



## Shape analysis based on depth-ordering



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### ABSTRACT

In this paper we propose a new method for shape analysis based on the ordering of shapes using band-depth. We use this band-depth to non-parametrically define a global depth for a shape with respect to a reference population, typically consisting of normal control subjects. This allows us to globally quantify differences with respect to “normality”. Using the depth-ordering of shapes also allows the detection of localized shape differences by using  $\alpha$ -central values of shapes. We propose permutation tests to statistically assess global and local shape differences. We further determine the directionality of shape differences (local inflation versus deflation). The method is evaluated on a synthetically generated striatum dataset, and applied to detect shape differences in the hippocampus between subjects with first-episode schizophrenia and normal controls.

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### 1. Introduction

Analyzing and comparing three-dimensional brain structures or objects in general can be as simple as comparing volumes. While informative, such a global measure cannot fully describe changes between objects. Shape analysis approaches have been proposed to assess object properties beyond global volume and to characterize shape variations across subjects and between subject populations (see Nitzken et al., 2014 for a brief survey). For instance, many shape analysis methods are based on the classical point distribution model (PDM) (Cootes and Taylor, 2004), which captures shape variations by computing a mean shape and the major modes around the mean of corresponding points in a set of shapes as illustrated in Fig. 1(a). The PDM assumes a Gaussian distribution of the points around the mean shape.

In contrast, shape characterizations built on concepts of order statistics have been explored recently (Hong et al., 2013, 2014a; Whitaker et al., 2013). These methods utilize depth-ordering of shapes to generalize order statistics, for example, the median and the interquartile range (IQR), to shapes, effectively obtaining the equivalent of a box-plot for shapes. Fig. 1(b) illustrates the depth-ordering model (DOM). Using shape-descriptions based on depth-ordering makes it possible to perform shape analysis without making strong distributional assumptions. While current approaches focus on using DOM to analyze shape variations within one population, this paper

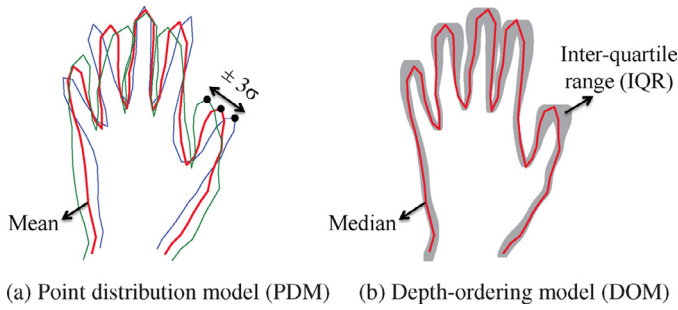
addresses the challenge of differentiating subject populations, for example subjects with a disorder versus normal controls, based on the depth-ordering model.

Existing methods for population-based shape analysis can be roughly subdivided into two categories: methods for global analysis and methods for local analysis. Global analysis methods are designed to detect whether population shape differences exist (Loncaric, 1998; Reuter et al., 2009; Wachinger et al., 2014), but they generally cannot locate or characterize these shape differences. This limits interpretability of results and consequentially insights into the underlying biological processes. The main attraction of such methods is that they often avoid establishing dense correspondences between shapes through registration. In contrast, local analysis methods require some form of point-to-point correspondence between shapes to allow precise local shape analysis. Establishing these correspondences is highly non-trivial and arguably one of the main sources of inaccuracy, because any misregistration may create artifacts with respect to the final shape analysis results. Nevertheless, a variety of methods for local shape analysis have been proposed and successfully used (Cates et al., 2008; Chung et al., 2008; Davies et al., 2008; Hosseinbor et al., 2014; Miller, 2004). Shape representations that fit an a-priori model to the data have also been used successfully, although they still need to establish some form of one-to-one correspondence via model fitting (Styner et al., 2004; Yushkevich and Zhang, 2013).

In this work, we explore an alternative method that allows for both global and local shape analyses, and only needs very limited (e.g., rigid or affine) spatial alignment of shapes. This is achieved by

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**Fig. 1.** Comparison between two types of models for capturing shape variations. The three shapes in PDM (a) correspond to the mean and varying shapes along the first mode at  $\pm 3$  standard deviations. In DOM (b), the red shape is the median of the shape population, and the grey area is the region covered by 50% of the shapes at the top ranking list of the populations, similar to the inter-quartile range (IQR) for scalar values visualized as part of a box-plot. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

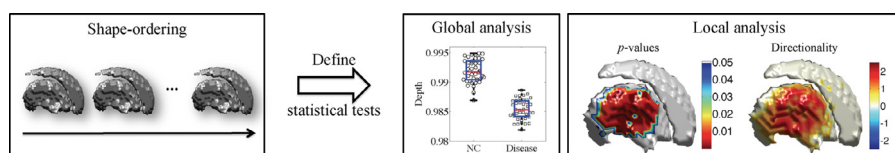
using the notion of band-depth (Hong et al., 2013; López-Pintado and Romo, 2009), which provides a notion of centrality of a shape with respect to a reference dataset. The deeper the shape the more similar it is to all other shapes in the dataset. We use this notion to detect small morphometric differences between two populations of neuroanatomical structures. Fig. 2 shows the general principle of the approach. First, shapes are depth-ordered with respect to a reference dataset. We then define a global statistical test directly on the shape depth, as well as a local statistical test to assess local shape differences. Our method is free from strong distributional assumptions by using principles from non-parametric order-statistics.

Our main contributions in this paper are:

- (1) We propose using depth-ordering on shapes for statistical shape analysis.
- (2) We develop an algorithm for the fast computation of band-depth for shapes represented by *binary* indicator functions.
- (3) We define statistical tests to detect potential global and local differences between shape populations without an explicit computation of dense correspondences.
- (4) We provide the directionality of shape differences to augment local measurements.

The method described in this paper is an extension of preliminary ideas presented in a recent conference paper (Hong et al., 2014b). This paper provides further details of our algorithms including the permutation tests for both global and local analyses, presents an additional technique for providing directionality of shape differences, and includes more comprehensive experiments on both synthetic and real datasets.

The paper is organized as follows: Section 2 describes how to order shapes by depth and how to compute such a depth-ordering fast. Section 3 proposes statistical approaches using depth-ordering for shape analysis. Section 4 discusses how to augment local analysis with directionality of shape differences. Section 5 presents experimental results on synthetic and real datasets. Section 6 concludes the paper with a summary.



**Fig. 2.** Overview of the depth-ordering-based shape analysis. Based on the depth and the ordering of a shape population, statistical tests are defined to globally separate control and disease groups using global analysis with a scalar value (depth) for each shape. Statistical difference for global analysis results can be established through permutation testing. Equivalently, local shape differences can be detected using local analysis with a corresponding local permutation test, resulting in  $p$ -values on the surface of a shape to establish local shape differences between populations. The directionality of the shape differences (inflation versus deflation) can also be determined.

## 2. Depth-ordering of shapes

Generalizing concepts from order-statistics to shape analysis faces the challenge that there is no canonical ordering of shapes. To define such an ordering we make use of the concept of band-depth and ordering of functions as developed in the statistics literature (López-Pintado and Romo, 2009) and extend it to shapes. Sun and Genton (2011) first proposed functional boxplots to order functions using the band-depth concept in López-Pintado and Romo (2009). The intuition of ordering functions based on band-depth is that the deeper a function is buried within a dataset the more central it is. The deepest function corresponds to the within-sample median function. Once defined, this ordering can be used to generalize traditional order statistics, such as the median or the inter-quartile range, to functions. For example, Whitaker et al. (2013) adapted traditional boxplots to *functional contour boxplots* for quantifying uncertainty in fluid simulations and for the visualization of ensemble data. What makes band-depth attractive for *shape-ordering* is that shapes can be represented by *indicator functions*, i.e., by binary functions that are 1 inside and 0 outside of a shape (Hong et al., 2013, 2014a).

Band-depth for binary shape representations relates to the amount of overlap between shapes, because the minimum and maximum operators on indicator functions correspond to the set intersections and unions respectively. Therefore, band-depth is a *natural and intuitive* choice to order a shape population for an indicator-function-based shape representation. In our current work, we use this binary function representation to compare shape populations. To improve the computational efficiency of our model, we propose a novel fast algorithm to compute the band-depth of shapes represented by binary maps. Most importantly we demonstrate how band-depth can be used to provide both global and local statistical tests to differentiate between shape populations.

Given a set of  $n$  shapes represented as 3D binary volumes,  $\{Y_1, Y_2, \dots, Y_n\}$ , with dimension of  $(s_x, s_y, s_z)$ , we vectorize them into binary vectors  $y_i \in \{0, 1\}^p$  ( $1 \leq i \leq n$ ), where  $p = s_x \times s_y \times s_z$ . The band-depth (BD) for each shape  $y$  is defined as follows:

$$BD_{n,J}(y) = \sum_{j=2}^J BD_n^{(j)}(y)$$

where

$$BD_n^{(j)}(y) = \frac{1}{C} \sum_{1 \leq i_1 < i_2 < \dots < i_j \leq n} I\{G(y) \subseteq B(y_{i_1}, \dots, y_{i_j})\}. \quad (1)$$

Here,  $2 \leq j \leq J$ , and  $J \in [2, n]$  is the number of observations used to define the band.  $C$  is a normalization constant equal to the number of admissible permutations, i.e.,  $\binom{n}{j}$ .  $G(y)$  is the graph of the function,  $G(y) = \{(\mathbf{x}, y(\mathbf{x})) : \mathbf{x} \in \mathbb{I}\}$ , and  $\mathbb{I}$  denotes the index range of the binary vector  $y$ .  $B$  is the band delimited by the observations given as its arguments. That is,  $B(y_{i_1}, \dots, y_{i_j}) = \{(\mathbf{x}, y(\mathbf{x})) : \mathbf{x} \in \mathbb{I}, \min_{r=i_1, \dots, i_j} y_r(\mathbf{x}) \leq y(\mathbf{x}) \leq \max_{r=i_1, \dots, i_j} y_r(\mathbf{x})\}$ .  $I\{\cdot\}$  denotes the indicator function, which evaluates to 1 if the graph of the function is within the band, or to 0, otherwise.

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