Unsupervised Selective Anisotropic Feature Diffusion for Cortical Surface Registration

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Keywords. Registration, geometric diffusion, cortical surface, diffusivity function, selective smoothing.

1 Introduction

Inter-patient registration of brain MR images is a central research topic in medical image processing. Even relatively crude methods such as projecting into the Talairach space are essential tools for diagnosis, surgical planning, comparative studies, ... Ideally, the goal is of course to reach point-to-point correspondence between the patient's anatomies, which would dramatically improve the accuracy of the above applications. While a variety of volumetric methods perform reasonably well in registering the deep structures of the brain, warping of the cortical surface has proven to be significantly more challenging due to the higher interpatient variability.

The need to make comparative measurements across subjects requires a surface-to-surface registration which not only matches overall cortical geometry, but also enforces structure-to-structure correspondence. Unfortunately, differences in the serial organization of cortical gyri prevent exact gyrus-by-gyrus matching due to the fact that some cortical areas are particularly subject to variations in the incidence and topology of accessory gyri, and one subject may have two or three gyri where one gyrus is found in another subject. The aim is to find a method able to extract first main cortex features (deep sulci) and secondly more local ones to perform a scale space registration.

In this paper we use the theory of geometric curve and surface evolution to diffuse an object preserving their important features. We do that using a curvature flow method with a novel diffusivity function. This diffusivity function takes profit from the characteristics of the level set representation to perform a directional diffusion. Its performance improves other diffusivity functions that evolve in such a way that though they diffuse noise, important features are also lost after some iterations.

2 Method

Directional difussion had been long studied trying to diffuse data in an anisotropic way; but Perona and Malik [4] were those who first formulated the problem in an elegant way by means of non linear PDEs:

$$\frac{\partial \phi(\boldsymbol{x}, t)}{\partial t} = div[g(\|\nabla \phi\|)\nabla \phi] \tag{1}$$

where $\|\nabla \phi\|$ is the gradient magnitude and $g(\|\nabla \phi\|)$ is an edge-stopping function that satisfies $g(x) \to 0$ when $x \to \infty$ so the diffusion is stopped across edges. Although $g(\|\nabla \phi\|)$ (which is proportional to diffusivity function, $\psi)(x) = xg(x)$) and its properties have been intensively studied [2][6] we propose a novel one which stops diffusion for outliers and also for zero values of the gradient (physically, there is no diffusion) and goes to one exponentially with a "speed" τ which controls how fast low gradients and outliers are going to be diffused and kept respectively.

$$g(\|\nabla \phi\|) = \begin{cases} 1 - e^{-\tau \|\nabla \phi\|^2} & \|\nabla \phi\| \leq \sigma \\ (1 - e^{-\tau \sigma^2}) e^{(-\tau (\|\nabla \phi\| - \sigma)^2)} & \|\nabla \phi\| > \sigma \end{cases} \tag{2}$$

We see that our stopping function is able to preserve sulci, which represent our important features, due to the behavior of the surface evolution, which keeps very low gradient zones of the level set as well as outliers. Ideally zero, but very low in practice, gradient is present between sulci when using the signed distance function as function for our level set evolution (references to level set methods in [7]). Consequently, these zones do not evolve, so the surface is going to remove small gyri, resulting in a smooth version of the cerebral cortex, but preserving sulci. This makes the difference between other curvature flows using typical diffusivity functions that smooth also sulci. Our diffusivity function has two parameters to be set: σ and τ. The first one is used to detect the information that had to be kept in our level set representation. The way to set this parameter has already been studied by Rousseeuw and Leroy [5]. They understand important information as outliers and suggest that σ can be calculated as follows:

$$\sigma_e = 1.4826 median[\|\nabla \phi - median(\|\nabla \phi\|)\|] \tag{3}$$

Later on, Black and Sapiro [3] proposed a method to calculate σ locally, in such a way that a local σ can not be smaller than the global one for a given window, adapting better the diffusion in each zone.

τ represents the speed with which the diffusivity function grows, and is related to the depth of the point in the brain. This is, ideally, if the value of the depth function in a certain point is high (bigger than a set threshold, δ), τ has to be infinite; on the contrary if the value of the depth function in a point is smaller than δ, τ has to be 1. We model that as the inverse of a step function (1 up to δ and 0 from delta). Such a representation lets diffusion evolve when sulci are not deeper than δ and stop it when they are deeper. δ is calculated as

detection of depth outliers. Of course, with such characteristics, a scale space representation of the brain cortex based on the depth is straightforward.

To perform the directional diffusion we use the affine invariant anisotropic diffusion proposed by Alvarez, Lions and Morel [1]. This flow performs the diffusion in the desired direction, perpendicular to the gradient, this is, parallel to the "edges". The directional diffusion flow is equivalent to:

$$\frac{\partial \phi(\boldsymbol{x}, t)}{\partial t} = g(\|\nabla \phi\|)\kappa\|\nabla \phi\| \tag{4}$$

which means that the level sets of ϕ are moving according to the geometric heat flow. *Directional diffusion is then equivalent to smoothing each one of the level sets according to the geometric heat flow.* To further stop diffusion across edges, we have added our stopping function.

3 Conclusion

Experiments show that, if the geometry of the object is important for our purposes, our technique performs better than the typical ones. For example, in the case of cerebral cortex registration, since gyri to gyri registration is impossible due to the inter-patient differences, a good extraction of the important features (those present in both patients) becomes a cornerstone. With the proposed diffusivity function, this becomes an easy task since only two parameters have to be set, and this is done in an automatic way. One important characteristic of this diffusivity function is that we can obtain a scale-space representation of the cortex.

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