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WARPING BRAIN MR IMAGES USING DEFORMABLE CONTOURS

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ABSTRACT

Image warping is necessary for automatic identification and labeling of different brain regions. It is also needed for quantitative analysis of shape variations of brain structure. In this paper, we introduce a new warping technique for brain MRI applications. We first use a deformable contour model to extract and warp the boundaries of two brain images. A mesh grid is constructed thereafter by using a distance transformation applied to the brain boundary. Finally, each brain image is matched to the other image by mapping the mesh coordinates. We have implemented and applied this method. It generates fast and accurate results for brain MRI.

1. INTRODUCTION

Image warping has many medical and non-medical applications. In medical field, matching atlas data to the sensor images of human body, automatic segmentation and identification of organs in medical images, and calculating shape variations caused by certain abnormalities are among a few examples of currently active research topics in which warping plays an important role.

In this work, we have developed a new method for warping brain MR images to other images or atlas data. We use a deformable contour model to capture the general shape of each brain from its boundary contour. Using a distance transformation, we create a mesh map for each brain thereafter. A brain image is mapped to the other image based on a one-to-one mapping between different layers of the two brain images that are defined in the mesh grid system. One of the important advantages of this model is that it does not need any user-defined landmarks. Another advantage is that it runs fast.

A basic assumption in our model is that the boundaries of two images can be mapped to each other homothetically, i.e., by a uniform scaling of the length and bending. This is a reasonable and applicable assumption to the MRI studies of the human brain. For applications in which this assumption is not valid, the limitation usually is overcome by using enough number of landmarks such that they define piece-wise homothetically warpable segments. The algorithm is described in details in the Methods Section.

2. BACKGROUND

There have been numerous approaches by different authors to the problem of image warping. Aboul-Ella *et al* [1] used an elastic body spline to generate a warp function for warping facial images. Their spline is based on a partial differential equation that describes the equilibrium displacement of the elastic body subjected to forces. Thompson *et al* [2] used a hybrid surface (based on super-quadrics and spherical harmonics) in a deformable model scheme to extract and warp surfaces of the ventricles and cortex in the brain images. One of the problems with the majority of current methods is that they need several landmarks, which demands for the human interaction and increases sensitivity and affects the reproducibility of the method [3].

Davatzikos has also used deformable models for normalization or warping of the brain images [4]. Their model is based on finding similar parts of the outer cortex and using the results in an elastic-matching algorithm. Their model is computationally demanding and needs human interaction. Bajcsy *et al* [5] proposed a method in which, the warping of one brain image to the other image is done by dividing each image to sub-blocks and finding a number of local features in each sub-block. An external force will be applied to one image, which is given elastic properties, and will push each block towards the most similar block in the target image. Similarity is measured based on the distance in the feature space. This model is sensitive to the image noise and needs careful selection and computation of appropriate features. This kind of elastic matching is also used by other authors, e.g. [6], [7].

In this paper, we present a new approach. We use deformable models, but we apply it to the brain outer boundary. Therefore, our model is not sensitive to noise. It also does not require any user interaction and is fast. In the following section, we describe details of our method and show its application to a human brain MRI.

3. METHODS

In the method which is described here, the mapping between two brain images is determined by mapping between their boundaries. This method is applicable to warping of brain images. This is because inter-subject shape deformation for structures in normal brains is mostly a function of the deformation of the entire brain shape, which is reflected in the brain boundaries. The problem of shape variations due to abnormalities will not be addressed in this paper. Let I and I' be two brain images, we map image I onto I' as follows. First two brain images are registered using an affine transform. Then a deformable contour model is used to extract the boundaries of two brains as well as the mapping between boundaries. A distance transformation used thereafter to construct a mesh grid coordinate system for bout brains based on their boundary information. Two brain images are mapped using the new coordinate system.

3.1 Initial Registration

In this section, we present the approach for compensating possible translation, rotation, and scale offsets between the two brain images. We apply an affine transformation T to I which minimizes the sum of the Euclidean distances between the two brain boundaries in I and I' [8]. The cost associated with T is defined as:

$$C(T) = \int_0^1 \left|T(B(\alpha)) - B'(\alpha)\right|^2 d\alpha \,, \qquad (1)$$

where $B(\alpha)$ and $B'(\alpha)$ represent the parametric form of the boundaries of I and I', respectively. In this stage we first extract the external contour of each brain image. This is a straightforward task that is done by low level image processing tools such as thresholding and morphometric operations [12]. This very first step of boundary extraction, as well as the next stage of global registration, which is described below does not need to be very accurate. We show the new registered brain images by I_r where:

$$I_r = T(I). \qquad (2)$$

In the next stage, we obtain the accurate boundary of each brain image by applying a discrete dynamic contour model which we have developed [9], [10]. Because we are only interested in external boundary of the brain in this stage, we can have the initial contour large enough to include the entire brain and use a shrinking force in contour evolution [10]. In this way, the task of creating the initial contour can be easily automated. Another advantage of using this initial contour and shrinking force is that it guarantees the model to converge to the right edge and not to get trapped into the local or undesired edges. We show the resulting contour by L. To make the distance between the successive points on the contour equal, we perform a re-sampling along L, which makes all the segment sizes equal to a fixed reference size, named l_{res}. l_{res} is one of the model parameters and determines its worst case resolution. We have used $l_{res}=1$ pixel in our experiments. Note that the resolution of the contour during the deformation process does not need to be equal to l_{res}. In fact, we use a coarse resolution (4 pixels in our experiments) in this deformation stage. We also use a rather large value for the internal force weight, w_{in}, (typically 2 to 4 times larger than external force weight) to obtain a smooth contour. The reason for these selections will be described later in this paper.

3.2 Applying Deformable Model on I'

In the second step, we need a contour that catches the shape of the brain in I'. For this purpose, we apply the same deformable contour model was applied to I_r. Here, we use L as the initial contour. A small outward scaling of L (scale factor or $k>1$) is used to ensure that the initial contour will still include the whole brain in I'. The resulting contour will be called L'. We need a corresponding reference point on L and L'. This is used to compensate for any possible rotational offset between the two contours and synchronizes the starting points of the contours (remember that we corrected translational, rotational, and scale offsets between two brain images in the previous stage). This goal is achieved by finding a single landmark point in the brain boundaries. Note that only one landmark point is needed in our model. We show this landmark point $P_{0,0}$ and $P'_{0,0}$ for I_r and I' respectively. Therefore, $I_r(P_{0,0})$ and $I'(P'_{0,0})$ correspond to the same brain location. During the contour evolution, a virtual force (see [10] for detail) will push the contour toward this landmark. We re-sample L' in the same fashion as L. Moreover, both L and L' are re-indexed such that the vertices at $P_{0,0}$ and $P'_{0,0}$ get the same index, say 0. In order to make the task of landmark definition automatic, we have chosen the superior sagittal sinus point as the landmark for sagittal cross sections and posterior point of the brain midline in the axial images. This point can be detected automatically, as the contour of the external boundary of the brain has the maximum curvature at this point. A coarse scale should be used for this purpose. If we use a fine scale, other high curvature locations in the cortex, such as sulci, may confuse the result. However, as described before, we use a coarse resolution and a high w_{in} to avoid this problem.

3.3 Creating the Mesh Map

In this, we use L and L' to generate a mesh for each brain. A distance transformation [11] is applied on L and L' and the resulting distance maps are called D and D', respectively. Only the internal region of the contour (brain pixels) is considered. A point on D will have a value equal to its Euclidean distance from the nearest point on L. The same argument is true for D' with respect to L'. We define the *scaling center* for L, called C, as the point with maximum value in D. If the maximum value corresponds to a set of points, the center of mass for the set is considered. C will be an equi-distance point for L. In the same way, C', the scaling center for L' is defined. Now we construct the internal layers for I_r and I'. For I, the layers $L_0, L_1,\ldots, L_{N-1}$ are produced by successive scaling of L relative to its center C. If we show the jth point of L_i by $P_{i,j}$, we will have:

$$P_{i+1,j} = \alpha\, P_{i,j} + (1-\alpha)C, \quad i = 0,\ldots,N-1 \qquad (3)$$

where

$$\alpha = \frac{1}{N} = \frac{1}{\max\{D(C), D'(C')\}}. \qquad (4)$$

$L'_0,\ldots, L'_{N-1}$ are generated for I' by shrinking L' using the same method. Note that L_0 and L'_0 are identical to L and L', respectively.

3.4 Mapping the Brain Images

Brain images will be mapped together using the mesh obtained in the previous step. The mesh grid on each brain defines an inhomogeneous coordinate system. A point with coordinates (i,j) is shown by $P_{i,j}$ where i shows the layer and j the relative position along the layer i. Layers of I_r will be mapped to the corresponding layers of I', and corresponding points in each pair of layers are mapped together accordingly. In more detail, for every i, the points along L_i are mapped to the points along L'_i linearly, i.e,

$$P_{i,j} \leftrightarrow P'_{i,j}. \qquad (5)$$

In particular we have:

$$P_{0,0} \leftrightarrow P'_{0,0}.$$

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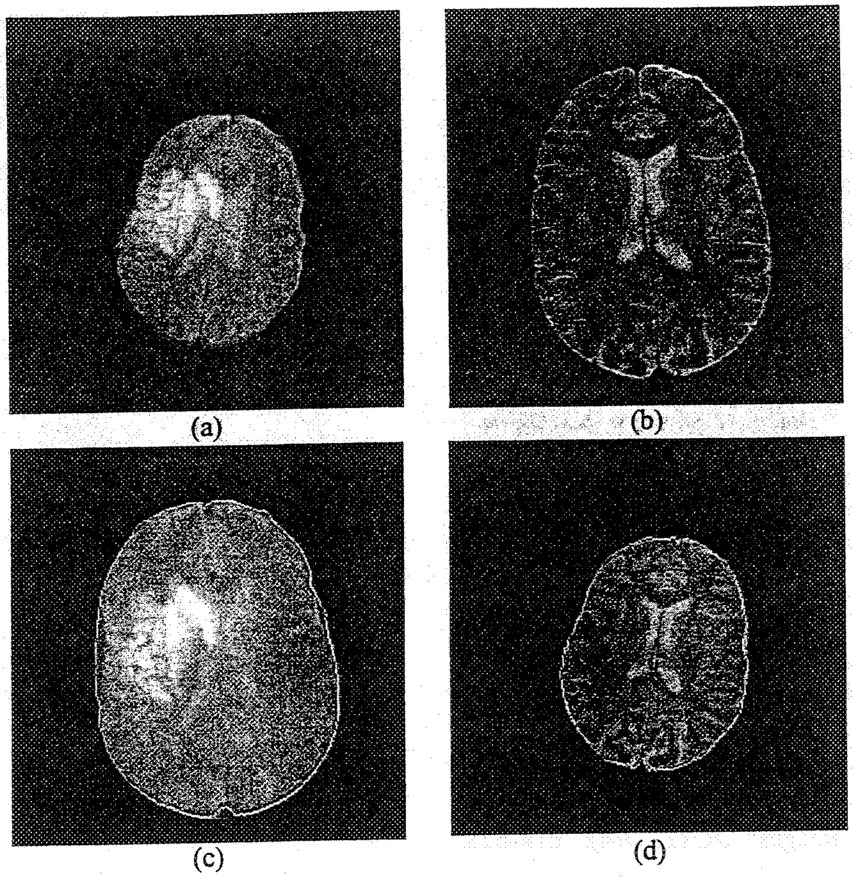

Figure 1. An example of the application of the proposed method to warping a patient stroke brain to a normal volunteer brain MR image. Contour of the second image is overlaid in each case. (a) Stroke patient brain image. (b) Normal volunteer brain image. (c) Stroke patient warped onto the normal volunteer image. (d) Normal volunteer image warped onto stroke patient image.

4. RESULTS

We have implemented the above method and applied it to MR images. The algorithm is fast and generates accurate results. We show an example here to illustrate the method.

Figure 1 shows an application of the method for warping a stroke patient brain image (Fig. 1(a)) onto a normal volunteer brain image (Fig. 1(b)). Images (c) and (d) show final results of warping the stroke patient to the normal brain image, and vice versa, respectively.

In this application, the goal was to label the defected region of the brain. The boundary of the target image is overlaid in each case to show the matching quality and accuracy of the results. The total time spent by the algorithm in this example was 20 seconds on a SUN Ultra1 workstation.

5. CONCLUSION

In this work, we have developed a new method for warping MR images of the human brain. The method is accurate and fast. One of the important advantages of the model is that it does not require any human interaction. There are several areas that our model can be extended or improved. Extending the model to 3D is one of the goals that we are presently working on. Enabling the model to automatically detect multiple landmark points and use them, instead of a single landmark, can improve the model in the cases that two brain images are not homothetically warpable. Finally, one of the weaknesses of the model is its dependence to a scaling center. It somehow can affect accuracy of the model in vicinity of this point. Finding a few landmarks or a region boundary inside the brain can be considered as an approach for solving this weakness.

6. REFERENCES

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