MRI and neuroreceptor SPECT brain images registration based on anisotropic diffusion [1]

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Abstract

Recent progress in medical imaging allows clinicians to use anatomical and functional modalities providing complementary information in order to visualize different aspects of an explored organ. In order to take advantage of these different techniques, image registration is required.

In our case of study, we deal with MRI and neuroreceptor SPECT images from the same patient with the fundamental constraint that no external landmarks are available. Due to particular acquisition technique, usually this kind of nuclear medicine images is never registered without using another perfusion SPECT study or manual help since they have a very complex appearance with diffuse marker fixation. This paper presents a new intrinsic method to rigidly register neuroreceptor SPECT and MRI images. A regularization process preserving image structure is first applied to SPECT images based on a particular anisotropic diffusion method. Fuzzy clustering segmentation is then performed to allow brain orientation computation, considered as invariant feature.

1. Introduction

Clinicians need different information of an explored organ and use more and more regularly several modalities for a single patient. Indeed, individual limits of each exploration technique require 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 differentiate:
- morphological structures provided by anatomical modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI)
- functional activity provided by nuclear medicine modalities, Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT). According to injected isotope, SPECT modality shows brain vascular or neuroreceptor activity.

Comparing and combining anatomical and functional information is of great interest for effective diagnosis. But, analysis and extraction of information from neuroreceptor SPECT images are traditionally realized by manual drawing of Regions Of Interest (ROI). Another way to register neuroreceptor images is to use a perfusion SPECT study. Two SPECT studies are realized with two kind of isotope (neuroreceptor and perfusion studies) at different time with the same patient's orientation. Afterwards, the perfusion SPECT study is registered with an anatomical modality like MRI and the rigid transformation is applied to neuroreceptor brain images.

In our case of study, we have two kinds of brain images, MRI and neuroreceptor SPECT images of the same patient without any external landmark. We propose a new method in order to register them without using another nuclear medicine vascular study for a pre-registration.

So, we present in section 2, a regularization process based on anisotropic diffusion that allows to obtain brain edges in neuroreceptor SPECT images.

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In section 3, we describe a rigid intrinsic registration and our approach with a preliminary fuzzy segmentation. And finally in section 4, we explain how registration is possible with an inertial method to compute rigid transformation parameters and we show the results of this registration process on MRI and neuroreceptor SPECT studies.

2. Diffusion process

2.1 Introduction

Due to neuroreceptor SPECT images low resolution, brain detection is impossible without a particular regularization process which preserves edges.

When considering the problem of image restoration, the PDE framework offers a great contribution [1], [2], [3].

First, it has been proved that heat equation [2] and Gaussian filter is an equivalent process and provides an isotropic image smoothing. For a two-dimensional image u, this equation is given by:

$$\frac{\partial u}{\partial t}(\underline{x},t) = \Delta(u(\underline{x},t)) \qquad (2)$$

where Δ represents the Laplacian operator and the Gaussian kernel is proportional to t, time solution.

An important drawback is that process can not preserve image discontinuities and contrast. To overcome this, [4] introduce the anisotropic diffusion process given by the new equation (3):

$$\frac{\partial u}{\partial t}(\underline{x},t) = \mathrm{div}\left(f\left(\left|\nabla(u(\underline{x},t)\right|\right).\nabla\left(u(\underline{x},t)\right)\right) \qquad (3)$$

where ∇ and *div* are respectively the Gradient and the divergence operators and f the diffusion function.

Different functions were proposed in the literature and have to following this two criteria:

- the diffusion has to be isotropic in the homogenous areas where $\nabla\left(u(\underline{x},t)\right)$ is near 0
- in the high gradient areas, the diffusion has to take effect only in the orthogonal direction of the gradient

2.2 Results

It is necessary to realize a discrete representation of anisotropic diffusion equation. We use the following approximation [5]:

$$u(\underline{x},t+dt) = u(\underline{x},t) + dt.\left(\frac{\partial u}{\partial t}(\underline{x},t)\right) \qquad (4)$$

If we consider a 2-pixels neighborhood and equation (3), $\frac{\partial u}{\partial t}(\underline{x},t)$ is approximated by :

$$\sum_{i=1}^{n}\frac{\partial}{\partial x_i}\left[g(\underline{x},t).\frac{1}{2h_i}\left(u(\underline{x}+h_i,t)-u(\underline{x}-h_i,t)\right)\right] \qquad (5)$$

And finally:

$$\sum_{i=1}^{n}\frac{1}{4h_i^{\,2}}\left[g(\underline{x}+h_i,t)\cdot\left(u(\underline{x}+2h_i,t)-u(\underline{x},t)\right) - g(\underline{x}-h_i,t)\cdot\left(u(\underline{x},t)-u(\underline{x}-2h_i,t)\right)\right] \qquad (6)$$

with $g(\underline{x},t) = f\left(\left|\nabla u(\underline{x},t)\right|\right)$ and where n represents the data dimension (equal to 2), f is the diffusion function.

Among several functions used in the literature, different simulations were realized for neuroreceptor SPECT images and the following diffusion function [6] provide the best compromise between regularization and edge preservation:

$$f(s) = \frac{1}{k^2.\sqrt{\frac{k^2+s^2}{k^2}}} \qquad (7)$$

where k is the gradient threshold.

Figure 2-2 shows an example of this diffusion process applied to neuroreceptor brain images (Figure 2-1).

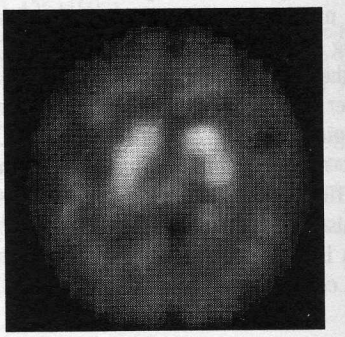

Figure 2-1: Neuroreceptor SPECT Image

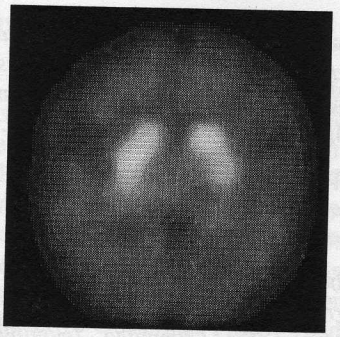

Figure 2-2: Neuroreceptor SPECT image after anisotropic diffusion process

3. Intrinsic features based registration

In order to register neuroreceptor SPECT and MRI images without any external landmark and without a pre-registration with a perfusion study, it is necessary to obtain invariant features in the two modalities. In the literature, intrinsic features based registration is realized by involving two main characteristics, either a structural information provided by brain surfaces or pixels intensity.

Brain surface registration has proved its efficiency and reliability based on automatic or semi-automatic segmentation of the two involved modalities [7], [8], [9] for example. Nevertheless, these registration processes were always realized with perfusion nuclear medicine brain studies.

Yet, medical image segmentation is not an obvious task. Indeed, due to their inherent complexities (inter-patients variability and anatomical particularities), it is not evident to provide a partition that matches as close as possible brain structures.

In this context, different algorithms are used in the literature but fuzzy image segmentation has proved its reliability, like the basic FCM clustering algorithm. Most clustering algorithms need to set clusters number at the beginning. To overcome this limitation of this kind of algorithms, we achieve image segmentation with competitive agglomeration clustering algorithm (CA) [10,12], which allows finding the optimal number of clusters. It is based on the minimization of the following objective functional:

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

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

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

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

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

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*, calculated by:

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

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).

Finally, the partition given by the minimization of J has to be "defuzzyfied" by a decision stage [11], [12] to provide the final segmented image.

After a regularization process applied to neuroreceptor SPECT images, this segmentation is efficient and reliable in order to segment them and to find brain edges. An example is presented Figure 3-1. With MRI images, morphological operations are also necessary to remove undesirable anatomical structures. More details about segmentation and brain edge detection can be found in our previous work [12].

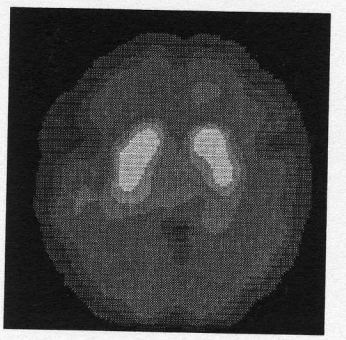

Figure 3-1: CA segmented neuroreceptor SPECT image (after anisotropic diffusion)

5. Conclusion

We have presented an intrinsic surfaces-based method for rigid registration of 2D neuroreceptor SPECT and MRI images of the brain of a single patient without any external landmark and without another vascular SPECT study.

A first neuroreceptor SPECT image regularization based on anisotropic diffusion to preserve brain edges is required. Owing to this process, hence it is possible to obtain brain surface after a preliminary segmentation based on fuzzy competitive clustering. Finally rigid registration parameters are calculated with inertial brain properties, considering brain orientation as invariant feature in the two modalities. Therefore, no external device is necessary and retrospective registration is also possible.

6. Acknowledgments

We thank E. Boulay for his precious help.

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