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Total variance based feature point selection and applications☆

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ABSTRACT

Feature points are used to capture geometric characteristics of an object and are usually associated with certain anatomical significance or geometric meaning. The selection of feature points is a fundamental problem with various applications, for example, in shape registration, cross-parameterization, sparse shape reconstruction, parametric shape design, and dimension construction.

In the literature, feature points are usually selected on a single shape by their differential property or saliency, and the information of similar shapes in the population are not considered. Though carefully chosen feature points can represent the corresponding shape well, the variations among different shapes within the population are overlooked.

In this paper, through statistical shape modeling, we evaluate the feature points by the amount of variance they capture of the shape population, which leads to an algorithm that sequentially selects and ranks the feature points. In this way, the selected feature points explicitly incorporate the population information of the shapes. Then, we demonstrate how the proposed feature point selection approach can be integrated in the applications of sparse shape reconstruction, construction of new dimensions and shape classification through sparse measurements.

The numerical examples have validated the effectiveness and efficiency of the proposed approach.

1. Introduction

Feature points are used to capture geometric characteristics of an object and are usually associated with certain anatomical significance or geometric meaning. For example, the left and right lateral malleolus points on the human body model in the CAESAR project [1] are among the anatomical feature points. The high curvature points and the extremity points are often used as geometric feature points. In [2], the heel point is defined as "the vertex having the smallest x-coordinate value".

The selection of feature points is a fundamental problem in computer graphics [3] and in CAD based custom data [4,5] with various applications. For example, feature points are used as landmarks to guide the deformation in shape registration [6–8]. In motion tracking and 3D animation, feature points are used as marker points based on which the 3D shape is reconstructed [9,10]. In parametric shape design, the selected feature points are used to generate semantic features [4,5] and are used as reference points for constructing meaningful sizing dimensions [2,11]. The selection of feature points has many more applications, including shape approximation [12] where a shape is approximated by a few points that respecting the key features, mesh segmentation [13] where each computed segment represents at least one feature point, and cross-parameterization [14,15] where the user defined vertices for correspondence are usually selected among meaningful feature points.

In the literature, feature point is selected on a single shape by its differential property or the saliency. For example, in [6] the feature points are automatically calculated on a shape by scale saliency [16]. In [17] a center–surround operator on Gaussian-weighted mean curvatures is used to calculate the saliency map on the shape. In [13], the vertices on the convex hull of the multi-dimensional scaling (MDS) transform of the 3D mesh are selected as the feature points. In [4,9] the landmarks on human body models were chosen by the anthropometry. In [7] 14 feature points are chosen from among local protrusion points, high-curvature points, and anatomically meaningful points.

Being carefully designed, feature points selected by the above approaches can represent the corresponding shape well. However, the population information of similar shapes are not considered and the variations among different shapes in the population are overlooked. Often, capturing the shape variations in the population is important, especially in sparse shape reconstruction and parametric shape design.

Shape reconstruction from sparse data is popular in motion tracking [9], shape completion and animation [18]. The inputs are the coordinates of the feature points (sparse markers), and

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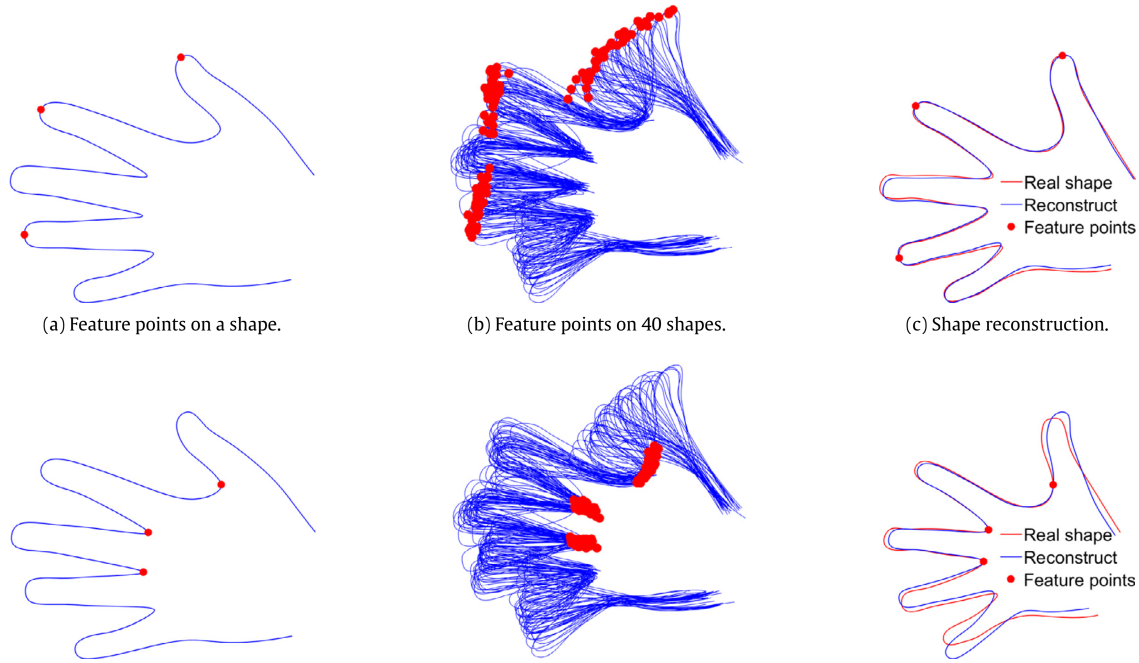

(a) Feature points on a shape. (b) Feature points on 40 shapes. (c) Shape reconstruction.

(d) Feature points on a shape. (e) Feature points on 40 shapes. (f) Shape reconstruction.

Fig. 1. The effects of different feature points on sparse shape reconstruction: (a) feature points on the finger tips; (c) the variations captured by the feature points over the shape population; (c) shape reconstruction based on the feature points on the finger tips by regularized linear regression; (d) feature points on the finger valleys; (e) the variations captured by the feature points over the shape population; (f) shape reconstruction based on the feature points on the finger valleys by regularized linear regression.

the output is the reconstructed shape. The mapping from feature points to a complete shape is learned by the regression analysis of the shape examples in the training set on the coordinates of the feature points [10]. If there exist variations in the population that are not captured by the feature points, then no matter how sophisticated the regression method is, the reconstructed shape would be very different from the real shape, since a part of the population information is missing.

Fig. 1 shows the effects of different feature points on sparse shape reconstruction. The feature points in the top row are located at the tips of the fingers, the feature points in the bottom row are located at the valleys of the fingers. From the perspective of saliency, both of them are prominent points at high curvature areas. However, as could be seen in Figs. 1(b) and 1(e), the feature points in the top row have captured the swings of the fingers while the feature points in the bottom row have not. Since swings of fingers are the major variations in the population (compared to size and local shape changes), failing to capture them would lead to major loss of the population information. As shown in Figs. 1(c) and 1(e), the shape reconstructed by the feature points in the top row is closer to the real shape than that of the bottom row.

Similarly for parametric shape design, where the inputs are sizing dimensions, the output is the synthesized shape. The mapping from sizing dimensions to a complete shape is learned by the regression analysis of the shape examples in the training set on the measured sizing dimensions [4,5]. The obtained parametric shape model can then be used in, for example, mass-customization of foot wear [2] and personalized item design (eyeglass) [11]. As pointed out in [11], there is no standardized method to determine what suitable dimensions are and how to choose them. In [2], 24-foot dimensions (including heel length and midfoot width) are manually chosen among the lengths and angles constructed from 14 geometric feature points. In [11], 12 dimensions that are related to facial anatomy are chosen by referring to the anatomical landmarks. Since capturing population information is helpful for shape reconstruction and synthesis, we hypothesize that the chosen sizing dimensions must capture the shape variations in the training set.

In the foregoing, for the purposes of shape reconstruction and synthesis it is desirable to have the chosen dimensions capture all the major variations in the shape population. There also exist applications that need the dimensions to capture specific variations in the population. Shape classification is among such applications. The ability of rapid shape classification is critical in clinic settings. For example, it can help diagnose healthy and unhealthy anatomical structures [19] and study the effects of surgeries [20]. It is ideal to have complete 3D shapes for classification. However, due to the tedious and error-prone process [5] of obtaining neat 3D shape models from images and scanned point clouds, its applications have been limited. Since the abnormality in unhealthy and post-surgical structures are often related to some particular shape variations, it would be helpful to have a few sizing dimensions that are tightly correlated to such shape variations.

In this paper, statistical shape modeling (SSM) [21,22] is used to learn the modes of shape variations within a population. The total variance is used to measure the amount of variations in the shape population, which is the squared sums of the projections of the shapes along the variation modes. Then, a metric is developed to quantify the amount of variance in the shape population captured by the feature points. The set of feature points that captures the highest amount of variance in the population is considered the best and is selected. Based on the selected feature points, a large pool of sizing dimensions are automatically constructed by combinatorially measuring the distances and angles composed by the feature points. Then, depending on the applications, a subset of dimensions are selected from the pool by either maximizing the variance captured of the total population or of some particular variation modes.

The selected feature points and dimensions are compared with the ones chosen by expert. In this paper, the expert system is