Statistical Shape Analysis of Anatomical Structures from Medical Images

Polina Golland & W. Eric L. Grimson

Artificial Intelligence Laboratory
Massachusetts Institue Of Technology
Cambridge, Massachusetts 02139

http://www.ai.mit.edu

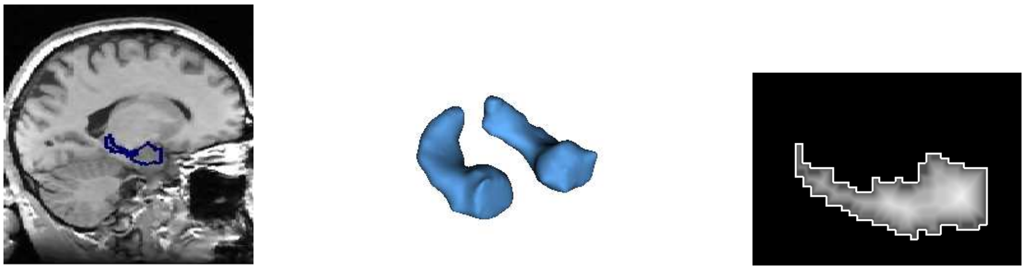
The Problem: The goal of this work is to develop an approach to shape representation and classification of anatomical structures. The shape information is extracted from segmented 3D medical scans and is used to detect statistical differences between two groups of subjects.

Motivation: Statistical shape analysis, or shape based classification, attempts to identify statistical differences between two groups of images of the same organ based on 3D images of the organ. It can be used to study a disease (patients vs. normal controls) or changes caused by aging (different age groups). Size and volume measurements have been widely used for this purpose, but they capture only a small subset of organ shape differences. If utilized properly, shape information can significantly improve our understanding of the anatomical changes due to a particular disorder.

Previous Work: Statistical shape modeling combines shape representation with statistical information on how the features vary across population. Principal Component Analysis (PCA) has been used by several authors for capturing statistical properties of the model. It was well suited for applications in segmentation and object localization, where the statistical properties of the model were used to restrict the space of possible deformations of the model. It has also been used in shape analysis [1, 4] to reduce the dimensionality of the model and find a decision boundary between the classes.

Approach: Our goal is to develop a principled approach to anatomical shape classification that makes as few assumptions as possible on the underlying distribution. In this paper, we demonstrate a framework for statistical shape analysis based on Support Vector Machines (SVMs) [5] that for small data sets provides results comparable to other techniques, and is guaranteed to converge to the optimal solution as the number of examples increases. Furthermore, the rate of convergence can be estimated using the capacity theory based on the notion of the VC dimension. Estimating the rate of convergence and the minimal number of training examples necessary for statistical significance of the results is crucial in this application, as the training data are difficult to acquire. We cannot hope to have the large number of training examples that might be available in other applications.

Numerous models have been proposed for shape description, and comparing their performance is one of the future research directions. Currently, we use distance transform as shape descriptors in out experiments. A distance transform, or distance map, is a function that for any point inside an object is equal to the distance from the point to the closest point on an outline. Distance transforms have been used extensively in Computer Vision for shape description, feature extraction, etc. Since the values of the distance transform at neighboring voxels are highly correlated, using it as a shape descriptor provides the learning algorithm with a lot of information on the structure of the feature space.



(a) Segmented MRI slice (b) Surface models (c) Distance transform slice

Figure 1: Data example. (a) An example sagittal slice with the hippocampus-amygdala complex segmented; (b) 3D surface model of the hippocampus-amygdala complex; (c) One slice of the 3D distance transform.

Descriptor	right volume	left volume	right shape	left shape
Training accuracy (%)	60.0	63.3	83.3	83.3
Cross-validation (%)	60.0 ± 17.5	63.3 ± 17.2	66.7 ± 16.9	60.0 ± 17.5

Descriptor	volume (both)	shape (both)	shape & volume	shape & relative volume
Training accuracy (%)	66.7	86.7	83.3	83.3
Cross-validation (%)	63.3 ± 17.2	70.0 ± 16.4	$\mathbf{73.3 \pm 15.8}$	70.0 ± 16.4

Table 1: Training and cross-validation accuracy for volume and shape. The results for cross-validation consist of estimated expected error, as well as 95% confidence interval. The training accuracy is reported for the parameter setting that yielded the best cross-validation results.

Another important property of the distance transform is what we call a *continuity of mapping*. The shape information extraction is an inherently noisy process, consisting of imaging, segmentation and feature extraction, with every step introducing errors. The vectors in the training set are therefore computed with uncertainty, and it is important that small errors in any of the steps do not cause significant displacements of the resulting feature vectors. Since the gradient magnitude of the distance map is bounded by 1 everywhere in the image, and changes in the outline have only local effect on the distance map, the distance between the new and the old feature vectors in the feature space is bounded by the "magnitude of transformation" in the image space.

Difficulty: The high complexity of shape models used in medical image analysis, combined with a typically small number of training examples, places the problem outside the realm of classical statistics. This difficulty is traditionally overcome by first reducing dimensionality of the shape representation (e.g., using PCA) and then performing training and classification in the reduced space defined by a few principal components. We propose to learn the shape differences between the classes in the original high dimensional parameter space, while controlling the capacity (generalization error) of the classifier. This approach makes significantly fewer assumptions on the properties and the distribution of the underlying data, which can be advantageous in anatomical shape analysis where little is known about the true nature of the input data.

Impact: This work will allow to quantify statistical shape differences of anatomical structures in different groups of subjects. We demonstrate the method by applying it to shape classification of the hippocampus-amygdala complex in a data set of 15 schizophrenia patients and 15 normal controls. The shape information is extracted from the 3D MRI scans of the brain. Using our technique, the separation between the classes and the confidence intervals are improved over a volume based analysis (Table 1).

Future Work: Future work includes interpretation of the shape differences as deformations of the original examples in the image domain and incorporation of the invariants into the classification process, as well as incorporating invariant information into the learning process.

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