ABSTRACT

This paper presents a new approach for the morphometrical characterization of brain structures using shape features calculated from normal fields. An orientable surface representation of the brain structure is derived allowing the estimation of the corresponding normal field without the need of a parameterized surface. In fact, the normal field is calculated from the application of the 3D wavelet transform. Rotation- and translation-invariant shape features extracted from the normal fields are defined and successful experimental results using data from neuroanatomic structures are presented.

1. INTRODUCTION

It is a well known fact that shape analysis techniques have played a key role in many important computer vision applications, from OCR to biomedical applications. Nevertheless, much of the work on shape analysis has been concentrated on 2D shape analysis throughout the last 2 decades. The advance of acquisition technologies has brought much interest to the problem of dealing with 3D shapes, which can currently be obtained by different means such as range images and tomography. The combined advances in imaging hardware and software have characterized a technological opportunity for systematically developing and applying effective 3D concepts and algorithms to the fast growing databases of 3D data. This situation is particularly promising in the area of medical imaging, where a myriad of data is generated and stored every day in hospitals and research centers. In a previous work, we introduced a framework for 3D shape analysis based on a wavelet transform, in an application to discriminate neuroanatomic structures [6]. The main limitation of that approach is the representation of cortical structures as a function of the form \( z = f(x, y) \), which is not always the case in practice. This work presents a more general approach by exploring a volume representation of the brain data and the 3D wavelet transform [9].

Our motivation for the work presented here comes from the popularity of the neuroimaging applications in the last decade. Several studies showed that the underlying morphological differences in neuroanatomy might be indicative of the functional variability in the brain. For instance, in the studies of auditory cortex, differences of morphology are reported between normal versus dyslexic or autistic populations. Also, new studies [7] on the functional delineation of the auditory cortex in normal populations revealed that there is a strong relationship between the topographies of anatomy and function. So far, in the literature, morphological analyses of anatomical structures are based solely on volumetric or statistical measures. However, we believe that the type of 3D shape variability in neuroanatomical structures is difficult to be captured exclusively by these representations in its entirety. Unfortunately, the relationship between the shape and function remains unexplored in spite of the fact that the spatial sensitivity of magnetic resonance imaging have reached millimeter precision. Motivated by this challenge, we devised wavelet-based methods for the quantification of shape variability in anatomical structures. In this study, our method is illustrated in an important player in the auditory cortex, Heschl’s gyrus, for which complicated shape variability is reported earlier [5].

This work is organized as follows. First, the adopted pre-processing steps for obtaining the volume representation are described and illustrated in Section 2. Our approach for calculating the normal fields from the volume representation using the 3D wavelet transform is explained in Section 3, followed by the introduction of shape features extracted from the normal fields in Section 4. Finally, some successful experimental results are presented on surfaces extracted from Heschl’s gyrus in Section 5, concluding with some comments about our ongoing work in Section 6.

2. FROM CONTOURS TO VOXELS

It is assumed that the structure of interest is either traced or segmented automatically from magnetic resonance images.
as sequences of points in form of level curves along a series of slices. This kind of brain surface cannot be represented in the form $z = f(x, y)$, which would allow the application of 2D wavelets for extracting the shape features [6]. Instead, we have developed an approach to derive a volumetric representation from the contours, which can be suitably analyzed by 3D wavelet transforms. Figure 1(a) shows a typical contour from a set to be processed. The first step to build the desired volumetric representation is to dilate the generate a polygonal line by linear interpolation between each pair of consecutive points of the contour, followed by dilation, thus resulting in the shape shown in Figure 1(b). The dilated shape is then manually divided in two parts by extending a pair of straight lines from the contour extremities, as shown in Figure 1(b). Each part consists of a 2D region whose outline include the original curve. The part corresponding to the external region of the original brain structure is deleted and the volume is then obtained by properly stacking the obtained filled contours (see Figure 1(c)).

3. NORMAL FIELD ESTIMATION USING 3D WAVELETS

An important approach to characterize surfaces regards their normal field. Previous works have already addressed the problem of characterizing brain structures using shape features extracted from the normal field [4, 2]. The standard approach is to obtain a parameterized version of the surface (e.g. triangulation or active models), which can thus be used to calculate the normal fields and other differential measures. The main problems with such approaches lie precisely on the need for calculating such parameterized representations, which still is an open problem with methods that present computational difficulties and do not guarantee to obtain satisfactory results.

A different approach has been adopted in our framework in order to circumvent the aforementioned problems. The basic idea is to avoid the need for a parameterized surface in order to calculate differential properties of it. Let $V$ be the volume obtained by the procedure explained in Section 2. We define $w = f(x, y, z)$ as

$$f(x, y, z) = \begin{cases} 1, & (x, y, z) \in V \\ 0, & \text{otherwise} \end{cases}$$

(1)

(2)

The function $f(x, y, z) = 1$ is said to be an orientable surface and it can be shown that its normal field may be defined as [1]

$$N(x, y, z) = \left( \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z} \right)$$

(3)

One of the main advantages of this formulation is that the surface’s normal field may be calculated from an implicit representation, thus avoiding the need for parameterization. There are many approaches for estimating the derivatives in Equation 3, and we have explored the capabilities of the wavelet transform to perform numerical differentiation [3]. We denote 3D points in the real plane as bold letters, e.g. $\mathbf{x} = (x, y, z)$ for simplicity’s sake. Therefore, we denote $f(\mathbf{x})$ as the volume function and the continuous wavelet transform of $f(\mathbf{x})$ is defined as:

$$W_\psi(b, a) = C_\psi^{-1/2} \frac{1}{a} \int \psi^* \left( a^{-1} (\mathbf{x} - b) \right) f(\mathbf{x}) \, d\mathbf{x}$$

where $C$, $\psi$, $b$ and $a$ stand for the normalizing constant, the mother wavelet, the translation vector, the dilation parameter, respectively. $\psi^*$ denotes the complex conjugate of the mother wavelet $\psi$. In order to estimate the derivatives of Equation 3, we have adopted the corresponding derivatives of a 3D gaussian function as mother wavelets, denoted as $\psi_x$, $\psi_y$ and $\psi_z$, leading to the transforms $W_{\psi_x}(b, a)$, $W_{\psi_y}(b, a)$ and $W_{\psi_z}(b, a)$, respectively. The application of the wavelet transform for numerical differentiation of $f$ allows controlling the analyzing scale, which is equivalent to smoothing the original volume representation. Figure 1(d) shows the smoothed version of the volumetric structure of Figure 1(c), as well as the calculated normal field.

4. FEATURE EXTRACTION

Once the normal fields are obtained, it is important to synthesize their most important geometrical properties in terms of a set of meaningful features. In the current application, the objective is to characterize differences between the geometrical properties of structures of interest across individuals. Part of the observed variability in an extracted structure could be due to differences in head positioning inside the scanner, or due to gross head shape and size differences between subjects. However, this type of gross variability is minimized after standardizing the given MRIs using global image registration techniques. After standardization, orientation, translation, scaling and shape differences still prevail in the images of a subject population as part of inherent variability in the individual structures [8]. Therefore, in order to focus exclusively on shape differences, the chosen features should be invariant to rotation, translation and scaling. After visual analysis of different structures, we decided to select (i) eigenaxis ratios and (ii) statistical moments of the distribution of the normal orientations around a small neighborhood centered at each surface point:

Eigenaxis ratios: Given the recovered surface, the covariance matrix of the coordinates of each of its constituent points is estimated by using standard statistical methods. It can be shown that the eigenaxes of this matrix corresponds...
Figure 1: Original points and interpolated contour from a slice in (a); Dilated contour in (b); Stacked volume obtained from dilated regions in (c); and the smoothed version of the volumetric structure of (c) with normal field in (d). The z-axis in (c) and (d) has been vertically elongated only for better visualization purposes, thus explaining the artificial vertical orientation of the normal field.

to the variances of the data after complete decorrelation. Given the 3D nature of our data, three variances (namely $\sigma_1^2 > \sigma_2^2 > \sigma_3^2$) are obtained. The elongation of the cortical structures can then be conveniently expressed in terms of the ratios $R_1 = \sigma_1/\sigma_2$, $R_2 = \sigma_1/\sigma_3$ and $R_3 = \sigma_2/\sigma_3$. Observe that these three features have global nature and are invariant to translation and rotation.

Local orientation distributions: In order to express local differences between the cortical surfaces, density histograms were obtained for the orientation of the normal vectors along the 6-neighborhood around each of the surface element. More specifically, for each point $(x, y, z)$ of the surface, the mean, maximum and minimum values of the angles defined between the normal at each surface point $(x, y, z)$ and the normals at each surface neighbor point are obtained and respective histograms, considering the entire surface, are built. Global features are extracted from such three histograms in order to reduce the dimensionality of the classification space. These 15 features include the mean value and the central moments from second to fifth order. Observe that each of these features preserve the invariance to translation and rotation of the original angles between normals. Together with the three ratios described in the previous section, we therefore have a total of 18 features. All $2 \times 2$ combinations of these features have been visually assessed and the best ones with respect to the present application have been selected, as shown in next section.

5. EXPERIMENTAL RESULTS

In order to demonstrate the shape analysis technique above, traces of one structure, the Heschl’s gyrus, is obtained from one hemisphere of 14 subjects using the tracing methodology of [5]. These 14 subjects are independently classified by an expert anatomist into three shape categories: Class 1, Single Heschl’s gyrus: The shape of the Heschl’s gyrus consists of one single bump as the slices go from lateral to medial; Class 2, Common Stem Heschl’s Gyrus: The shape of the Heschl’s gyrus starts as two bumps laterally, but merge into one bump as slices proceed medially; Class 3, Posteriorly Duplicated Heschl’s Gyrus: The shape of the Heschl’s gyrus consists of two bumps as slices proceed lateral to medial.

The anatomist informed us that usually there is a continuum of shape variability among these three classes, indicating Class 1 is more similar to Class 2, and Class 2 is more similar to Class 3. Therefore, if the selected features are representative quantitatively, the spatial distribution of the classes in the feature space should be neighboring according to this similarity. The feature spaces in Figure 2(a), (b) and (c) are obtained after we applied the proposed shape analysis procedure to the given structures completely blindly to the class assignments given above. As seen from this figure, similar classes are indeed neighboring in the feature space, when pairs of features are projected on the graphs. Hence,
we conclude that the shape characterization method that we propose captures the variations in the Heschl’s gyrus satisfactorily. At this point, the correlation between these features -which reflect shape properties- with behavioral features -which reflect functionality of the brain- still remains to be explored. However, we demonstrated that quantification of complex morphological properties of anatomical structures using shape analysis techniques is possible. In order to investigate how effective are the calculated features to discriminate the above classes, we have visually assessed all combinations of 1, 2 and 3 features, and three successful examples are shown in Figure 2(a), (b) and (c).

![Figure 2](image-url)

Figure 2: Three successful feature spaces obtained by visual analysis of all combinations of 1, 2 and 3 features (see text for a discussion).

6. CONCLUDING REMARKS

Establishment of a link between the shape and functionality of neuroanatomic structures is an unexplored, challenging endeavor, which highlights several possible applications such as the study of anatomic correlates of function, the prediction of risk factors in evaluation of population groups, and precise investigation of developmental neuroanatomy.

The above experimental results corroborated the effectiveness of the introduced approach in the characterization of 3D brain structures. Some of the main advantages of the proposed framework include the fact that there is no need for obtaining a parameterized representation of the 3D data and the features invariance to rotation and translation. Our ongoing work aims at applying automatic feature selection methods for the identification of relevant feature sets as well as correlating and interpreting the thus obtained features under the light of clinical information.

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7. REFERENCES