Continuous Visibility Feature

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Abstract

In this work, we propose a new type of visibility measurement named Continuous Visibility Feature (CVF). We say that a point q on the mesh is continuously visible from another point p if there exists a geodesic path connecting p and q that is entirely visible by p. In order to efficiently estimate the continuous visibility for all the vertices in a model, we propose two approaches that use specific CVF properties to avoid exhaustive visibility tests. CVF is then measured as the area of the continuously visible region. With this stronger visibility measure, we show that CVF better encodes the surface and part information of mesh than the tradition line-of-sight based visibility. For example, we show that existing segmentation algorithms can generate better segmentation results using CVF and its variants than using other visibility-based shape descriptors, such as shape diameter function. Similar to visibility and other mesh surface features, continuous visibility would have many applications.

1. Introduction

Feature extraction often serves as a fundamental engineering task for higher level applications. For example, almost all of the recognition tasks start with defining or learning features. This is particularly true for two-dimensional image that has a simple and uniform grid structure and pixels can be indexed by a 2D vector in a continuous coordinate system. Each pixel has fixed number (usually 4 or 8) of neighbors. Thus most of the image features are defined by the convolution operations of the local areas. Consequently, there are some default features like SIFT [2] and HOG [1] used widely in computer vision research. Unlike images, 3D models are usually modeled in the continuous domain which makes defining 3D features challenging. Consequently, many of the features defined for 3D models usually are designed for specific types of shapes. For example, visibility among points inside a given shape has been used directly or indirectly as shape features,in particular for the task of semantic shape segmentation. The intuition behind most of these visibility-based features is from the observation that two points sampled from the same semantic part tend to be visible from each other. For example, shape diameter function (SDF) is a descriptor to describe the thickness of a mesh defined via local visibility. The idea is initially proposed for shape segmentation based on the assumption that a visually meaningful component should have similar thickness everywhere. However, this assumption does not hold in many cases. For example, for a long component, such as a leg, the thickness at one end of the component may have different thickness from the other end. Another example is a flat component or a component whose size grows gradually in a certain direction. We believe that the traditional line-of-sight visibility used in all existing visibility-based shape features is insufficient. In this paper, we will describe a new feature named continuous visibility feature. The feature provides stronger visibility measure by considering the continuously visible region for a vertex or facet. Thus this feature is defined in a per-vertex manner. We say that a q is continuously visible by a point p if there exists a geodesic path connecting p and q that is entirely visible by p. CVF of p is defined as the area of a set of continuously visible points by p. A more precise definition of CVF can be found in Sections 3. We show that CVF better encodes the surface and part information of mesh than SDF does. Figure 1 illustrates some example models color mapped by CVF and SDF values. We also show that existing segmentation algorithms can generate better segmentation results using CVF than using other shape descriptors, such as shape diameter function [3]. We will demonstrate the segmentation results using the Princeton Segmentation Benchmark and applications of CVF and its variants (namely CVFavg, strong CVF and weak CVF) beyond segmentation. A major technical challenge of computing CVF is the computational efficiency because it is known the determining the visibility of two points is expensive and determining their continuous visibility will require many more pairwise visibility checks.We will present two ways to compute CVF efficiently. The first approach will use the continuous property of CVF to construct the continuously visible region in a Breadth-First-Search manner. The second approach further

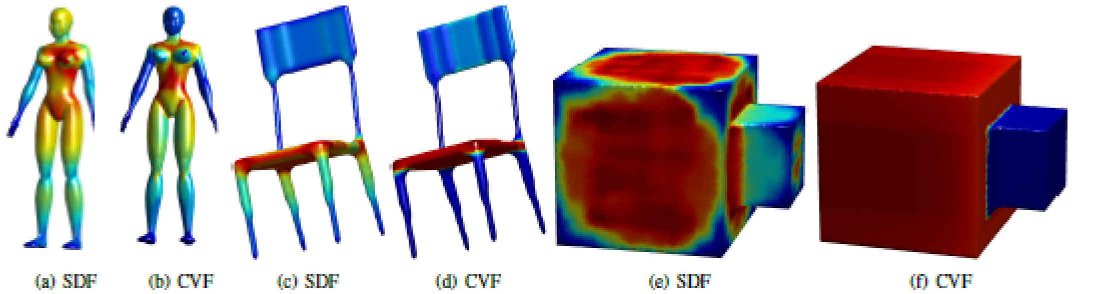

Figure 1. Examples of SDF and CVF on the same models. Red and blue indicate the largest and smallest SDF and CVF values, respectively. From these examples, we can see that CVF provides a better metric to distinguish visually different parts of a model. More extensive comparison can be found

improves the efficiency by first collecting the potential continuous visible region and then using visibility test to search the true boundaries of the continuous visible region. We find that the second approach provides significant speedup over the first approach.

2. Related Work

Extracting shape features from 3D model is a fundamental operation in shape segmentation, matching, retrieval and even deformation. These features can be roughly classified into per-vertex/facet features and global signatures. However, we should point out that some global signatures are also generated from per-vertex/facet features via statistical approaches. Osada*et al.* introduced Shape Distributions to capture the statistical information of vertices and facets shape function values. Shape matching is achieved by measuring the similarity between two shapes distribution. Even though the feature function is simple, it paves the way for many research works in shape matching, shape retrieval and other shape analysis tasks. Features can be further classified into several categories depending on whether they are invariant to translation, scaling, and deformation. Some features are designed to be invariant to rigid transformation, e.g., spin image and shape context. Invariance to deformation has attracted more attention. For example, geodesic distance is used to build deformation invariance features in a multidimensional scaling based approach and spectral domain analysis. The idea of heat diffusion process has triggered the emergence of diffusion geometry. These features are usually using Laplaca-Beltrami operator, e.g., heat kernel signature, global point signature and multi-solution spectral descriptor. Most of the aforementioned features are designed for shape matching, retrieval and correspondence. In shape segmentation, researchers have developed other types of features. These features directly control the quality of the final segmentation results for the approaches based on k-means clustering [4], fuzzy clustering, Gaussianmixture model followed by graph cut [3]. Some other recent work on segmentation which acquires better result also needs some feature definition. Liu *et al.* used concavity as features. Kalogerakis *et al.* and Huang proposed the learning-based segmentation using a rich collection of the features.

Visibility-based Features. Several recent works use visibility to derive part-aware features. The intuition behind most of these visibility-based features is that two points in the a visually or functionally meaningful part (such as the leg of a table) tend to be visible from each other. For example, Shape Diameter Function (SDF) [3] captures the thickness of a shape locally among visible points. SDF is determined by sampling rays inside the cone in the antinormal direction of a facet. The SDF value is the sum of the projected length of the rays inside the model. However, SDF may not correspond well to a visually meaningful component if the thickness is not evenly distributed. For example, as shown in Figure 1, the tabletop has quite different feature values at its center from those on the boundary. In addition, the feature values at the ends of the leg are also quite different from those closer to the tabletop. Another visibility-based feature is Volumetric Shape Image (VSI). With the motivation of capturing the general volumetric context instead of only getting the local volumetric context of the local cone used for sampling rays, VSI tries to sample rays in more directions. The VSI feature is computed by first finding the proxy center for each vertex and then sampling ray at fixed direction. The field of VSI is achieved by comparing the difference between the sampling of a source vertex and other vertices on the mesh. Recently, weak convex decomposition proposed also uses lines-of-sights. It first computes the pairwise visibility between all pairs of the vertices/facets on the mesh. Then the similarity matrix is constructed with each entrys value to be 0 or 1 indicating the pairwise invisibility or visibility, followed by spectral clustering. Even though

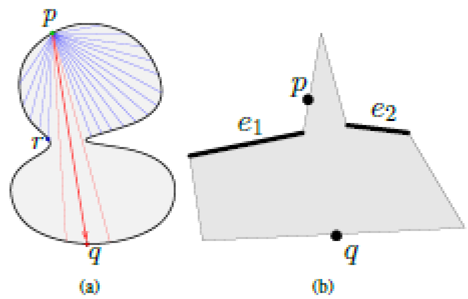

Figure 2. (a) Example of 2D continuous visibility. The vertex r is continuously visible from the vertex p but the vertex q is not. (b) While p is continuously visible from q, q is not continuously visible from p.

the mathematical background seems to be quite straightforward by referring to the similar issues in machine learning problem, the decomposition sometimes is not satisfying especially when a mesh model has a large area of bended parts. van Kaick *et al.* used the technique as preprocessing step to over-segment the mesh, but it also needs a lot of post-merging. In all of these features [3], traditional lineofsight visibility is used. However, from the Figure 2, we could see that the continuous visibility makes more sense than the general visibility in terms of charactering a potential component.

3. Definitions and Properties of CVF

Visibility among the points inside a given shape has been used directly or indirectly as shape features in the past. The intuition behind most of these visibility-based features is from the observation that two points sampled from the same (visual or functional) part tend to be visible from each other. It usually remains true if we state the property the other way around: two points that are visible from each other are likely to be from the same part. However, there are many exceptions. For example, in a human model in a standing pose, a point from the head may see a point in the heel and in most cases we would distinguish head and heel as different parts of the model.

References

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