation *T*, that relates them. Then a fusion of the registered images may be performed.

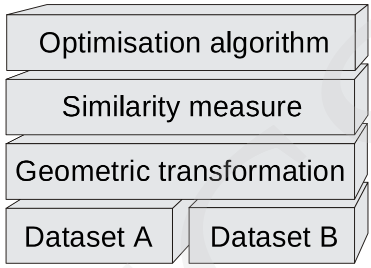

Fig. 4. The optimisation framework

There are two main classes of registration methods: feature-based and voxel-based techniques. In the first case some corresponding points (either external artificial markers or anatomical structures localized by an expert) need to be recognized prior to the registration. In the voxel-based techniques a function of similarity of two images is computed with the intensities of all (or most of) voxels in the images. Neither segmentation nor special pre-processing is required. This approach is becoming more and more popular. However, it requires more processing time.

Regardless of the method used, the registration framework is always similar (Fig. 4 [1]). It is also necessary to implement an efficient similarity measure optimisation procedure in order to find transformation *T* parameters.

4. Information theory and registration

If we treat images as random variables, we can apply statistical techniques in processing them. This approach is commonly used in voxel-based registration methods. Below we present a theoretical background of the implemented registration procedure [1-3].

The most commonly used measure of information is the Shannon-Wiener entropy measure. The average information supplied by a set of *n* symbols whose probabilities are given by $\{p_1,p_2,\ldots\ldots p_n\}$, can be expressed as:

$$H\left(p_1,p_2,\ldots.p_n\right)=-\sum_{i=0}^{n}p_i\log p_i. \tag{1}$$

The entropy *H* of a discrete random variable *X* with the values in the set $\{x_1,x_2,\ldots..x_n\}$ is defined as:

$$H\left(X\right)=-\sum_{i=0}^{n}p_i\log p_i, \tag{2}$$

where $p_i = \Pr[X=x_i]$.

The entropy definition of a single random variable can be extended to a pair of random variables. Let us consider random variable Y with the probabilities q_i. The joint entropy of a pair of discrete random variables (X,Y) with a joint distribution $p(x,y)$ is defined as:

$$H(X,Y) = -\sum_{i=0}^{n}\sum_{j=1}^{m} p_{ij}\log p_{ij}, \tag{3}$$

where $p_{ij} = \Pr[\, X=x_i,\, Y=y_j \,]$.

The conditional entropy is defined as:

$$\begin{aligned} H(X\mid Y) &= \sum_{j=1}^{m} q_j H(X \mid Y = y_j) = -\sum_{i=0}^{n}\sum_{j=1}^{m} p_{ij}\log p_{ij} \\ &= -\sum_{j=1}^{m}\sum_{i=1}^{n} p_{ij}\log p_{i|j}, \end{aligned} \tag{4}$$

where $p_{i|j} = \Pr[\, X=x_i | Y=y_j \,]$, $p_{ij} = q_j p_{i|j} = p_i p_{j|i}$.

The mutual information between the two discrete random variables X and Y is defined as:

$$I(X,Y) = H(X) - H(X\mid Y). \tag{5}$$

The mutual information represents the amount of information that one random variable gives about the other random variable. $I(X,Y)$ is a measure of the information shared between X and Y.

The normalized mutual information [4] is defined as:

$$NI(X,Y) = \frac{H(X)+H(Y)}{H(X,Y)}. \tag{6}$$

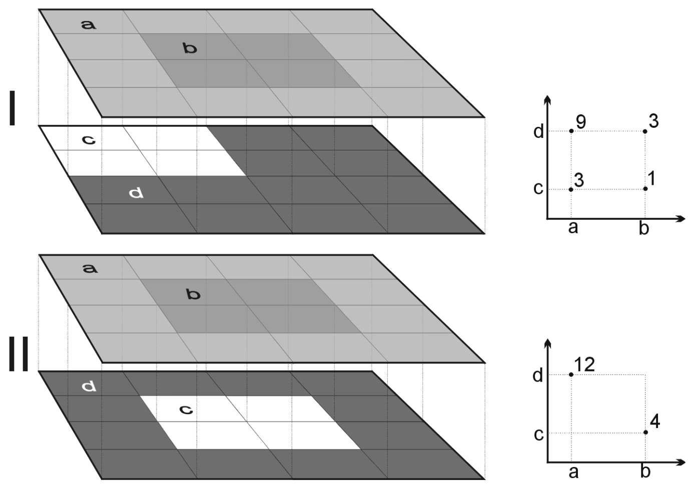

Fig. 5. Two pairs of images and their 2-dimensional histograms

The joint entropy defined above could be used as a similarity measure between two images. In the example (Fig. 5) there are two pairs of images and their 2-dimensional histograms (scatter-plots). They can be used for entropy calculations as follows:

$$H_I(M,N) = -\left(\frac{3}{16}\log\frac{3}{16} + \frac{1}{16}\log\frac{1}{16} + \frac{9}{16}\log\frac{9}{16} + \frac{3}{16}\log\frac{3}{16}\right) \approx 0.488, \qquad (7)$$

$$H_{II}(M,N) = -\left(\frac{12}{16}\log\frac{12}{16} + \frac{4}{16}\log\frac{4}{16}\right) \approx 0.244. \qquad (8)$$

The more similar two images the lower their joint entropy. However, its optimisation may lead into incorrect solutions when the images do not overlap completely during a registration process.

Mutual information is a significantly better candidate for a registration criterion. It can be proved, that two images are properly matched when their mutual information is maximal [5].

5. Optimisation methods

An optimisation procedure is used to search for a global optimum (minimum or maximum, depending on a convention) of the registration criterion (similarity measure) in order to find the optimal transformation parameters.

A review of the most often used methods can be found in [6]. Non-deterministic algorithms (e.g. simulated annealing) are successful in many real-world tasks, including registration. However, they typically require much computing time. Deterministic ones (Powell, Davidon-Fletcher-Powell, Levenberg-Marquardt, etc. [7]) are faster, but they fail in the presence of a large number of local extrema. To address this problem and to speed up the convergence multi-scale or sub-sampling techniques are utilized [8].

6. CT and MRI alignment

CT and MRI are probably the most commonly acquired pair of medical images. In Figure 6 we can slice from two unregistered datasets.

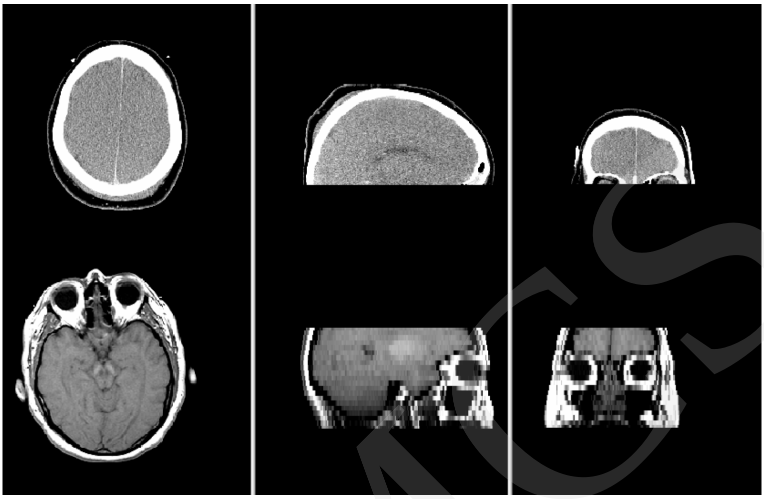

Fig. 6. Source CT and MRI 3D images

Figure 7 shows 2D histograms (constructed as described in Chapter 4) of the images before and after the registration.

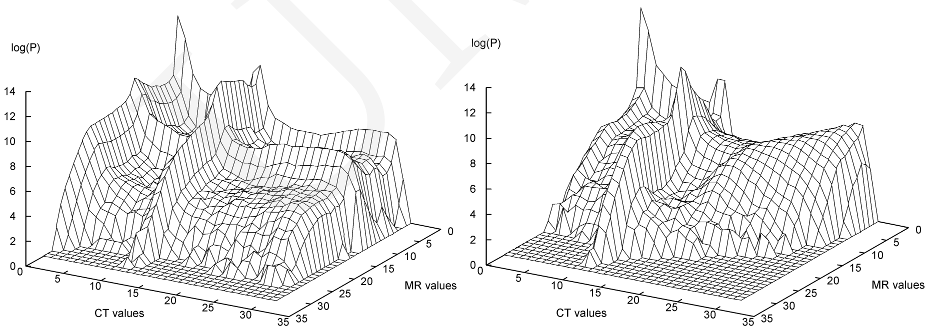

Fig. 7. 2D histograms before (*I*=0.26) and after the registration (*I*=0.72)

The images have been transformed with a rigid body transformation described by 6 parameters (T_x, T_y, T_z, R_x, R_y, R_z). The similarity measure (mutual information, fig. 8) has been optimised using the Powell's algorithm [7] with a pyramidal multiscale method. The result is shown in Figures 9 and 10. The combination of these techniques, despite its simplicity, provided acceptable results within reasonable time (less than 1 minute on a PC with an Athlon 1600+ processor, under RedHat Linux 7.3).

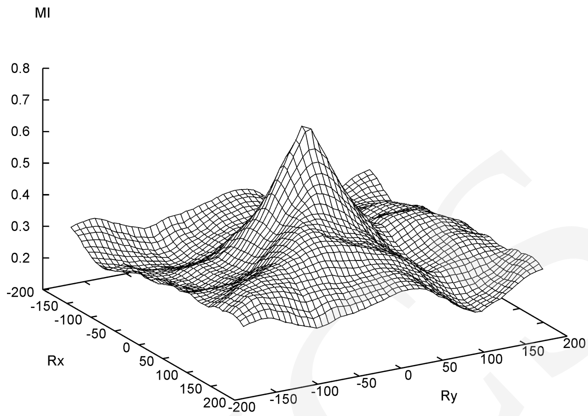

Fig. 8. Mutual information as a function of R_x and R_y, while the other parameters are set in the optimum

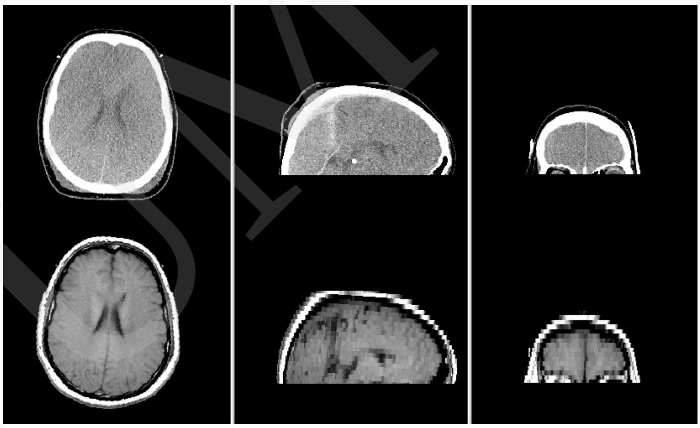

Fig. 9. The registered images

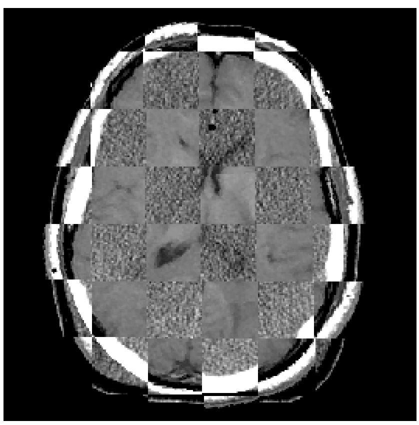

Fig. 10. The registered images – a checkerboard test

7. Conclusions

Modern medical routines require new advanced image processing techniques. The information theory provides means to create highly automated systems. In the case of registration there is no need of pre-processing or expert's work. Computational complexity and occurrence of local extrema are still important concerns; however on a modern PC it is possible to achieve satisfactory results within reasonable time.

Acknowledgment

The CT and MRI data presented in the paper come from the Visible Human Project and from the Center for Morphometric Analysis at Massachusetts General Hospital (http://neuro-www.mgh.harvard.edu/cma/ibsr).

This study has been partially financed by the Polish State Committee for Scientific Research (research project no. 7T11E01921).

References

[1] Kuczyński K., Mikołajczak P., *Mutual Information Based Registration of Brain Images*, Journal of Medical Informatics & Technologies, 3 (2002).

[2] Cover T., Thomas J., *Elements of Information Theory*, A Wiley–Interscience Publication, New York, (1991).

[3] Shannon C.E., *A Mathematical Theory of Communication*, The Bell System Technical Journal, 27 (1948) 379 and 623.

[4] Studholme C., Hill D.L.G., Hawkes D.J., *An overlap invariant measure of 3D image alignment*, Pattern Recognition, 32 (1998).

[5] Viola P.A., *Alignment by Maximization of Mutual Information*, A.I. Technical Report, 1548 MIT, (1995).

[6] Maintz J.B., Viergever M.A., *A survey of medical image registration*, Medical Image Analysis, Oxford University Press, 2 (1998) 1.

[7] Press W.H., Teukolsky S.A., Vetterling W.T., Flannery B.P., *Numerical Recipes in C++*, Cambridge University Press, (2002).

[8] Hill D.L.G., *Combination of 3D medical Images from multiple modalities*, University of London, (1993).