Consistent Segment-wise Matching with Multi-Layer Graphs

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Abstract

Segment-wise matching is an important problem for higher-level understanding of shapes and geometry analysis. Many existing segment-wise matching techniques assume perfect segmentation, and would suffer from imperfect or over-segmentation inputs. To handle this shortcoming, we propose a multi-layer graph (MLG) to represent possible partially merged segments of input shape. We adapt the diffusion pruning technique on the MLGs to find high quality segment-wise matching. Experimental results on man-made shapes demonstrate the effectiveness of our method.

CCS Concepts
●*Computing methodologies* → *Mesh models; Shape analysis;*

1. Introduction

Given two similar 3D meshes and their segmentations, 3D segment-wise matching aims to establish meaningful correspondences of segments between the two meshes. It is an important problem as it helps with higher-level understanding in geometry analysis [ZYL*17], and has many applications, including defining better similarity measures between 3D models [KvKSHCO15, SSS*10, KO17], functionality analysis [vKXZ*13], surface registration [HAWG08] and structure-aware analysis [MWZ*13].

Existing segment-wise graph-based matching techniques can be roughly classified into two categories. The first category takes a structural strategy to find the best matching that respects both geometry and topological variations. [AXZ*15] uses a combinatorial tree search and deformation energy constraint to establish meaningful segment-wise correspondences. [ZYL*17] finds the best binary segmentation in a top-down manner, via matches along the object hierarchy and recognition measures to better handle structural variations and imperfect initial segmentation than [AXZ*15]. The second category derives from notable spectral matching techniques [LH05]. SHED (Shape Editing Distance) [KvKSHCO15] takes shape segments and performs matching to define a better shape similarity measure. It innovates to find both one-to-one and one-to-many segment-wise correspondences, using both geometry and topology information. [KO17] uses HKS features for presegmentation, and spectral matching to find segment-wise correspondences, with special focus on symmetric issues.

We observed two problems in these works. First, most of these techniques request a perfect input segmentation. Imperfect input segmentation would lead to bad matching. In Figure 1, the two handles are over-segmented, which affects the topology (graph distance) of the underlying segment graph, and easily leads to
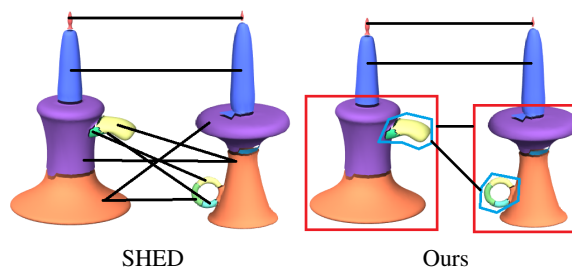

Figure 1: Given imperfect input segmentation, [KvKSHCO15] (left) produces many incorrect matchings. The over-segmented handles in both candles are particularly challenging. Our technique (right) can find more meaningful merged segment-wise matching. Colors indicate segmentation, and lines indicate output segment-wise correspondences. Merged segments are indicated in polygons.

bad matching. Second, correct segment matching also depends on the global shapes and functionality. For example, in Figure 1 the two handles are connected to two different segments in respective meshes. This requires merging of two base segments, before a meaningful consistent segment-wise matching can be established. These observations inspire us to investigate the following **research questions**: Can merged segments help improve the accuracy of segment-wise matching with imperfect and over-segmented inputs? How can we develop a representation that facilitates matching of merged segments, and a technique for segment-wise matching?

Contributions. To address these questions, we construct a multi-layer graph (MLG) consisting of nodes with input and merged segments, built in a bottom-up manner. We further adapt diffusion pruning [TMRL14] to such MLGs using geometry and topology constraints. Early stage results are encouraging.
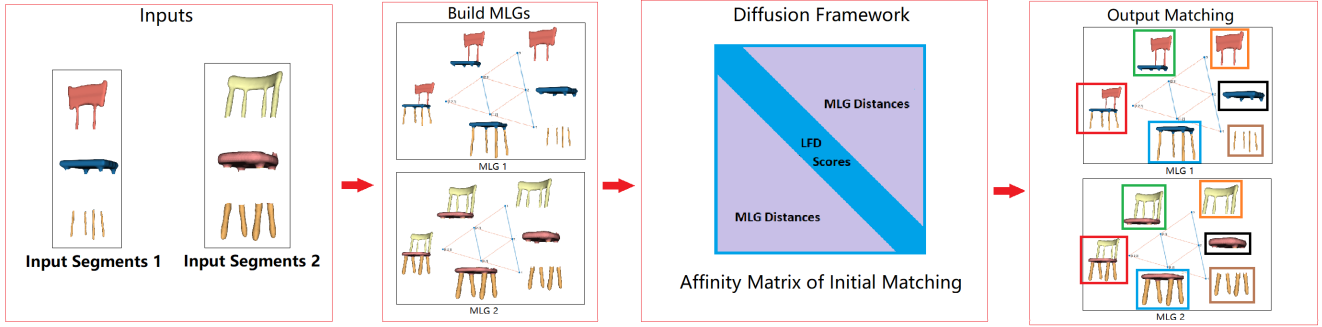
Figure 2: Overview. We take pre-segmented shapes as input and use MLGs to represent the input meshes with provided segmentation. Next we adapt diffusion pruning to the MLGs to find reliable matchings.

2. MLG and Diffusion Pruning

We define a multi-layer graph as a hierarchical representation covering possible combinations of the segmented shape. The lowest layer consists of nodes representing the input segments, and the highest layer consists of one node representing the entire shape. Nodes in internal layers are defined by merging nodes in lower layers. We then adapt diffusion pruning techniques to obtain matchings. An overview of the method is shown in Figure 2.

Let $\mathcal{S} = \{S_1, S_2, S_3, ...\}$ be all segments of an input shape $\mathcal{S}$. Denote by $N_i^{[n]}$ the ith node in the nth layer of a MLG, which satisfies $N_i^{[n]} \subset \mathcal{S}$. (We use $^{[n]}$ to indicate the layer and to differentiate it from the power operator). Nodes in the bottom layer (layer 1) is defined as $N_i^{[1]} = S_i$. Next, we define the merging operator between 2 nodes $N_i^{[n]}$ and $N_j^{[n]}$ ($i \neq j$) to form a new node $N_k^{[n+1]}$ as

$$N_k^{[n+1]} = merge(N_i^{[n]}, N_j^{[n]}) = N_i^{[n]} \cup N_j^{[n]}$$

where $N_i^{[n]}$, $N_j^{[n]}$ share some vertices or faces. All nodes $N_i^{[n]}$ in internal layers can be defined by the merging operator recursively. Merging stops when the entire shape $\mathcal{S}$ is reached. To reduce the complexity of MLG, we further apply a user defined volume constraint to limit how large a new node can be in each layer. In this way, the volume constraint controls how many layers will be formed in the MLG. For every pair of nodes in the same MLG (within and across layers) with shared vertices/faces, an edge is formed to connect them. All edges are weighted as 1. MLG distance between nodes can be defined by their shortest path.

Once the MLGs are built, we construct an affinity matrix to encode both geometry similarity and topological consistency, using Light-Field Descriptor (LFD) scores [CTSO03] and graph distance on MLGs. We then adapt and apply diffusion pruning twice. First we only involve bottom layer (layer 1) to find useful segment-wise correspondences as anchors. Then, with these anchors, we involve higher layers for final output computation.

3. Results

Figure 3 shows one set of results, compared against SHED [KvK-SHCO15]. Due to imperfect segmentation, SHED often produces inconsistent matching (Figure 3(a)). For example, the T-shaped segment in the right lamp (green circle) should not be matched sepa-

(a) SHED matching result   (b) Layer 1 matching result

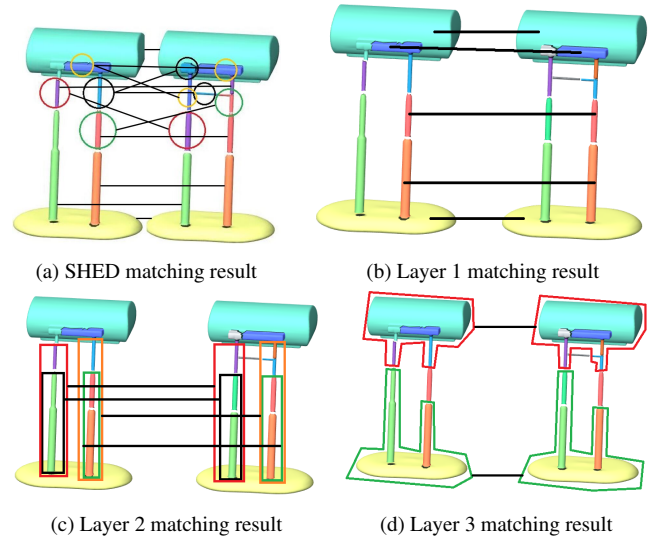(c) Layer 2 matching result   (d) Layer 3 matching result

Figure 3: Results comparison, colors indicate segmentation only. In a) Circles indicate inconsistent matching from SHED. In (b), (c), (d) polygons with same color indicate our matching results.

rately. The upper (red circles) and lower left stick are inconsistently matched, in terms of position, to the upper right and lower left stick respectively. In Figures 3(b), (c) and (d), ours can find consistent one-to-one, one-to-merged and merged-to-merged segment correspondences, with the help of multi-layer graphs.

4. Conclusion and Further Work

In this paper, we propose a MLG representation and adapt diffusion pruning to find segment-wise matching. The early results suggest that our technique can find meaningful segment-wise matching under imperfect and over-segmented inputs. Since our technique builds MLGs in a bottom-up manner, one limitation is the high number of possible internal nodes relative to the number of input segments. We hope to address this issue in the future by developing better merging constraints and using fewer layers in the matching.

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