Extracting Lines of Maximal Depth from MR Images of the Human Brain

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Abstract

This paper describes a new approach to the automatic detection of the bottom lines of the main cortical sulci using MR images of the human brain. The principle idea is to extract lines of maximal depth as measured from the smoothed brain surface. The main advantage of our approach over existing methods is that it is not based on curvature estimation. It is therefore much more robust and easier to implement.

1. Introduction

This paper describes a new approach to the automatic detection of anatomical landmarks from MR (magnetic resonance) images of the human brain. The landmarks we are particularly interested in are the bottom lines of the main cortical sulci. The brain's sulci are deep narrow valleys or folds that increase the size of the cortical surface.

Their bottom lines are of interest in two respects. Firstly, they allow us to represent an entire sulcus by a tree like structure of curves rather than of surfaces, and thus present a highly condensed representation of prominent landmarks. Secondly, the sulcus bottoms are areas of great anatomical interest in themselves and have been the subject of a number of anatomical studies [9]. Their automatic detection will be a useful tool in human brain mapping as it will help to perform comparative structural studies across subjects.

The principle idea underlying our approach is to extract lines of maximal depth as measured from a smoothed brain surface. Those lines are found in the following way. Each indentation or valley in the brain's surface is filled up by layers of voxels in an iterative way, where the iteration starts at a smoothed out idealized surface and moves inward until the bottom of the valley is reached. In the process, each voxel receives a label that encodes its depth as measured from the starting layer. In this way, the innermost layers of voxels receive the highest labels, the outermost voxels have label zero. The way in which the voxels are placed to fill up the valley is reminiscient of a brick laying process.

Once the sulci are filled up by depth labelled voxels, we apply a 3D thinning algorithm to extract a medial surface of each sulcus. In a final step, we extract the bottom line of that medial surface by eroding progressively deeper levels of the medial surface until the bottom is reached.

2. Related Work

There appears to be no previous work aimed at the extraction of the sulcus bottoms. However, there are a number of papers closely related to our work that also deal with the extraction of prominent lines as landmarks in MR images.

One group of papers focuses on the computation of curvature properties and ridge line extraction. The methods described in [2],[6],[7],[12], fall into that category.

Our approach differs in that it extracts lines of *maximal depth* as measured from a smoothed brain surface as opposed to lines of *maximal curvature*. The advantage is that depth is much easier to compute than curvature. Tests that we performed using ridge line methods for detecting prominent lines on the brain surface did not produce satisfactory results. Also note that the bottoms of the sulci do not always coincide with lines of maximum curvature.

The work by [3] is directed towards identification of the main sulci using Voronoi diagrams. Our method presented here avoids the use of Voronoi diagrams and is therefore much faster.

Another closely related type of work is reported in

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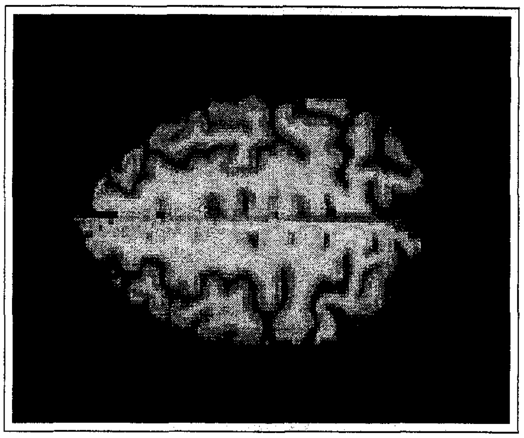

Figure 1. MR image

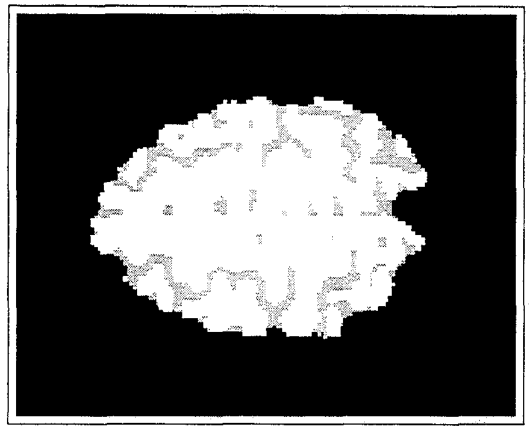

Figure 2. initial segmentation

[4]. The authors focus on the representation of the cortical topography as relational graphs using homotopic transformations. Our work differs from this one in that it does not employ optimization techniques and is essentially parameter free. We therefore hope to obtain more robust results while requiring less computation time.

The use of skeletonization methods for the analysis of 3D medical images is widespread (see for instance [8],[11]). In addition to the traditional topological thinning methods we use a variation of these methods which allow us to extract bottom lines of medial surfaces of sulci.

3. Depth labelling

The first step in our scheme consists of a "depth labelling" procedure applied to the sulcus interiors. The basic idea is to fill each sulcus in a manner similar to region growing starting from the brain's surface and working our way inward until the sulcus bottom is met.

The input into the algorithm is a segmented image in which each voxel is either labelled as "sulcus", "brain interior" or as "exterior". Figure 2 shows one slice of such an initial segmentation that serves as input into the algorithm. This initial segmentation is obtained by a k-means clustering segmentation [10] that separates brain from non-brain voxels. In a second step, the sulci are closed by a morphological closing filter [5]. The difference between the segmented image and the morphologically closed image yields the sulcal areas.

The algorithm attaches a label to each "sulcus" voxel which corresponds to its depth. It begins by attaching the label "1" to the outer layer of sulcus voxels. As the algorithm moves along, progessively deeper levels of the "filling material" receive higher labels, until finally each sulcus is filled with layers of labelled voxels.

At each iteration, all voxels in the image are scanned. During the scan, each sulcus voxel that is 6-adjacent to a voxel that was already depth labelled in the previous scan receives a new depth label. The depth label is incremented after each scan through the entire image. As the process is reminiscent of brick laying, we call this procedure the *"brick layer algorithm"*. The result is in fact independent of the direction of the scan.

Note that this algorithm also enables us to separate the sulci: we simply threshold the brick layered image, and apply a connected components algorithm.

Below a small portion of an image slice after brick laying is shown. The brain interior is coded as 255, the exterior is coded as 0, and the rest of the voxels have labels corresponding to their depth.

0	0	0	0	0	0
255	1	1	1	1	255
255	2	2	2	2	255
255	3	3	3	3	255
255	4	4	4	4	255
255	5	4	4	4	255
255	255	4	4	4	255
255	255	5	5	5	255
255	255	255	6	6	255
255	255	255	255	255	255

Note that there is a group of voxels that receive the same label even though some voxels in the group appear to be deeper than others. This is due to the fact that the algorithm works in a three-dimensional setting, where the distance to the surface is in fact equal for all members of this group.

In the following, a pseudo-code version of the algorithm is given, where $input(v)$ denotes the value of the

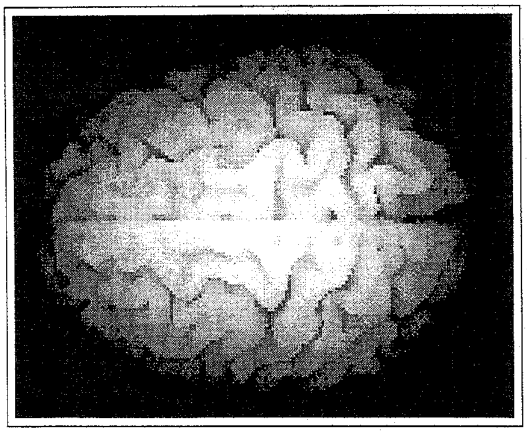

Figure 3. segmented MR image

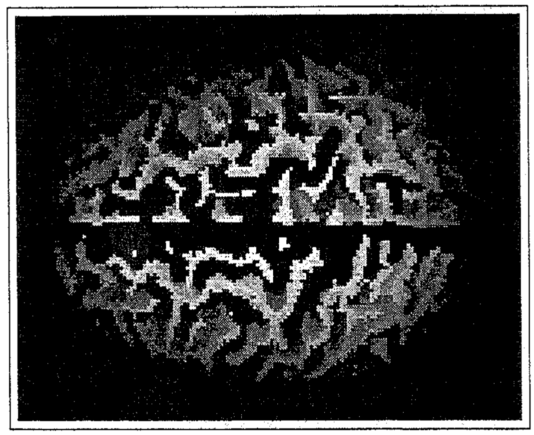

Figure 4. thinned sulci

voxel at location v in the input image, and $output(v)$ denotes the value at location v in the output image.

```
procedure brick_layer
{
  create an output image;
  initialize its voxels to zero;
  set old_label := 0;
  set new_label := old_label + 1;
  set n := 1;
  while (n > 0) do: {
   n = 0;
   for all voxels v in the input image do:
    if input(v) equals "sulcus" do:
     for all 6-neighbours w of v do:
      if output(w) equals old_label do:
       output(v) := new_label;
       n := n + 1;
       skip checking the rest of the neighbours;
  }
}
```

4. Locating sulcus bottoms

Of particular interest are the bottom lines of the sulcus valleys. Unfortunately, the sulcus bottoms do not have constant depth. The bottoms may actually be quite rugged. Therefore, it is not feasible to simply threshold the output of the brick laying algorithm. We propose the following procedure instead. The first step consists in reducing the sulcus interior to its medial surface. This can be done by applying a 3D topological thinning method. In our experiments, we used the method described in [13] with the simple point characterization replaced by the method described in [1]. Figure 4 shows the result of this step.

The second step consists in further reducing the medial surface such that only its bottom line remains. We use a modification of the thinning algorithm to achieve this. The basic idea is to remove voxels at progessively deeper layers while leaving voxels at the sulcus ends unchanged. The criteria used in deciding which voxels to remove are simliar to the criteria used in topological thinning.

Only border voxels at the current depth level are considered for deletion. A voxel is called a *border voxel* in a given principal direction (north, south, west, east, top, bottom) if its neighbour in that direction is zero. Obviously, simple points (i.e. points whose removal would alter the topology) are not removed. In addition, end points are also not removed. End points are characterized by the fact that there are no more than two non-zero 26-adjacent voxels. Other criteria such as the "checking plane" condition employed by [13] are not used here.

A pseudocode version of the algorithm is given below. Note that it is essentially Tsao's thinning algorithm [13] with an outer loop through the depth levels added and the checking plane condition omitted.

```
procedure bottom_line
{
for (depth=1; depth<maxdepth; depth++) {
  while (marked voxels exist) {
    for all principal directions (N,S,E,W,T,B) do:
      for all voxels v do:
        if (label(v) != depth) skip;
        if (not BorderPoint(v, current direction))
          skip;
        if (not EndPoint(v)) skip;
        if (not SimplePoint(v)) skip;
        mark_for_deletion(v);
    }
    delete all marked voxels;
  }
}
```

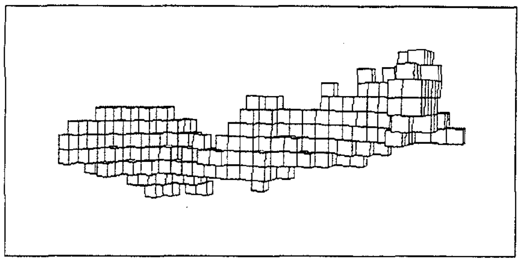

Figure 5. medial surface

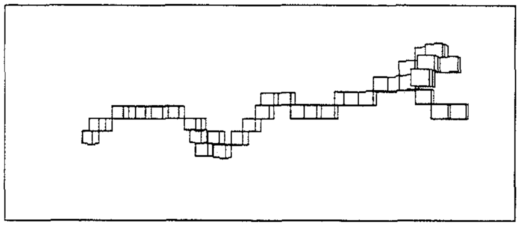

Figure 6. bottom line

Figures 5,6 illustrate the effect of this algorithm when applied to an individual sulcus. Figure 5 shows the medial surface of this sulcus, figure 6 shows the result after the bottom line extraction was applied.

5. Experiments

The experiments were performed on several data sets. In each case, we used segmented data sets as input, in which the brain matter had been extracted. We opened the sulci by applying a 3D morphological opening operator using a $3 \times 3 \times 3$ sphere as a structuring element, after which the brick laying and bottom line extraction were performed. In a final step, the bottom lines were converted into a graph structure. The results so far have been quite promising.

Figures 7,8 show the result of an experiment involving a data set consisting of 40 slices of size 64×155 voxels. Some of the main sulci are labelled to provide better orientation. (1: sulcus centralis, 2: sulcus postcentralis, 3: sulcus frontalis superior, 4: sulcus frontalis inferior) A more thorough anatomical validation is under way. The computing time was approximately 1.5 minutes (after segmentation) on a DEC-Alpha Unix-workstation, where most of the the time was spent on morphological filtering and medial surface extraction (3D thinning).

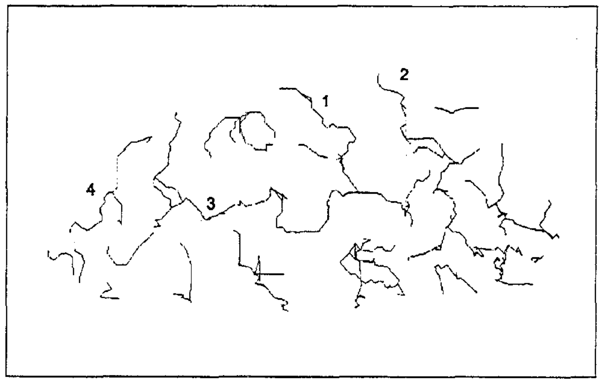

Figure 7. sulcus bottom lines (top view of left hemisphere), 1: sulcus centralis, 2: sulcus postcentralis, 3: sulcus frontalis superior, 4: sulcus frontalis inferior

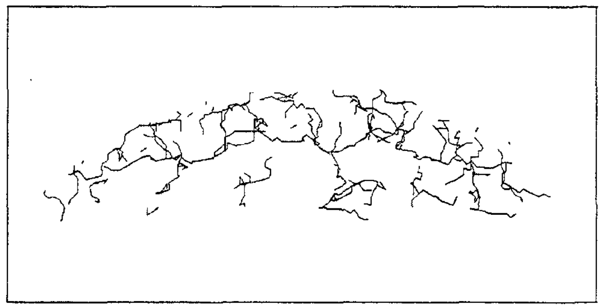

Figure 8. sulcus bottom lines (side view)

6. Conclusion

A new method of extracting relevant anatomical landmarks from MR images of the human brain was presented. The landmarks that were extracted are the bottom lines of the cortical sulci, which correspond to lines of maximal depth as measured from the smoothed surface. The principal advantage of our method is that it is parameter free and thus very robust. Compared to ridge line extraction methods it produces far better results and is also easier to implement.

The main tool that we proposed here was the "brick layer" algorithm, that performs a depth labelling of the sulci. The brick layer algorithm provides an easy method of separating sulci from one another, and it allows us to investigate the sulcus properties at various depths. By eroding the sulcus medial surface we can easily extract the sulcus bottom.

Future work will be aimed at an automatic labelling of the detected sulci using features such as direction, length, depth and adjacency relations.

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