Mining 3D Shape Data for Morphometric Pattern Discovery

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INTRODUCTION

Recent technological advances in 3D digitizing, non-invasive scanning, and interactive authoring have resulted in an explosive growth of 3D models in the digital world. There is a critical need to develop new 3D data mining techniques for facilitating the indexing, retrieval, clustering, comparison, and analysis of large collections of 3D models. These approaches will have important impacts in numerous applications including multimedia databases and mining, industrial design, biomedical imaging, bioinformatics, computer vision, and graphics.

For example, in similarity search, new shape indexing schemes (e.g. (Funkhouser et al., 2003)) are studied for retrieving similar objects from databases of 3D models. These shape indices are designed to be quick to compute, concise to store, and easy to index, and so they are often relatively compact. In computer vision and medical imaging, more powerful shape descriptors are developed for morphometric pattern discovery (e.g., (Bookstein, 1997; Cootes, Taylor, Cooper, & Graham, 1995; Gerig, Styner, Jones, Weinberger, & Lieberman, 2001; Styner, Gerig, Lieberman, Jones, & Weinberger, 2003)) that aims to detect or localize shape changes between groups of 3D objects. This chapter describes a general shape-based 3D data mining framework for morphometric pattern discovery.

BACKGROUND

The challenges of morphometric pattern discovery are twofold: (1) How to describe a 3D shape and extract shape features; and (2) how to use shape features for pattern analysis to find discriminative regions. Several shape descriptors have been proposed for extracting shape features, including landmark-based descriptors (Bookstein, 1997; Cootes, Taylor, Cooper, & Graham, 1995), deformation fields (Csernansky et al., 1998), distance transforms (Golland, Grimson, Shenton, & Kikinis, 2001), medial axes (Styner, Gerig, Lieberman, Jones, & Weinberger, 2003), and parametric surfaces (Gerig, Styner, Jones, Weinberger, & Lieberman, 2001). Using these features, researchers have developed different pattern analysis techniques for discovering morphometric patterns, including linear discriminant analysis (Csernansky et al., 1998), support vector machines (Golland, Grimson, Shenton, & Kikinis, 2001), principal component analysis (Saykin et al., 2003), and random field theory (Chung et al., 2005).

This chapter describes a general surface-based computational framework for mining 3D objects to localize shape changes between groups. The spherical harmonic (SPHARM) method is employed for surface modeling, where several important shape analysis issues are addressed, including spherical parameterization, surface registration, and multi-object alignment. Two types of techniques are employed for statistical shape analysis: (1) linear classifiers based on a point distribution model, and (2) random field theory combined with heat kernel smoothing.

MAIN FOCUS

Given a set of labeled 3D objects from two distinct shape classes, our task is to identify morphometric patterns that can distinguish these two classes. An important real-life application is to detect anatomical changes due to pathology in biomedical imaging. A surface-based computational framework is presented to solve this problem in three steps: data collection and preprocessing, surface modeling for feature extraction, and pattern analysis and visualization.

Data Collection and Preprocessing

3D models can be collected using different methods including 3D digitizing, non-invasive scanning and interactive authoring. This chapter focuses on the analysis of 3D models whose surface topology is spherical. For example, in medical domain, many human organs and structures belong to this category. After performing segmentation on 3D medical scans (e.g., CT, MRI), the boundary of a structure of interest can be extracted. Since such a 3D boundary model may contain unwanted holes, a preprocessing step sometimes is required to close these 3D holes (Aktouf, Bertrand, & Perroton, 2002). An alternative approach is to perform automatic segmentation with appropriate constraints and create topologically correct results directly from images. After removing unwanted 3D holes, the surface of the 3D model has a spherical topology, which meets the requirement of our surface modeling approach.

Surface Modeling

Spherical harmonics were first used as a type of parametric surface representation for radial surfaces r(θ,ϕ) in (Ballard & Brown, 1982), where the harmonics were used as basis functions to expand r(θ,ϕ). Recently, an extended method, called SPHARM, was proposed in (Brechbuhler, Gerig, & Kubler, 1995) to model arbitrarily shaped but simply connected 3D objects, where three functions of θ and ϕ were used to represent a surface. SPHARM is suitable for surface comparison and can deal with protrusions and intrusions. Due to its numerous advantages such as inherent interpolation, implicit correspondence, and accurate scaling, SPHARM is employed here, requiring three processing steps: (1) spherical parameterization, (2) SPHARM expansion, and (3) SPHARM normalization.

(1) *Spherical parameterization* creates a continuous and uniform mapping from the object surface onto the unit sphere, and its result is a bijective mapping between each point *v* on the object surface and spherical coordinates θ and φ:

$$v(\theta,\phi) = (x(\theta,\phi), y(\theta,\phi), z(\theta,\phi))^T$$

The classical approach exploits the uniform quadrilateral structure of a voxel surface and solves a constrained optimization problem to minimize area

and angle distortions of the parameterization. The approach can be applied only to voxel surfaces and not to general triangle meshes. A new algorithm CALD (Shen & Makedon, 2006) has been proposed to control both area and length distortions and make SPHARM applicable to general triangle meshes.

(2) The *SPHARM expansion* requires a spherical parameterization performed in advance. The parameterization has the form of:

$$v(\theta,\phi) = (x(\theta,\phi), y(\theta,\phi), z(\theta,\phi))^T ,$$

Where *x(θ,φ)*, *y(θ,φ)* and *z(θ,φ)* are three spherical functions. Spherical harmonics are a natural choice of basis functions for representing any twice-differentiable spherical function. To describe the object surface, we can expand these three spherical functions using spherical harmonics $Y_l^m(\theta,\phi)$, where $Y_l^m(\theta,\phi)$ denotes the spherical harmonic of degree *l* and order *m*. The expansion takes the form:

$$v(\theta,\phi) = \sum_{l=0}^{\infty} \sum_{m=-l}^{l} c_l^m Y_l^m(\theta,\phi),$$

Where

$$c_l^m = (c_{lx}^m, c_{ly}^m, c_{lz}^m)^T.$$

The coefficients c_l^m up to a user-desired degree can be estimated by solving a linear system. The object surface can be reconstructed using these coefficients, and using more coefficients leads to a more detailed reconstruction (Figure 1).

(3) *SPHARM normalization* creates a shape descriptor (*i.e.*, excluding translation, rotation, and scaling) from a normalized set of SPHARM coefficients, which are comparable across objects. A typical approach is as follows: (1) Rotation invariance is achieved by aligning the degree one ellipsoid; (2) scaling invariance is achieved by dividing all the coefficients by a scaling factor; (3) ignoring the degree zero coefficient results in translation invariance.

Using the degree one ellipsoid for establishing surface correspondence and aligning objects may not be sufficient in many cases (e.g., the ellipsoid becomes a sphere). A more general method for establishing surface correspondence is to minimize the mean squared distance between two corresponding surfaces (Huang et al., 2005).

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