Journal of Neuroscience Methods 172 (2008) 122–130

Contents lists available at ScienceDirect

Journal of Neuroscience Methods

journal homepage: www.elsevier.com/locate/jneumeth

A robust and accurate algorithm for estimating the complexity of the cortical surface

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ARTICLE INFO

Article history:
Received 18 December 2007
Received in revised form 13 March 2008
Accepted 16 April 2008

Keywords:
Anatomic MRI
Box-counting
Cortical complexity
Fractal dimension
Reconstructed cortical surface

ABSTRACT

A fractal dimension (FD) gives a highly compact description of the shape characteristics of the human brain and has been employed in many studies on brain morphology. The accuracy of FD estimation depends on the precision of the input shape description. Facilitated by automatic cerebral cortical surface reconstruction algorithms, the shape of the cerebral cortex can be more precisely modeled using Magnetic Resonance (MR) imaging. Since the reconstructed cortical surface is represented by triangles, rather than by points, as is typical of models that use voxels, the voxel-based FD estimation algorithms that have been used in previous studies do not work when using the cortical surface as the input. Thus, designing a new algorithm that is able to estimate the FD from a surface representation becomes of particular interest. In this paper, a robust and accurate FD estimation algorithm is proposed. The algorithm is based on a box–triangle intersection checking strategy, which is used for the first time in brain analyses, and a box-counting method, which has been widely used in FD computations of the human brain and other natural objects. These two features endowed the algorithm with robustness. The accuracy of the algorithm was validated via several experiments using both manually generated datasets and real MR images. As a result of these features, the algorithm is also suitable for estimating the FD of fractals in addition to that of the cerebral cortex.

1. Introduction

The human cerebral cortex plays a crucial role in human intelligence. For years, many researchers have dedicated themselves to investigating its structural features and to comparing the cortical folding patterns between groups of individuals. However, due to the intricate geometry of the cortex, quantifying cortical morphology has always been a difficult task. Measurements such as thickness, sulcal depth and curvature only reflect local features of the cortex. The Gyrification Index (GI) (Zilles et al., 1988), although it gives a global description of cortical complexity, is sensitive to the direction of slicing (Thompson et al., 2005). Thus, a compact measurement which is able to characterize the folding pattern of the whole cortex or at least a lobe of the cortex will be of great value for researchers.

The fractal, first proposed by Mandlebrot (1982), has been widely used to describe self-similar structures to which it is difficult to apply shape analysis in a usual way. Due to its highly convoluted gyri and sulci, the human brain is a fractal in some spatial scales (Kiselev et al., 2003). The shape complexity of a fractal is measured by its fractal dimension (FD), a single value that summarizes the variability of an object: the more complex an object (e.g. a brain with more, deeper folds, or more involuted folding patterns), the greater its FD value. FD is usually estimated using the box-counting method (Gangepain and Roques-Carmes, 1986; Liebovitch and Toth, 1989; Sarraille and Myers, 1994) because of its robustness in dealing with fractals which do not have strict self-similarity. Since the human brain is not self-similar at all scales, the box-counting method is especially suitable for computing the FD of the human brain.

Many research studies have adopted fractal analysis to explore the morphological properties of the human brain using segmented Magnetic Resonance (MR) images (Bullmore et al., 1994; Cook et al., 1995; Esteban et al., 2007; Free et al., 1996; Kedzia et al., 1997; Kiselev et al., 2003; Li et al., 2007; Takahashi et al., 2004; Zhang et al., 2007). In these studies, the FD of white matter (WM), gray matter (GM), WM/GM surface, and GM/Cerebrospinal fluid (CSF) surface were computed, mostly by the box-counting method. In order to eliminate the influence of thickness and give a more compact description of the shape, skeletons were employed to study the cortical folding pattern (Mangin et al., 2004). Some researchers computed the skeletons of the cerebral cortex (Ha et al., 2005;

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doi:10.1016/j.jneumeth.2008.04.018

Lee et al., 2004) and cerebellum (Liu et al., 2003) from the segmented MR images and then used box-counting to obtain the FD. The above cited works calculated the skeletons slice by slice. Zhang et al. (2005, 2007) applied a 3D skeletonization algorithm to WM, and then analyzed the FD of the skeletons. However, voxel-based methods have two major drawbacks: they cannot preserve the topology of cortical surface (e.g. the skeletons and surfaces may include holes); nor can discrete voxels accurately present a continuous structure.

Because it overcomes these two drawbacks, the surface of an object is a better choice for shape analysis, especially in research on the cerebral cortex because the cortex is thin. The pattern of gyrification and fissuration reflects a fractal nature (Luders et al., 2004), which indicates that the FD can be a useful measure when applied to reconstructed cortical surfaces. The surface-based method was first presented by Thompson et al. (1996), using manually outlined sulcal surfaces. Over the next several years, a number of automatic cortical surface reconstruction algorithms were invented (Dale et al., 1999; Han et al., 2004; Kim et al., 2005; MacDonald et al., 2000; Xu et al., 2006). An extracted surface provides more accurate details of the cerebral cortex than a segmented MRI image, so these reconstruction algorithms have been widely employed in research on abnormal FDs in schizophrenia (Narr et al., 2001, 2004), Williams syndrome (Thompson et al., 2005) and gender differences of cortical complexity (Luders et al., 2004). In addition, Im et al. (2006) did a thorough study of the relationship between FD and other factors like cortical thickness, sulcal depth and folding area. However, the FD estimation method in this work is unstable under different parameter choices. We will discuss this in greater detail in Section 4.

In this paper, we propose a robust and accurate FD estimation algorithm which is able to measure cortical folding complexity. This algorithm uses extracted cortical surfaces as input. The box-counting method and a box–surface intersection checking method are employed to increase robustness. The accuracy was supported by a series of experiments. In addition, the algorithm is both easily written into code in popular programming languages such as C, C++, Java, C#, etc. and easily used because the user only needs to set a few parameters. After that, it runs without human intervention.

The remainder of this paper is organized as follows: Section 2 describes the MR images acquisition and pre-processing, and the FD estimation algorithm in detail; Section 3 gives the experimental results using both artificial data and real MR image data; Section 4 discusses this method, including a comparison between our algorithm and the algorithm in Im et al. (2006), issues relating to parameters, a conclusion and some future research directions.

2. Materials and methods

2.1. MR images

57 normal subjects (27 males and 30 females, 23.6 ± 3.9 years old) participated in this study. All subjects were right-handed. MR images were scanned on a 3T SIEMENS TrioTim scanner using a magnetization prepared rapid acquisition gradient echo (MP-RAGE) three-dimensional T1-weighted sequence (voxel size = 1 mm × 1 mm × 1 mm; TR = 2000 ms; TE = 2.6 ms; Nex = 1, slice thickness = 1 mm).

2.2. Pre-processing

Each scan was processed using Freesurfer (http://surfer.nmr.mgh.harvard.edu/)(Dale et al., 1999; Fischl et al., 1999). In brief, the pre-processing stage contained four steps. First, intensity nonuniformity correction and normalization to stereotaxic space using linear transformation were applied to the input image. Second, the voxels of the brain were segmented into GM, WM, CSF and background. Third, tessellations of the GM/WM boundary, boundary smoothing and automated topological correction (in order to remove holes and genus on the surface) were performed to obtain the initial surface. Fourth, the obtained surface was used as the initial value for the deformable model to reconstruct the pial surface. Thus, for each scan we got a GM/WM surface and a pial surface for each hemisphere. We used pial surfaces and their smoothed version (smoothed using the mris_smooth command of FreeSurfer) in this study, because we are interested in the sulcal and gyral convolutions of gray matter. The FD of the GM/WM surfaces can be estimated as well for those who are interested in white matter folding.

A standard brain surface divided into regions of interest (ROI) (Desikan et al., 2006) was mapped back to each subject's native image space with a high-resolution spherical morphing procedure. ROIs were homologous across subjects. To compute the FD of lobes of a hemisphere, the surface was divided into prefrontal, parietal, temporal and occipital lobes by merging the regions of interest in the same lobe. The cingulate and insular regions were not included in the above four regions.

In addition, for each scan, the thickness and curvature at each vertex were calculated using Freesurfer in the native space.

2.3. Box-counting method

Generally, box-counting of an object is done by placing the object of interest onto a cubic grid of size r, and counting the number of boxes occupied by the object, namely, $N(r)$. By changing r, a series of $N(r)$s are obtained. Then $\ln N(r)$ is fitted with $\ln 1/r$. The fitted slope is the FD estimation of the object. A more detailed introduction to the box-counting method can be found in Zhang et al. (2005). In this context in which the object was a reconstructed cortical surface which consists of many triangles, we counted the boxes occupied by one or more triangles. Thus, we divided the box-counting on the cortical surface into three sub-procedures: for each triangle on the cortical surface, we marked boxes that intersected it as “occupied boxes”; we counted the number of occupied boxes; and we computed the FD by applying linear fitting. The last two sub-procedures are trivial so we focused on the first step. To check the intersection of a box and a triangle, the part of the triangle inside the box was calculated. If the part was empty, the box was not occupied by a triangle; otherwise, an intersection existed and the box was marked. For clarity, we have chosen to illustrate the computation of the interior under a 2D condition; nevertheless, this method could be easily extended to 3D. As shown in Fig. 1, a box in 2D is a square bounded by four lines. The part of a convex polygon (a triangle is a special case) which is inside the box can be calculated by iteratively cutting it using the four lines and abandoning the parts outside the square. A line cutting a convex polygon results in two parts. It is easy to determine which part to throw away since the position of the line is known. For example, if the upper bounding line of the square cuts a polygon into two parts, the part above the line is dropped. In a 3D situation, cutting the triangle with the six faces of a box gives the interior part of the triangle.

Obviously, testing every triangle–box pair for intersection requires too much computation and makes estimation impractical. Thus, bounding-box technique (Parent, 2002) was employed to reduce the numbers of boxes checked for intersection without losing precision. In this approach, each triangle is bounded in a bounding cuboid, whose six faces are determined by the minimum/maximum x, y, z coordinates of the triangle vertices. The cuboid gives a range of boxes which may be occupied by the