Brain Image Registration based on Fuzzy Competitive Segmentation and Possibilistic Shell Detection[1]

S. Cormier*, ‡, N. Boujemaa‡, F. Tranquart*, G. Roux‡, L. Pourcelot*

‡ LI / E3I - Université de Tours
64, avenue Jean Portalis
37200 Tours - France

* INSERM Unité 316
2 bis, boulevard Tonnellé
BP 3223
37032 Tours Cedex - France

e-mail: {boujemaa, cormier}@univ-tours.fr, tranquart@med.univ-tours.fr

Abstract

Recent progress in medical imaging allows clinicians to use anatomical and functional modalities in order to visualize different aspects of the explored organ. In order to achieve a comparison between these different kinds of modalities, a preliminary image registration is necessary.

Our aim in this paper is to describe a registration technique of multimodal brain images (MRI and SPECT) of a single patient without any external landmark, based on a competitive fuzzy clustering method and using brain orientation considered as invariant feature. We also show an improvement of our method based on possibilistic shell clustering technique in order to deal with pathological cases.

1. Introduction

To have different information of an explored organ, clinicians use more and more regularly several modalities for a single patient. Indeed, individual limits of each exploration technique requires several of them to realize more complete diagnosis or more complex therapeutic acts (video surgery, radiotherapy for example). So, it is necessary to achieve a registration in order to fit these different kinds of information.

In brain imaging we have principally on the one hand Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) which show anatomical structures and on the other hand Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) which show functional activity. Comparing and combining anatomical and functional information is of great interest for effective diagnosis.

Medical image registration can be defined by different criteria especially the kind of transformation between two different modalities ([5], [10]).

In our case of study, we have two kinds of brain images, MRI and SPECT modalities of a single patient without any external landmark. In section 2, we present an image segmentation method based on fuzzy competitive clustering and we describe the rigid registration obtained with inertial methods and finally, in section 3, we introduce a possibilistic shell clustering improvement to deal with serious pathological cases.

2. Segmentation and Registration Methods

Medical images segmentation is not an obvious task because of the inherent complexity of this kind of image. A significant difficulty consists in the variability between patients and their anatomical particularities. So, it is not easy to provide a partition that matches as close as possible brain structures.

Different fuzzy methods are used in the literature [3], particularly the basic FCM clustering algorithm [2]. Nevertheless, this algorithm requires to set initially the number of clusters. To overcome this difficulty, image segmentation is achieved using competitive agglomeration fuzzy clustering algorithm (CA) [8].

Given the redundant information of gray level feature, we deal with histograms whatever the image dimensions may be.

[1] This work is supported by the « Région Centre » and ANVAR.

2.1 Segmentation Method

2.1.1 Fuzzy Competitive Clustering Algorithm

The CA algorithm begins with a great number of small clusters. During iterations, a competition process takes place between adjacent clusters to reduce iteratively the number of them. CA algorithm generates a fuzzy partition based on the minimization of the following fuzzy functional:

$$(1)\quad J = \sum_{i=1}^{C}\sum_{j=1}^{N}(u_{ij})^2(d_{ij})^2 - \alpha\sum_{i=1}^{C}\left[\sum_{j=1}^{N}u_{ij}\right]^2$$

where (u_{ij}) is the membership degree of the j^{th} data vector X_j in the i^{th} cluster and $(d_{ij})^2$ is the corresponding Euclidean distance.

N is the total number of data vectors (total number of gray levels) and C the number of clusters to be found (in (1) C is dynamically updated).

We have to keep in mind there is an underlying constraint:

$$\sum_{i=1}^{C}u_{ij} = 1 \ \ \forall j \in \{1,\dots,N\} \text{ and } u_{ij} \in [0,1]$$

The first component of the functional (FCM algorithm with $m = 2$) allows to control the dimension of each cluster and to obtain compact clusters. The global minimum of this component is reached when C is equal to N. The second component allows to control the number of clusters. The global minimum of this component is reached when all data are in one cluster only.

Final solution of J is obtained when the intra-clusters distance is minimized and the optimal number of clusters is determined. It is reached recursively, updating the new membership degrees (u_{ij}) and the new prototypes (V_{ij}) in the following way:

$$u_{ij} = u_{ij}^{FCM} + u_{ij}^{Bias} = \frac{\frac{1}{d_{ij}}}{\sum_{k=1}^{C}\frac{1}{d_{kj}^{\,2}}} + \frac{\alpha\left(N_i - \tilde{N}_j\right)}{d_{ij}^{\,2}} \quad and$$

$$V_i^{(k)} = \frac{\sum_{j=1}^{N}(u_{ij})^2.H(j).j}{\sum_{j=1}^{N}(u_{ij})^2.H(j)}$$

where H(j) is the weight of the j^{th} gray level in the histogram,

$$\tilde{N}_j = \frac{\sum_{k=1}^{C}\frac{1}{d_{kj}^{\,2}}N_k}{\sum_{k=1}^{C}\frac{1}{d_{kj}^{\,2}}},$$

and N_i the cardinality of cluster i.

So, the cardinality is calculated by:

$$N_i = \sum_{j=1}^{N}u_{ij} \ \ \forall i = 1..C$$

Cluster i vanishes when N_i is less than a minimum required.

Parameter α have an influence upon CA algorithm behavior. It allows to control the importance of the second term of the functional (1) relative to the first term. It must decrease exponentially in the course of iterations and be proportional to the ratio between the two components of the functional. In [8], the following formula is proposed, at the k^{th} iteration:

$$\alpha(k) = \eta_0.e^{-k/\tau}.\frac{\sum_{i=1}^{C}\sum_{j=1}^{N}(u_{ij})^2.(d_{ij})^2}{\sum_{i=1}^{C}\left[\sum_{j=1}^{N}u_{ij}\right]^2}$$

where τ is the time constant and η_0 is the initial value.

2.1.2 Decision Step

After obtaining the final and optimal fuzzy partition according to functional (1), it is necessary to make a « defuzzyfication ». We proceed in two steps [4]. The first one reveals the most ambiguous (weak membership degree) pixels from the remaining strong ones (high membership degree) which represent the coarse information of the image. Weak pixels are assigned, in the second step, with regard to their spatial context. Indeed, we consider every neighbor of the ambiguous pixel. If there is no ambiguous neighbor, the pixel is assigned to the majority cluster in its vicinity. Obviously, it is frequent to deal with pixels whose neighbors are also ambiguous. So, it is necessary to sort these pixels and begin with ambiguous pixels owing less ambiguous neighbors. This way, our decision function is invariant to rotation and translation. Weak pixels (weak membership degree) that represent «ambiguous» data are assigned with regard to their spatial context. Indeed, we consider every neighbor of the ambiguous pixel (eight pixels in 2D). Therefore, if there is no ambiguous neighbor and a majority cluster, the pixel is assigned to the gray level of the majority cluster in its vicinity.

An original SPECT image and the results of the segmentation are presented in Figure 1 and Figure 2.

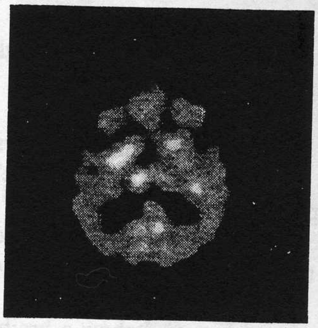

Figure 1: Original brain SPECT image

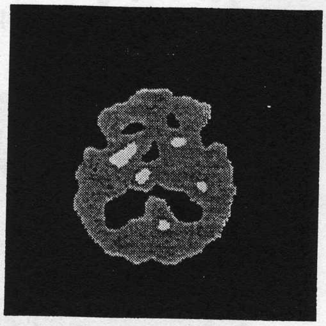

Figure 2: Segmented SPECT image

2.2 Registration method

We deal with two different modalities of brain images, SPECT and MRI without any external landmark. Our aim is to achieve a rigid registration, therefore to determine the rigid transformation, rotation and translation, that match the two kinds of images, based on anatomical invariant landmark.

Our approach is to find brain orientation in the two modalities, considered as invariant feature for a same patient. Hence, we use a technique based on inertial moments ([1], [7]).

Several properties, principal axes and inertia matrix, identify brain shape, considered as a rigid body.

Since MRI and SPECT images are segmented, we compute the inertial properties which allow to determine the general orientation of brain and to register images by superimposing its principal axis and its center of mass.

Figure 3 and Figure 4 present detected principal axes superimposed on each original image and general results of this method are shown in Figure 5 (a brain MRI image and SPECT edges superimposed).

According to experienced clinicians who are used with anatomical structure, this technique allows to obtain good result.

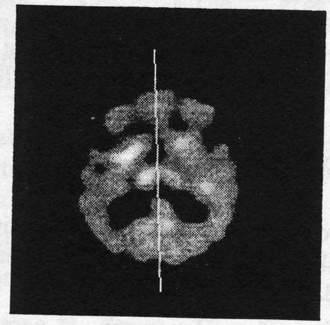

Figure 3: SPECT image and principal axis superimposed

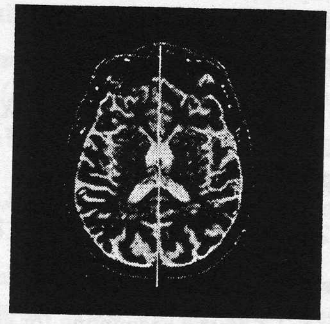

Figure 4: MRI image and principal axis superimposed

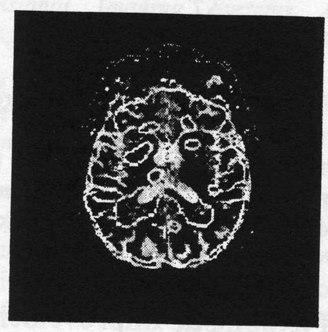

Figure 5: Brain MRI image and SPECT edges superimposed

3. Pathological case missing information processing

Particular diseases may affect brain structure and image information may miss. Therefore, inertia techniques can't be used with the described method before. Nevertheless, the global brain pattern can be approached by an ellipse. That is the reason why we propose these two steps before inertial proprieties computing.

First of all, we segment images with CA algorithm, find edges and detect ellipse with Dave & Bhaswan's algorithm [6]. Finally, we use possibilistic Krishnapuram & al.'s improvement [9] to keep only data which are involved in a good ellipse.

3.1 Ellipse detection

In order to determine the best ellipse (least squares), we solve the system of nonlinear equations given by [6] (standard numerical minimization techniques can be used):

$$\sum_{k=1}^{n} \frac{D_k}{d_k}(x_k - v) = 0$$

$$\sum_{k=1}^{n} \frac{D_k}{d_k}(x_k - v)(x_k - v)^T = 0$$

where D_k is the distance from point $X_k=[X_{k1}\ X_{k2}]^T$ to the ellipse prototype at center $v=[v_1\ v_2]$ and d_k the distance from point X_k to center v:

$$(D_k)^2 = \left(\left[(x_k - v)^T A (x_k - v)\right]^{1/2} - 1\right)^2$$

where A is a matrix accounting for size, orientation and eccentricity of the ellipse

$$(d_k)^2 = (x_k - v)^T A\ (x_k - v)$$

With pathological cases presenting missing information, all edge points are not « interesting » because they don't really contribute to an ellipse fitting brain pattern. So, in order to only keep these points, we use the detected ellipse as initialization of a possibilistic improvement.

3.2 Possibilistic Improvement

We use a possibilistic algorithm proposed by Krishnapuram & al [9] in order to improve ellipse detection.

With fuzzy parameters, equations given by [6] are:

$$\sum_{k=1}^{n} (u_k)^m \frac{D_k}{d_k}(x_k - v) = 0$$

$$\sum_{k=1}^{n} (u_k)^m \frac{D_k}{d_k}(x_k - v)(x_k - v)^T = 0$$

where m is the 'fuzzifier' (equal to 2).

The membership degrees are calculated by:

$$u_j = \frac{1}{1 + \left(\frac{d_j^2}{\eta}\right)^{\frac{1}{m-1}}}$$

where η represents the square of the expected ellipse thickness.

Iteratively, the algorithm allows to consider only points which are involved in an ellipse and to leave other points.

Then, inertial properties of the ellipse allows us to make registration as described previously.

Figure 6 and Figure 7 show a brain SPECT image and the results of detected ellipse.
Figure 8 and Figure 9 present the corresponding MRI image and the results of detected ellipse.

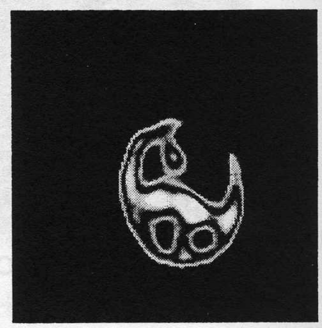

Figure 6: SPECT brain image

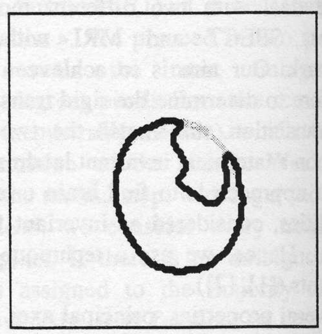

Figure 7: Thickened edge and detected ellipse

Figure 8: MRI corresponding image

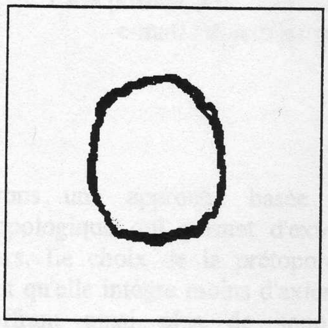

Figure 9: Thickened edge and detected ellipse

4. Conclusion

We have presented a method for rigid registration of 2D SPECT and MRI images of the brain of a single patient without any external landmark. Brain orientation is considered as invariant feature in the two modalities.

Therefore, no external devices are necessary and registration is also possible with previous acquisitions.

Our method is achieved in two steps, on the one hand a segmentation with fuzzy competitive clustering and on the other hand a matching with inertial properties.

In order to improve this method to deal with serious pathological cases, we use fuzzy possibilistic methods of ellipse detection applied to brain contour to compensate missing information in brain shape.

5. Acknowledgments

We wish to thank I.Bullot, B. Le Divenah, F. Guérinet and D. Pinto for their precious help.

6. References

[1] **Alpert N.M., Bradshaw J.F., Kennedy D., Correia J.A.,** « The Principal Axes Transformation - A Method for Image Registration », *Journal of Nuclear Medicine,* 1990, 31, 1717-1722

[2] **Bezdek J .C.,** « Pattern Recognition with Fuzzy Objective Function Algorithms », Plenum Press New York, 1981

[3] **Bezdek & Pal,** « Fuzzy Models for Pattern Recognition », IEEE Press 1992

[4] **Boujemaa N., Stamon G.,** « Fuzzy Modeling in Early Vision - Application to Medical Image Segmentation », *Progress in Image Analysis and Processing III,* 649-656, Ed. S. Impedovo - World Scientific 1994

[5] **Brown L.G.,** « Image Registration Techniques », *ACM Computing Survey,* 1992, 24(4), 325-376

[6] **Dave R.N., Bhaswan K.,** « Adaptative Fuzzy c-Shells Clustering and Detection of Ellipses », *IEEE Transactions on Neural Networks,* 1992, 5 (3), 643-662

[7] **Engelstad B. L., Meyers H.J., Hanson W.A., O'Connell J.W., Taylor R.C., Bernestein R.,** « Information Extraction From Multi-Modality Medical Imaging », *Proceedings of SPIE: Three-Dimensional Imaging Systems And Remote Sensing Imaging,* 1988, 902, 144-149

[8] **Frigui H., Krishnapuram R.,** « Clustering by Competitive Agglomeration », *Pattern Recognition Letters,* 07-1997, 30 (7), 1109-1119

[9] **Krishnapuram R., Frigui H., Nasraoui O.,** « Fuzzy and Possibilisitic Shell Clustering Algorithms and Their Application to Boundary Detection and Surface Approximation - Part I », *IEEE Transactions on Fuzzy Systems,* 1995, 1 (3), 29-43

[10] **Van den Elsen P.A., Pol E.-J. D., Viergever M.A.,** « Medical Image Matching - A Review with Classification », *IEEE Engineering in Medicine and Biology,* 1993, 26-36