Delineation of Brain Structures from Positron Emission Tomography Images with Deformable Models

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Abstract

Segmentation of positron emission tomography (PET) images is a difficult task. In this study, we propose a new method for delineation of brain structures according to the tracer uptake. The method is based on a new deformable model which is particularly designed for extracting surfaces automatically from noisy images. The automation is achieved by using a global optimization algorithm for minimizing the energy of the deformable model. As an example, the coarse cortical structure was extracted from FDG PET brain images by delineating first the brain surface and then the white matter surface. We have tested the method with the image of the brain phantom and images from a small number (N=17) of FDG brain studies. The cortical structure was automatically and reliably found from all the images. The proposed method provides new opportunities for automatic and repeatable structure extraction applicable for regional quantification of the tracer uptake.

Keywords: Deformable surface model; structure extraction; funtional brain structure; segmentation

1. Introduction

An automatic structure extraction from positron emission tomography (PET) images is a desirable aim, for example, to improve the image fusion and the movement correction in PET. By a structure we mean a volume in PET image which has distinguishable (positive) uptake from its surroundings. Manual delineation of structures, or volumes of interest (VOIs), becomes a laborious task when dealing with the large and complex structures such as the cortical brain structure. In practice, a large set of images cannot be processed this way. Segmentation of PET brain images is difficult to perform in automatic way because of poor contrast and high noise level in images.

A standard procedure to delineate structures from PET brain images is to segment structures from the corresponding anatomical magnetic resonance (MR) images and then to superimpose these on the PET image. This method relies on an accurate coregistration between the imaging modalities. However, this is not a straightforward task due to initial incongruity of structure and function. Advanced coregistration methods could benefit from reliable segmentation of PET images and accuracy of image fusion could be improved, especially when considering inner structures of brain. However, this requires segmentation of PET images without relying on the corresponding anatomical MR images.

Thresholding method provides a direct way to segment PET images. We have studied the thresholding method for extracting structures interactively from PET brain images [1]. With locally uniform radioactivity concentration and consistent structures, the thresholding was appropriate method to delineate complete structures from the PET images.

Structures with noisy boundaries require more advanced methods such as deformable models [2]. We have studied two-dimensional generalized snakes (g-snakes) to extract the cortical structure from PET brain images [3,4]. The g-snakes were interactively applied to refine the VOIs obtained from the corresponding anatomical MR image, which was coregistered to the PET image. The method could adapt to changes in individual radioactivity concentrations in images. The cortical VOIs were extracted from PET brain images. However, relatively close initializations for these VOIs were needed and this restricts the automatic use of the method.

To be able to segment structures automatically from noisy PET images, a new three-dimensional deformable surface model was developed in our research group [5]. The deformable model is based on the energy model and the deterministic dual surface minimization algorithm. In contrast to the earlier two-dimensional method, the structures can be searched in a global way and no anatomical references are required. In this paper, the method will briefly be described and an example of its application to extract cortical structure from brain PET images will be presented. This opens up new possibilities for a fully automatic method for extracting complete structures from PET brain images to be applicable for functional image analysis.

2. Methods

Surfaces are extracted from volumetric images by minimizing the energy function of the deformable model. *An image* is here defined as a three-dimensional array of voxels associated to intensity values. A voxel is a volume element, which has the shape of rectangular parallelepiped. Surfaces are approximated by simplex meshes [6]. A set of discrete points $\mathbf{W} = \{\boldsymbol{w}_1, \boldsymbol{w}_2, ..., \boldsymbol{w}_n\}$, called mexels ($\in \mathbf{R}^3$), and adjacency relations between mexels define a simplex mesh. Adjacency relations are known and constant, hence symbol $\mathbf{W}$ is used for a simplex mesh.

The total energy of the surface mesh $\mathbf{W}$ is defined as

$$\begin{aligned} E(\mathbf{W}) &= \lambda E_{int}(\mathbf{W}) + (1-\lambda) E_{ext}(\mathbf{W}) \\ &= \frac{1}{n}\sum_{i=1}^{n}\Big(\lambda E_{int}(\mathbf{w}_i) + (1-\lambda)E_{ext}(\mathbf{w}_i)\Big). \end{aligned} \tag{1}$$

The regularisation parameter λ is in range [0,1]. The external energy E_{ext} couples $\mathbf{W}$ to the salient image features. The internal energy E_{int} regularises the shape of the surface and is defined as

$$E_{int}(\mathbf{w}_i) = (A(\mathbf{W}))^{-1} ||\mathbf{w}_i - \alpha \sum_{j=1}^{3} \mathbf{w}_{i_j}||^2, \tag{2}$$

where $\mathbf{w}_{ij}$ are the neighbouring mexels of $\mathbf{w}_i$ in the mesh, $A(\mathbf{W})$ is the average area of the faces of the mesh, and α is the shape parameter. For the thin-plate shape model α=1/3 and for the sphere shape model [5]

$$\alpha = \left(3\cos\left(2\arctan\frac{2\left(\sqrt{\pi\sqrt{3}}\right)}{3\left(\sqrt{n}\right)}\right)\right)^{-1}. \tag{3}$$

The sphere shape model is more complicated, but applying it often leads better results than applying the simpler thin-plate shape model. The external energy E_{ext} is defined as

$$E_{ext}(\mathbf{w}_i) = 1 - \frac{||\nabla I(\mathbf{w}_i)||}{\max_{\mathbf{x}\in\mathbb{R}^3} ||\nabla I(\mathbf{x})||}, \tag{4}$$

where the I is the image. Equation (5) defines *the energy image*, where the gradient is computed by the three-dimensional Sobel operator [7].

The energy function (1) is likely to have multiple local minima. Therefore, its global minimization is necessary to render the deformable model insensitive to its initialization. We have proposed an dual surface minimization (DSM) algorithm for the global optimization task in [5]. The algorithm is based on the iterative optimization of two surface meshes, which approach the surface of interest from different directions. We name the energy based deformable model (DM) with the DSM algorithm as *the DM-DSM method*.

The DSM algorithm begins with two meshes: the outer mesh and the inner mesh. These are created from a given initial mesh preserving its properties, except the size. Their sizes are set in such a way that the surface of the searched structure lies in the space between them. This is *the search volume* for the minimization process.

The search is based on the iterative minimization of the energies of the outer and inner surfaces. The energies for the both surfaces are calculated from Eq. (1). During each iteration, the energy of the mesh is minimized using a greedy method adapted from [8]. It is used in such a way, that the outer surface shrinks and the inner surface grows. After each iteration, the DSM algorithm compares the energies of the outer and inner surfaces and continues minimization with the surface having higher energy. If the surface having higher energy gets stuck in a local minimum, the energy of the current surface position is increased until the surface moves again. The DSM algorithm is stopped when the volume inside of the inner surface exceeds the volume of the outer surface. The algorithm selects the surface having the lower energy as the result.

It is sometimes advantageous to approach the surface of interest from a specified direction, e.g. from outside. In this case DSM algorithm is modified in such a way that only one of the two surfaces is allowed to move and the other one is used only for computing the stopping condition. Then, the algorithm just remembers the mesh of the lowest energy that has already been found and compares meshes found in subsequent iterations of the algorithm to it. The variant is called DSM-OS (DSM- outer surface modification).

In the energy image, the brain surface has relatively high contrast against background. Also, the noise level in the energy image is much lower outside of the brain volume than inside of it. Hence, we apply DSM-OS modification approaching brain surface from outside for extraction of it. Ellipsoids are used as initial surfaces. Their centres are set into the mass centre of voxel intensities. From this, the DM-DSM method delineates the surface of brain. The thin-plate shape model is used in the brain surface extraction. The delineated brain surface provides a good individual initial surface for the search of the white matter surface. The white matter surface is the boundary between the tracer uptake levels in white matter and gray matter tissues visible in FDG-PET image. We apply the standard DSM algorithm for the search. Both shape models, the thin-plate and the sphere, can be applied to the extraction of the white matter surface. The delineated brain surface and the delineated white matter surface define the coarse cortical structure in the image.

3. Materials

In the evaluation, we used the Hoffman brain phantom (JB003, Nuclemed N.V./S.A., Roeselare, Belgium) which was filled with FDG. Experiments with the phantom study were used to find suitable parameters for the DM-DSM method. Seventeen FDG brain studies of healthy volunteers were included in the evaluation of the method and its parameters. The cortex has the highest uptake of FDG. Hence, it can be extracted from the PET images. The extracted surfaces were visually compared to the original FDG images. All the PET acquisitions were made with GE Advance scanner (GE, Milwaukee, USA) and were reconstructed with the MRP method to the image cross-section size of 128×128 [9]. The images consisted of 35 continuous transaxial image slices.

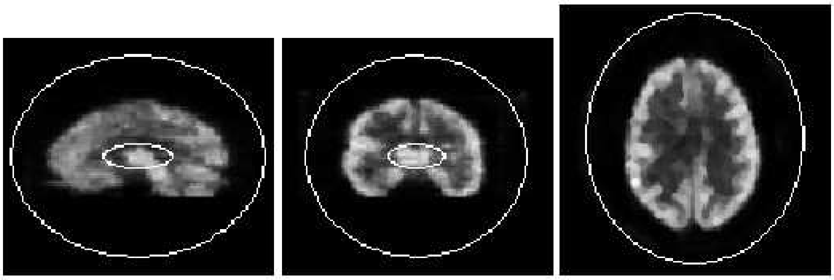

Figure 1- The ellipsoid initialization applied to brain surface extraction for the phantom image. From left, sagittal, coronal and transaxial cross-section views. Recall that the inner surface is only for computing the stopping condition for DSM-OS.

4. Results

From all the PET brain images, the new DM-DSM method was able to automatically and reliably extract the brain surface and the white matter surface. Brain surfaces were delineated with the ellipsoid initialization shown in Figure 1.

The DM-DSM method was insensitive to the sizes of the initial surfaces if the brain surface was located in the volume between the outer and the inner initial surfaces. The white matter surfaces were found with the ellipsoid and the extracted brain surface initializations. Also, the method was not sensitive to the size of the search volume.

The test results of the phantom study gave the initial settings and parameters for the evaluation of the FDG brain studies. The mesh size of 1280 mexels was found to be appropriate and it was applied for all surfaces. The brain surface was extracted with the thin-plate shape model. With the phantom study, both the shape models were examined with the white matter surface. The sphere shape model was found to be slightly better than the thin-plate shape model in delineation of the white matter surface. The search of the brain surface was not sensitive to the parameter λ and values from 0.005 to 0.5 were found applicable. With the search of white matter surface λ needed to be selected between values 0.05 and 0.2. The noise level in the FDG brain images was significantly higher than in the phantom image. Therefore, higher values of the parameter λ were found to be appropriate and the values λ=0.3 and λ=0.2, respectively, for the brain surface and for the white matter surface were applied.

Cortical structure extraction was performed for 17 FDG-PET images. The results were evaluated visually by superimposing the extracted surfaces on the original images and on the corresponding energy images. The brain surfaces for all 17 individual images were properly found. For the white matter surface, energy images were not as good as with the brain surface. However, in visual inspection, the delineated surfaces followed in an acceptable way the visible white matter surfaces.

Three examples of the delineation results are represented in Figure 2. The quality of extracted white matter surfaces differed more than the quality of extracted brain surfaces. The shown example images are chosen and ranked based on the extracted white matter surfaces. The best result, subject 1, follows the surface details slightly better than the typical result, subject 2. The worst case, subject 3, has an error which can be seen on top of sagittal cross-section view. However, as the inspection of neighbouring cross-sections pointed out, this is a relatively small error compared to the size of the structure.

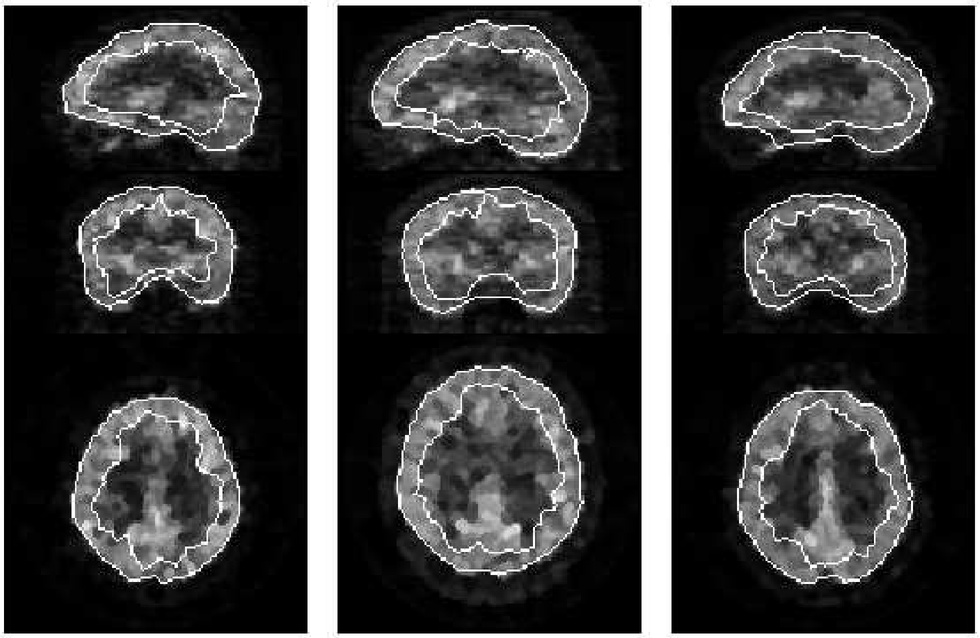

Figure 2- Automatically delineated brain surfaces (with DSM-OS algorithm) and white matter surfaces (with the standard DSM algorithm) from the FDG-PET brain images of three healthy volunteers overlaid on the original image. Subject 1 is the best result, subject 2 represents a typical result and subject 3 is the worst result. From top, sagittal, coronal and transaxial cross-section views.

5. Discussion

We have applied the new deformable model with the dual surface minimization for delineation of the cortical structure from functional positron emission tomography (PET) brain images. The first experiments with 17 normal PET studies and one phantom study all gave acceptable extraction results. As a consequence, the method is applicable for automatic segmentation of functional images. The images were segmented using only data from PET images. Therefore, the method opens up new possibilities for image fusion between PET and anatomical images and movement correction in PET studies.

Deformable models can delineate whole and geometrically continuous structures from noisy three-dimensional images. This is due to image independent constraints that are set. With the global dual surface minimization algorithm, our deformable model is particularly tolerant to noise in the images, which is an important feature in PET. The DM-DSM method is deterministic, the same initial surface and the same parameters with the same image produce the same result surface. This is an important property for reproducible image analysis.

The identification of the brain surface is the starting point for extraction of any other structures from the brain image. In this study, we extracted the white matter surface after delineation of the brain surface. In a similar way, also other structures could iteratively be extracted by starting from, for example, regions of the highest uptake of the radiopharmaceuticals, or from the largest structures. Inside the brain volume in PET image, the structure extraction becomes more difficult.

In this study, we have proposed a new method for delineating structures according to the tracer uptake from PET brain images. The method was tested with phantom and human studies. It was successful in extracting the cortical structure from the tested FDG brain images. The method provides new possibilities to automate the difficult PET image segmentation problem.

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