Local Shape Modelling for Brain Morphometry using Curvature Scale Space

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Abstract. Methods to capture the morphological variability of the human brain are needed to improve the diagnosis and treatment of neuro-degenerative diseases. This work presents an approach for local shape modelling that models self-similar curves to derive shape information. The method is based on two main techniques: Curvature Scale Space (CCS) as a way to represent contours and obtain a set of meaningful shapes to be analysed, and Statistical Shape Models to characterize the shape variation. The evolution of the curve in the CSS is used to partition the contour into locally similar parts which are then aligned and their variability modelled by PCA. We present the method and demonstrate results on a set of white-matter brain contours.

1 Introduction

Computational Anatomy has emerged as a new discipline with the objective to create algorithmic tools to help in the analysis of the substructures of the human brain. Fundamental features of the brain structure or function (in health ans disease) are revealed by medical imaging, but due to the complexity of the human brain, quantitative analysis is a challenging area of research [1]. Identification of structural brain changes is associated with different neuro-degenerative diseases, so identifying such variation can bring valuable information in the diagnosis and treatment of many pathologies [2]. This has led to the creation of brain atlases to model the variability of neuro-anatomical structures across a population, e.g. [3] amongst many others. In [2] an approach called *deformation-based morphometry* is used to characterise differences in macroscopic anatomy among structural brain images. *Statistical Shape Modelling* (SSM) [4] is the basis of a number methods described for brain morphometry. Shen *et al.* [5], presents a deformable model for segmentation and definition of point correspondences in brain images using an adaptive-focus deformable statistical model based on affine-invariant attribute vectors, minimisation of an energy function and PCA. Techniques have also focussed on the brain surface, e.g. [6], where a conformal mapping and correction are used to map accurately the cortex to an intermediate surface. Shape modelling has shown that brain shape variation can be successfully captured [7], in which an approach for shape representation that utilises medial representations derived from a spherical harmonics boundary description to study Hippocampus schizophrenia is described. Xue *et al.* [8] propose an automatic segmentation algorithm for neonatal brain MRI using a knowledge based approach to identify and reduce MLPV in the EM-MRF scheme. More recently, Rao *et al.* [9], have used canonical correlation analysis and partial least squares regression to quantify and predict correlated behaviour in sub-cortical structures.

Work on shape modelling is constrained by many unsolved problems such as how to segment structures, dependency on manual data preprocessing, finding correspondence between similar structures and difficulties in modelling *local* versus *global* variation. Much of the work on brain surface atlases have used global approaches. The correspondence problem can be dealt with by elastic registration, or if landmarks are used, by optimizing the locations of landmarks to construct compact shape models. The locality of the shape modelling has been investigated by considering the evolution of the shape over scale, such as by using wavelet decompositions or Gaussian scale-space representations. Here, we present a method for analysis of local variation in brain structures, based on the use of a SSM and the Curvature Scale Space to localise and partition the shape into similar parts. The novel contribution of this work is the creation of a descriptor that provides a simple way to cut-up a self similar contour, obtain a set of meaningful shapes, obtain the shape variation and reconstruct the contours without explicit correspondence being given. We present results on white-matter contours and describe how the method can be incorporated into a supervised analysis of local shape variation. After a discussion of the results, we make proposals on how this work can be taken forward.

2 Method

The input to the method is a set of contours, S_i, defined as collections of points: $S_i = \{(x,y)_j\}, 1 \leq j \leq N$. We define a partition, P_k, of any given shape, S_i as a subset of ordered points along part of the shape

$$P_k = \{\mathbf{p}_j\} = \{(x,y)_{j+0}, (x,y)_{j+1}, ..., (x,y)_{j+M-1}\} \subset S_i, \ 0 < M \leq N. \tag{1}$$
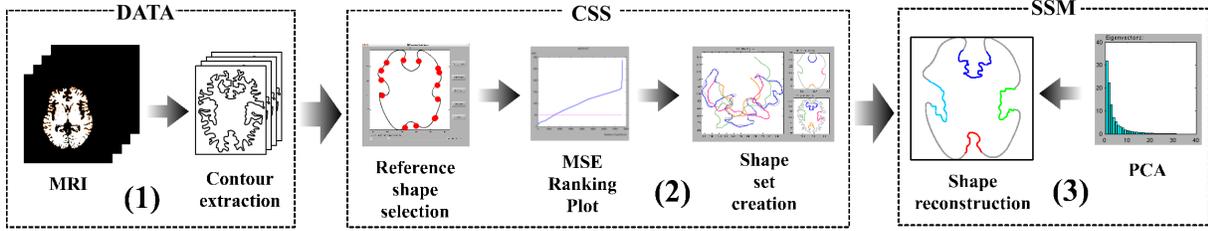
Figure 1. Overview CSS based Local Shape Modelling: (1) Contours segmented from MRI brain data; (2) CSS is used first to obtain a reference shape from the smoothing of a target contour at some large scale, σ. A pair of zero-crossings selects a prototype section and all others are ranked accordingly by search and rigid alignment; (3) Statistical Shape Modelling and reconstruction based on selected modes.

We assume that N is large enough to allows a reasonable piece-wise-linear approximation of the shape and that the partitions can capture local shape variation. Any partition is defined in S by picking its end points $\{\mathbf{p}_{j+0}, \mathbf{p}_{j+M-1}\}$ to be closest to two given points $\{\gamma_k, \gamma_{k+1}\}$. In this way, P_k is 'cut out' of a given S_i.

An overview of the proposed method is shown in figure 1. The contours from the input data, S, are decomposed into a Curvature Scale Space representation and extrema of curvature are calculated at each scale, σ. A particular pair of extrema at a very smooth scale is picked to mark a reference or prototype local shape. Then, all consecutive pairs of extrema, $\{\gamma_k, \gamma_{k+1}\}$ are used to partition every shape. Partitioned shapes are aligned to the reference shape and scored by their distance. The closest shapes, nearer than some user threshold, are used to build the shape space.

2.1 Curvature Scale Space Zero-Crossings

Curvature Scale Space is a technique for object representation, invariant under *pose* variations and based on the scale space [10]. To build the CSS representation the curve needs to be considered as a parametric vector equation $\Gamma(t) = (x(t), y(t))$, then a series of *evolved versions* of $\Gamma(t)$ are produced by increasing the scale parameter, σ, from 0 to ∞. Every new evolved version is defined as $\Gamma_\sigma = (X(t, \sigma), Y(t, \sigma))$, where

$$X(t,\sigma) = x(t) \circledast g(t,\sigma) \ , \ Y(t,\sigma) = y(t) \circledast g(t,\sigma).$$

Here, $\circledast$ denotes the convolution operator and $g(t, \sigma)$ is a Gaussian of width σ. Since the CSS representation contains curvature zero-crossings or extrema points from the evolved version of the input curve, these are calculated directly from any Γ_σ by:

$$k(t) = \frac{\dot{X}(t,\sigma)\ddot{Y}(t,\sigma) - \dot{Y}(t,\sigma)\ddot{X}(t,\sigma)}{(\dot{X}(t,\sigma)^2 + \dot{Y}(t,\sigma)^2)^{3/2}},$$

where

$$\dot{X}(t,\sigma) = \frac{\partial[x(t) \circledast g(t,\sigma)]}{\partial t} = X(t) \circledast \left(\frac{\partial g(t,\sigma)}{\partial t}\right), \quad \ddot{X}(t,\sigma) = \frac{\partial^2[x(t) \circledast g(t,\sigma)]}{\partial t^2} = X(t) \circledast \left(\frac{\partial^2 g(t,\sigma)}{\partial t^2}\right).$$

(2)

Similar equations are used to compute $\dot{Y}(t,\sigma)$ and $\ddot{Y}(t,\sigma)$. The final step is the construction of the CSS image, but only the generation of evolved versions of the curve and the locations of the curvature zero-crossings are relevant for this work, for further details see [10]. The generation of evolved versions of the curve (Figure 2-(2)), produces a set of zero-crossings of the second derivative where there is a change on the curvature of the contour. These points provide a basic but efficient way to create meaningful partitions contours that exhibit self-similar variation.

2.2 Local Pose Alignment and Ranking of Partitions

Each partition is ranked after pose alignment with the prototype partition (Figure 3-(1)). Thus an affine alignment is done over the set, where each shape is aligned to the selected reference shape.

Rigid body transformation parameters can be used to transform the points from any partition to the frame of the reference partition, this relationship can be expressed as $W = AP_k + \mathbf{t}$ where W is the reference shape
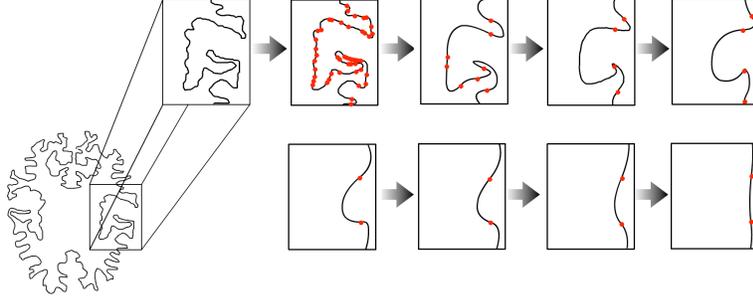
Figure 2. CSS evolution of a white-matter brain contour. At some appropriate level of smoothing, a set of meaningful partitions can be identified. Pairs of zero-crossings (red points) are used to search and rank local parts on the original shape.

and P_i any partition from the data contours. To determine both the rotation matrix A and the translation vector $\mathbf{t}$ a least squares method is used and the problem is equivalent to minimising:

$$\frac{1}{M} \sum_{j=1}^{M} (A_k \mathbf{p}_{kj} + \mathbf{t} - \mathbf{w}_j)^T (A_k \mathbf{p}_{kj} + \mathbf{t} - \mathbf{w}_j). \tag{3}$$

By first moving the shapes to the origin, the solution is obtained in the standard way using SVD. We retain the pose parameters of each partition, $\{A_k, \mathbf{t}_k\}$ and re-use them for reconstructing from the resultant local shape model.

The main reason to use the CSS is that the extrema points are constant over the scale, ie, as σ increases no new curvature zero-crossings can appear on the contour (Figure 2). Also, since the brain contours exhibit self-similarity, using the CS, at certain scales the potential partitions derived from the extrema points look the same (Figure 3-(2), upper right). This provides a natural way to identify consistent parts in the the contour by their local variation. Note that the evolved contours (Figure 2) can be regarded as an early version of *active contours (snakes)* as they present similar behaviour in the absence of external constraints. In this case, both tend to shrink and minimise their curvature.
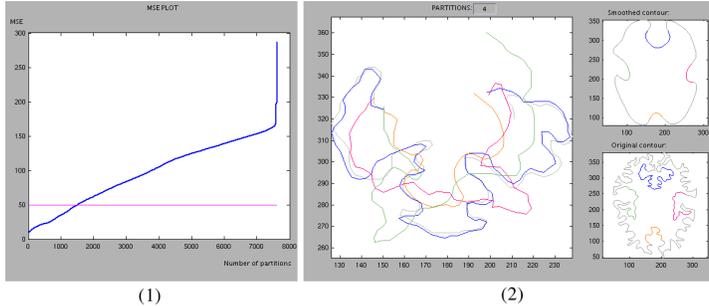

Figure 3. (1) Calculation of the MSE for each of the shapes results in plot used for ranking; (2) A manual threshold selects the number of shapes to be used in statistical shape analysis (pose alignment is already done); (3) Selected shapes from (2) along with they original positions in the smoothed and non-smoothed version of a given shape.

2.3 Statistical Shape Analysis and Shape Blending

A Point Distribution Model [4] is used to analyse the variability of the local shapes obtained from the CSS partitioning scheme outlined above. Having obtained a set of ranked and pose-aligned partitions, P, we apply principal component analysis after resampling the partitions to the same dimensionality vector space. Now under correspondence free conditions, the modes of variation of the aligned shapes can be found by applying principal component analysis.

A deviation, D_k, from the mean shape is calculated as $D_k = P_k - \overline{P}$ and the point covariance matrix, $C = \frac{1}{N_P} \sum_k D_k D_k^T$, is then decomposed to obtain M modes of variation, E_k and corresponding eigenvalues

λ_k. The principal axes of this decomposition are the most significant modes of shape variation, E'. We can now take appropriate linear combinations of these modes, to reconstruct an approximation of the partition in the local frame, and then affine transform it to return it to the coordinate system of the original shape [11]:

$$\hat{P}_k = A_k^{-1} \left[(E'^T(A_k(P_k - \overline{P}) + \mathbf{t}_k)E' - \mathbf{t}_k \right] + \overline{P}. \tag{4}$$

For visualization purposes, we can blend the modelled partitions back into the original contour at any level of the scale space, Γ_σ. This enables us to examine the variability against a 'defocussed' version of the original. The blending is performed by a suitable window function, such as a cosine squared centred on the contour and the neighbouring partitions. Each window is made to overlap by 50% so that they sum to 1. For example, if Q and R are neighbouring partitions, we can use a window $\omega(j)$ centred on the vertex $\mathbf{q}_{M/2}$ and on vertex $\mathbf{r}_{M/2}$, of size M, such that each blended point, $\mathbf{v}_j, 0 \le j \le 3M/2 - 1$, is given by

$$\mathbf{v}_j = \omega(2\pi(j - M/2)/M)\mathbf{q}_j + \omega(2\pi(j - M)/M)\mathbf{r}_{j-M/2}, \qquad \omega(x) = \cos^2(x), -\pi/2 \le x \le \pi/2. \tag{5}$$

3   Experiments and Discussion

A set of 40 simulated digital brain phantom images from normal subjects was used in this study. Each digital brain was created after registering and averaging four T1, T2 and PD-weighted MRI scans from normal adults. For further details see [3]. We have use the white-matter regions from these data sets as the source of our input contours to demonstrate the CSS based local modelling process.

Figure 3 illustrates the supervised prototype selection and ranking process. The two figures on the right-hand-side show the smoothed CSS contour and the corresponding extrema based partitions are mapped to the original contour. Any of these coloured partitions can be used as a prototype. The centre figure is a selected set of pose aligned partitions based on the ranking error plot shown on the left. The interface allows any given partitions to be selected and ranked against all remaining partitions. Figure 4 shows modal reconstructions from the local shape model, with the partitions blended back into a smooth version of the original. The method works well in general in two ways: the local parts are similar and localised according to the prototype selection; the shape space is kept relatively compact by the MSE ranking. We have not yet fully investigated how the MSE ranking relates to the compactness of the shape-space. If the space is convex, then the ranking error should be equivalent to the reconstruction error, but this would assume that there is no mixing of dissimilar local partitions.

The main feature of this work has been the use of the consistency of the curvature extrema at low resolutions of the contour to partition and pose-align locally similar parts of a irregular shape, such as brain contour. This localization allows a linear shape space to be used directly on the aligned parts. We have introduced a simple windowing and blending technique which allows the modelled parts to be reconstructed back into the original global shape but it is also useful for visual feedback. A limitation of the presented method is the need to resample the partitions to have the same length in order to align and perform PCA. Unless the original contour has many points, any small local part does not have enough to do simple piece-wise-linear resampling. Here, a basis representation would help. In [11], we used Legendre functions to both represent and align parts. The CSS itself is a wavelet representation (by Gaussians), so it could be used directly in a parametric, dimensionless way. An un-supervised version of the this method can be envisaged if the prototype selection and ranking step is replaced by an unsupervised clustering. The clusters could be used to build a set of shape-models, or, alternatively, a non-linear shape learning could be used [12]. The method needs to be extended to surfaces to be properly validated with clinical data but it is not clear a this time how the local partitioning could be easily extended to surface patches.

Acknowledgements

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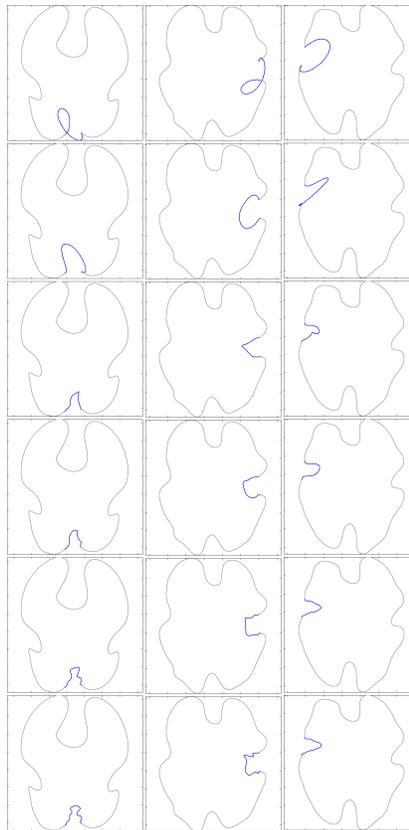
Figure 4. Reconstruction of the chosen set of shapes, by added a sequence of principal modes of variation: 0, 2, 4, 8, 16, 32. The modelled partitions are blended back into a smooth scale of the CSS, Γ^σ defocussing the general, irrelevant shape variations for the purposes of visualization.

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