A 3-D Morphological Algorithm for Automated Labelling of the Cortex in Magnetic Resonance Brain Images

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Abstract

In this paper we describe a new method for automatic extraction and anatomic labelling of the cortical surface in Magnetic Resonance (MR) images of the human brain. Our algorithm consists of a series of morphological operations which automatically find the cortical surface and detect sulci in an MR volume image. The extracted surface points are labelled as "sulcus" or "not sulcus".

Introduction

In our work, we want to obtain an accurate, detailed description of an individual's brain from three dimensional (3-D) MR images. This type of brain surface description can provide valuable information in clinical and research studies. For example, the visualization of complex neuroanatomical structures (e.g. cortical sulci and gyri) in MR brain images is important to brain researchers. Other problems require more than just visualization of anatomy. For instance, by measuring the magnetic field outside the head, magnetoencephalography (MEG) noninvasively monitors brain activity. MEG can be used to estimate current distributions inside the brain, and knowledge from MR images, about location and orientation of cortical folds, can dramatically improve an MEG current source estimate [2]. Anatomically labelled MR images provide necessary information for these brain research problems.

Automatic cortical labelling can be viewed as a computer vision task in which the system interprets a given image using *a priori* knowledge in the form of a model. In most of the existing labelling schemes the model is an anatomical atlas which is elastically or rigidly transformed to fit the subject's brain [3]. In general these techniques are interactive,requiring the user to manipulate the atlas or data to obtain a fit between the atlas and subject images. In [1] an elastic matching scheme is implemented. Although it does not require user interaction, this process may be inadequate for matching structures that are small or have complex shapes.

The labelling procedure described in this paper is an application of 3-D binary mathematical morphology, which is a powerful set theoretic method of image analysis [4]. In contrast to existing techniques which label regions of a brain image that correspond to a physical model, such as an anatomical atlas, our algorithm labels image regions which remain after filtering by morphological transformations. More detailed labels can be assigned to the extracted regions, using an image to model matching approach such as deformable atlas matching. Model matching and morphological processing complement each other well, since a preprocessed image is required to derive accurate results with deformable models.

2 A Morphological Algorithm

We use standard notation from mathematical morphology to describe the steps of our algorithm. In binary morphology we denote a binary image as a set X in N-dimensional discrete space $\mathbf{Z}^N$; the set complement X^c denotes the image background. We transform the image by performing operations defined between X and a set $B \subseteq \mathbf{Z}^N$, the set structuring element. A dilation of X by B is denoted $X \oplus B$, and erosion is represented by $X \ominus B$. Morphological opening and closing are denoted by $X \circ B$ and $X \bullet B$ repspectively, and finally we denote a set difference operation between sets X and Y by $X \setminus Y$.

We have developed a 3-D morphological algorithm to automatically extract and label the cortex in an MR brain image. The algorithm requires a binary volume, which we generate by modifying a Marr Hildreth edge detected image. This edge image is already in a form close to our requirement, since voxels are either black or white depending on whether or not they represent region boundaries. A Marr Hildreth detector always creates closed contours - regions belonging to the head (including skull, scalp, and brain) appear as white areas completely surrounded by black boundaries. When we color the background of an edge detected image black, we arrive at a binary volume, which consists of a white object in a black background.

We represent a binary head image by a 3-D set, denoted X. Set X represents other anatomical regions, not just the brain. The brain is a connected 3-D subset of X, where any two points in this subset can be joined by a 3-D path entirely contained within the brain volume. And, because of noise, the partial volume effect, or true anatomical connections, X may contain voxels that link brain regions to extraneous surrounding structures, such as dura mater or skin. To sever unwanted connections and extract only the brain from an image, we first perform an erosion, which shrinks the brain volume and eliminates all regions smaller than the structuring element. We have chosen a 3-D rhombus structuring element of discrete size 1 (R1), which is a 3-D digital cross 3 voxels wide in the x, y, and z directions. Therefore, transforming by R1 will eliminate regions which have a size of 2 voxels or less in any direction and shrink a majority of the brain surface by 1 voxel. This element deletes narrow connections without globally damaging or distorting an image.

After erosion we carry out a 3-D flood filling operation. This step is necessary because although erosion eliminates undesirable connections, non-brain regions, such as eyeballs or skull, still remain. We want to select only brain voxels. A 3-D flood filling routine finds all voxels connected to a seed point in the brain. Specification of an arbitrary seed point is the only user interaction required for our entire labelling procedure; every other step is automatic. We will denote this eroded and flood filled set of brain voxels as X_{EBrain}.

Since erosion shrinks the brain surface and widens holes in the volume, X_{EBrain} is not a true representation of an entire brain. We fill holes in X_{EBrain} by closing the set with an octagon structuring element of size 2, denoted $O2$. This isotropic element, which is a digital approximation to a sphere in Euclidean space, has a width of 9 voxels. We choose size 2 because an octagon of size 1 is only 5 voxels wide and may not be large enough to close all holes that were widened by erosion. Besides filling image holes, a closing operation replaces portions of an object's boundary with the structuring element's boundary. Therefore, this operation will result in a brain volume in which boundaries are smooth and all holes less than 9 voxels wide are closed (see figure 1 (b)). We will denote the result of this operation X_{CBrain}:

$$X_{CBrain} = X_{EBrain} \bullet O2.$$

Set X_{CBrain} is a smooth image that serves as a template on which we can reintroduce fine details from the original binary volume, X. That is, when we take the difference $X_{CBrain} \setminus X$ we obtain a set which represents all gaps and holes belonging to the brain (see figure 1 (c)). We denote this set X_{Holes}. A difference operation between the closed brain and its set of holes yields our final brain volume:

$$X_{Brain} = X_{CBrain} \setminus X_{Holes}.$$

Figure 2 (a) shows a slice from a brain extracted by this morphological processing.

Below, we summarize six processing steps which we require for extracting a brain from a head image. These steps comprise the first part of our automated algorithm:

1. Color the background of an edge detected image to arrive at a binary image X.
2. $X_{Int} = X \ominus R1$.
3. Flood-fill X_{Int} to arrive at X_{EBrain}.
4. $X_{CBrain} = X_{EBrain} \bullet O2$.
5. $X_{Holes} = X_{CBrain} \setminus X$.
6. $X_{Brain} = X_{CBrain} \setminus X_{Holes}$.

The algorithm's next portion labels elements of X_{Brain} corresponding to cortical regions. A cortex is a convoluted structure whose anatomy is defined by deep grooves (sulci) which cross its surface. Each sulcus is surrounded by ridges (gyri) and is assigned an anatomical label according to its location. The cortical surface is the outer contour of our binary brain image, X_{Brain}, and sulci appear as regions bordering holes and gaps in X_{Brain}. By tracing this outer contour one 2-D slice at a time, we find portions of X_{Brain} corresponding to the cortical surface (the outer contour of a binary object is found with a simple boundary following routine). Because the brain has a convoluted surface, finding its outline a slice at a time simplifies cortex-tracing procedures. However, we must take into account the brain's complexity as a 3-D object if we are to process it successfully on a 2-D basis. For example, on certain 2-D slices, deep sulci make the brain appear to be comprised of disconnected regions. Therefore, the outer contour of every patch of connected pixels on every 2-D slice is traced and labelled as part of the cortical surface. We will call the set of surface points found by this procedure X_{Cortex}. Furthermore, because the cortex folds over on itself, on some 2-D slices the cortical surface may appear to be interior to the brain; the contour tracing routine will miss these regions, since it traces only exterior boundaries. Interior regions are found by further morphological processing steps, and the extracted surface is labelled as "sulcus" or "non-sulcus".

In step five of our algorithm, we created X_{Holes}, a set representing all gaps and holes in a brain image. A portion of these holes are due to sulci, but others are created by noise or anatomical structures. A feature which differentiates a sulcus opening from any other is that given any point in this opening, we can find a connected path of voxels from that point to the image background which lies outside the brain. If we compare corresponding slices of X_{Holes} and X_{CBrain}, we find that sulci openings intersect the boundary of X_{CBrain}, the closed brain image, somewhere in the volume. We conclude this section by providing a detailed list of necessary steps to find all sulci openings in the cortex. These steps form the second part of our automated algorithm.

1. Trace the boundary of X_{CBrain}, and initialize the next processing steps on the first slice of X_{CBrain}. In addition, initialize a set called $X_{AllSulci}$ which starts out as an empty set, but after this part of the algorithm is complete, it will contain all voxels corresponding to sulci openings.

2. Find a point on X_{CBrain}'s boundary that intersects X_{Holes}, and mark it as a sulcus point.

3. Find all voxels in X_{Holes} connected to the sulcus point found in step 2 (we denote this set of connected voxels X_{Sulcus}). As in the first part of our algorithm, we use a 3-D flood filling routine to find all voxels connected to a particular point.

4. Perform the following set union: $X_{AllSulci} = X_{AllSulci} \bigcup X_{Sulcus}$. That is, add X_{Sulcus} to the set of all brain sulci.

5. Redefine X_{Holes} as: $X_{Holes} = X_{Holes} \setminus X_{Sulcus}$. That is, remove X_{Sulcus} from X_{Holes}.

6. Return to step 2, and continue processing in this manner until X_{CBrain} volume has been traversed in its entirety.

7. Redefine the set of cortical surface locations as: $X_{Cortex} = X_{Cortex} \bigcup X_{AllSulci}$.

8. Find the intersection: $X_{Cortex} \bigcap X_{AllSulci}$, and label those surface points in the intersection as cortical sulci.

Once this processing is complete, we arrive at a set X_{Cortex} which is a point by point description of the cortical surface. Also, X_{Cortex} is labelled as to which surface points correspond to sulci. Figure 2 (b) shows one slice through X_{Cortex}, the cortical surface found by the above processing steps; part (c) shows points that the morphological processing labels as sulci - these points are superimposed on the original gray scale image of the slice.

The algorithm was able to successfully locate the cortical surface and differentiate sulci from other brain openings. An advantage to our approach is that once an arbitrary point inside the brain has been specified, the processing is entirely automatic. Also, this point-wise surface description can be sampled and the samples used to find a closed-form, analytic description of the surface, which is useful for determining geometric properties such as surface normals. Future work will concentrate on methods for sampling the convoluted surface and for assigning final anatomical labels to each sulcus.

References

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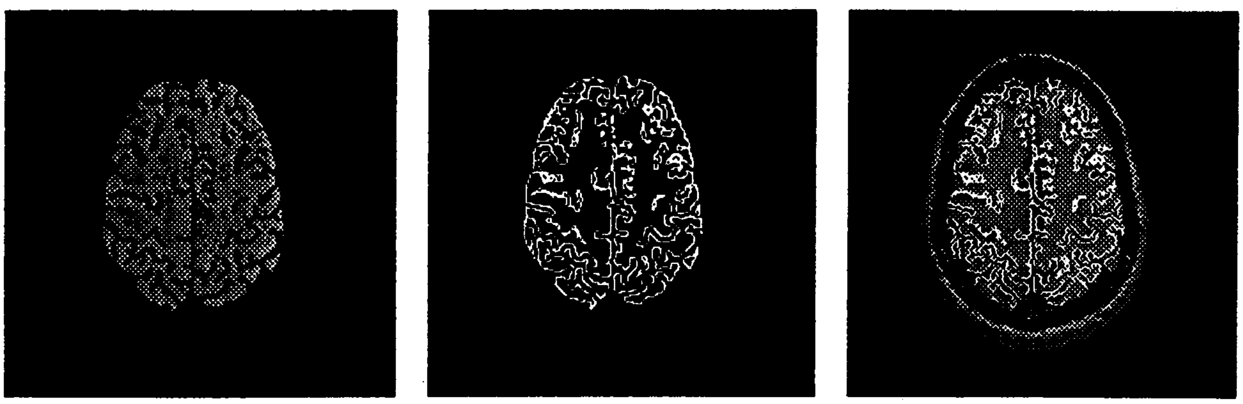
(a) (b) (c)

Figure 1: (a) A transverse slice through an MR volume. (b) The same transverse slice through the morphologically closed image. (c) Results of the set difference between the closed and the original binary brain images.



(a) (b) (c)

Figure 2: (a) Transverse slice through extracted binary brain image. (b) The extracted cortical surface. (c) The sulci detected by the morphological algorithm