A Unified Framework for Mesh Segmentation and Part Annotation

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Abstract

This paper proposed a unified framework to generate consistent segmentation and annotate part semantic for 3D mesh simultaneously. The core idea of the proposed framework is to bridge the semantic gap between low-level geometry feature and high-level semantic feature by structure ontology. The structure ontology makes a consistence representation for mesh structure, geometry feature, semantic concept and semantic rules. So it can be used in the process of segmentation and part annotation. Comparing with the previous work, the proposed framework has the two distinctive characters. Firstly, it can avoid inconsistence segmentation problems deduced from existing segmentation algorithms. Secondly, it can recognize part semantic automatically by defined semantic rules. Finally, this paper shows some experiment results to further verify the effect of the proposed framework.

Keywords: Structure Ontology; Part Annotation; Mesh Segmentation; Semantic Rules

1 Introduction

Mesh segmentation and part annotation are two basic but most important problems in computer graphics and computer vision. Mesh segmentation is used to partition the 3D model into some meaningful parts, and it is an important step for part annotation. While the main task of part annotation is used to recognize semantic feature for each segmented part. Part annotation can not only understand the inner structure of a mesh, but also bridge the semantic gap between low-level geometry and high-level semantic knowledge for 3D model[1]. This topic has attracted more and more research interests in recent years as well.

In part annotation, a challenging problem is how to identify part semantic of a mesh in an automatic way. To do this, two problems should be resolved together: correct segmentation result and correct semantic recognition algorithm. However, existing segmentation algorithms are difficult to answer the problem about ”which is the correct segmentation for mesh structure”.

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This problem is also called inconsistent segmentation: a set of meshes with same structure appears to be very different segmentation results. Undoubtedly, automatic part annotation using these segmentation algorithms directly will cause a wrong result. Therefore, we need to generate a common standard for segmentation result. So the segmentation process is to approximate such a common structure to avoid the inconsistence problem. It can also be regarded as the answer for ”which is the correct segmentation for mesh structure”. On the other hand, existing research about semantic recognition only uses some geometry attributes, few semantic rules are defined. However, similar geometry attributes in different semantic classes may have distinctive semantic feature. For example, the tail of a horse may have similar geometry attributes with the arm of a human. So geometry attribute is not enough for semantic recognition.

Based on the above analysis, this paper proposed a unified framework for mesh segmentation and part annotation. The proposed framework is not only to generate a consistent segmentation representation for a set of meshes, but also to recognize part semantic automatically. The core idea of the proposed framework is to define structure ontology, which includes geometry attribute, mesh structure, part semantic and semantic rules. It makes a consistent representation for low-level geometry attribute to high-level semantic knowledge as well. The proposed framework is an extension of Attene’s work[2], and we highlight our main contribution as:

1) Semantic based consistent mesh segmentation. It defines a consistent segmentation result by structure ontology. So the defined knowledge can be as a constraint in segmentation process. It answers the question ”which is the correct segmentation”.

2) Semantic rules based automatic part annotation. For specified semantic class, we extract its geometry attribute and define semantic rules to generate correspondence between low-level geometry and high-level semantic. So the part semantic can be recognized automatically by the defined rules.

2 Related Work

2.1 Mesh segmentation

Segmentation of 3D meshes is a basic problem in computer graphics. It has plenty of applications, like shape retrieval, deformation, compression, simplification, texture mapping and modeling. A detailed survey can be found in reference[3, 4].

Among all proposed approaches, watershed segmentation algorithm is the most popular region-growing approach, which is an extension of watershed segmentation in image processing[5]. The algorithm uses curvature to control the merging operation in 3D shape segmentation. It can use other measurements, like surface normal and electrical charge distributions as well[6, 7]. An improved watershed method, called fast marching watersheds, is developed by using hill climbing[8]. The watershed algorithm is fast and does not need to specify the number of parts. However, it is prone to over-segmentation. Recently, cluster algorithm has been used widely in mesh segmentation. For example, fuzzy k-means cluster algorithm uses geodesic distance and angle between faces to decomposes the given 3D shape into several parts[9]. It also uses graph cut to refine segmentation boundary. Similar work including random walks[10], spectral clustering [11]. Another work is to extract a main part from the input mesh, like core extraction[12], and Poisson equation[13]. Comparing to watershed based region growing algorithms, theses algorithms
can overcome over-segmentation problem. However, these algorithms may produce inconsistent segmentation result due to the model pose, different proportions between parts of the model and so on. To avoid the inconsistent segmentation problem, Shapira et al proposed a more robust shape measure called shape diameter function (SDF) [14]. It can generate consistent segmentations for some meshes with different pose. But it still fails for some models with different diameter percentage. Golovinsky et al proposed a distinctive work to avoid the problem of inconsistent segmentation [15]. It segments a set of models simultaneously and creates correspondences between segments. But Golovinskiy’s work needs to generate a graph for all input models, so it is difficult to process plenty of models due to high complexity.

2.2 Part annotation

In 3D retrieval, how to resolve the semantic gap between geometrical features and semantic knowledge remained a challenging problem. The problem has been widely researched in the field of image retrieval [16]. Many algorithms can be used for 3D retrieval [17, 18]. However, these methods describe the object as a whole and mainly to assign semantic class for each object. Differing with global semantic recognition, part annotation is to recognize semantic for each part, which is to understand inner structure of a 3D model [19]. Recent work by AIM@SHAPE shows that 3D knowledge is organized by three levels, including geometric data, topology structure, and semantic annotation of objects and objects’ parts [20]. So part annotation, which understand shapes, would also provide a significant support for modeling by example [21]. Recent application, like part analogies and modeling with interchangeable parts further prove the importance in understanding its subparts [22, 23]. In consequence, part annotation has attracted more and more research interests.

The project ”3DK (3D Knowledge)” carried by Arizona State University has made an important contribution about this research topic [24]. Their research first segments 3D model into difference parts. Then they annotate semantic knowledge for each part manually. The Virtual Humans build an ontology representation for human shapes. It uses multi-scale morphological analysis to extract some landmarks of the human shape [25]. A most important work about part annotation is the tool ShapeAnnotator, which is developed by Marco Attene [2]. It develops a flexible and modular interactive system for part-based annotation of 3D objects. The ShapeAnnotator provides several kinds of segmentation algorithms and user can easily select the part associated with specified concept by the ontology. The main contribution of the ShapeAnnotator include multi-segmentation framework for 3D model, geometric and topological calculation, the ontology module for user browsing.

In conclusion, part annotation has attracted more and more research interests, and some works have been done before. However, the main problem of existing work about shape annotator process will be done manually, and no automatic annotation algorithm is proposed. In addition, the existing segmentation algorithms, which only use different shape measures, cannot output the correct segmentation result. So it can not used for part annotation directly. Therefore, this paper considers the two problems together and proposes a unified framework to generate consistent segmentation and part annotation for 3D model simultaneously.

3 Overview the Unified Framework
This section gives a flowchart of the proposed algorithm. The whole algorithm mainly consists of off-line and on-line two parts, as shown in Fig. 1. The off-line process is to define structure ontology manually for semantic class, which defines the number of part, the semantic for each part, geometry attribute for each part and semantic rules for part annotation etc. So it generates a bridge between low-level geometry feature and high-level semantic feature to drive the process of segmentation and part annotation. The on-line process is to perform automatic part annotation by the following three steps. Firstly, the algorithm performs a K-way segmentation to get part set for the input 3D model. Secondly, it extracts some geometry attributes for each part. Finally, it performs a part annotation process by the defined semantic rules.

![Flowchart of the proposed framework](image)

### 4 Structural Ontology

Our main objective is to develop a general framework for structuring and semantically annotating 3D models. So we need to generate a structure semantic representation for 3D models prior to mesh segmentation and part annotation. Though there are many possible knowledge representation strategies, we prefer to use ontology for representation. The main advantage of ontology is suitable for expressing multimedia content and corresponding semantic[26]. Furthermore, the ontology representation is increasingly as a usual standard in information sharing and reusing. The structure ontology can be defined with following representation:

$$SO = \{P, C, R_{1P \rightarrow P}, R_{2P \rightarrow C}, Rules\}$$

Here $P = \{p_1, p_2, \cdots, p_i, \cdots, p_K\}$ and $C = \{c_1, c_2, \cdots, c_j, \cdots, c_M\}$ denotes the part set and semantic set respectively. The symbol $K$ and $M$ are the number of meaningful parts and semantic concepts respectively. The mapping relation $R_{1P \rightarrow P}$ defines the topology structure for specified semantic class. For any two parts $p_i, p_j \in P$, the element $r_{ij} \in R1$ has a value $r_{ij} = 1$ or does not connect $r_{ij} = 0$. The mapping relation $R_{2P \rightarrow C}$ gives a semantic representation for each part. So for each part $p_i \in P$, it has a semantic concept $c_j \in C$. The rule set $Rules$ is to generate
some geometry attributes based rules to recognize part semantic automatically. Fig.2 shows a
definition of structure ontology for semantic class human. The relations among semantic concepts
have been visualized in the topology structure of the 3D model. It means that the concepts
“Head”, “Arm”, “Leg” are adjacent to “Torso”. Furthermore, the semantic recognition rules
uses some geometry attributes are important for part annotation. The first two rules can be used
in generating consistent segmentation and other rules can be used in part semantic recognition.
The main advantage of such structure ontology definition is to bridge low-level feature and high-
level semantic feature for 3D model. It is not only to define the high-level feature of domain
knowledge, but also to be associated with low-level geometry attribute for 3D model. Since
genometry attributes are calculated independently of any ontology and any semantic knowledge,
the structure ontology can establish a set of connections between geometric descriptors and class
attributes. That’s to say, it makes a unified representation for 3D model with geometry, structure,
semantic concept and semantic rules.

Furthermore, based on the definition of structure ontology, we can convert the input 3D model
from low-level geometry data to high-level knowledge representation. It is done by the Resource
Description Framework (RDF) standard, which is proposed for Semantic Web[27]. RDF is the
framework in which Semantic Web metadata statements are expressed and usually represented as
graphs. The RDF model is based on the idea of making statements about resources in the form
of a subject-predicate-object expression. Relation can be visualized as a graph, in which every
node represents a concept and each edge between two nodes constitutes a contextual relation
between the respective concepts. Representing the graph in RDF is a straight forward task, since
the RDF structure itself. Table 1 shows the description for "head" part in human ontology. As
shown in Table 1, the definition gives not only a semantic description for this part, but also some
necessary geometry attribute for defining semantic rules.

![Fig. 2: Structure ontology for human (the semantic tags in the left figure are associated with
topology representation)](image-url)
Table 1: RDF representation for "Head" part

```
<rdf:RDF
  <owl:imports rdf:resource="file:\\3DPart\\humanBody.owl"/>
  <rdfs:comment xml:lang="en">Created by ShapeAnnotator 2.0beta</rdfs:comment>
</owl:Ontology>
<Head rdf:id="Head">
  <Shann_Segment_ID rdf:datatype="http://www.w3.org/2001/XMLSchema#int">1</Shann_Segment_ID>
  <FarthestX rdf:datatype="http://www.w3.org/2001/XMLSchema#float">0.0415</FarthestX>
  <FarthestY rdf:datatype="http://www.w3.org/2001/XMLSchema#float">-0.0032</FarthestY>
  <FarthestZ rdf:datatype="http://www.w3.org/2001/XMLSchema#float">0.8851</FarthestZ>
  <Signature rdf:datatype="http://www.w3.org/2001/XMLSchema#float">0.4</Signature>
</Head>
```

5 K-way Segmentation

Due to the known part count and connection relation in definition of structure ontology, the problem for segmenting input 3D model is easy and direct. The main task is to extract a core part firstly. There are many existing segmentation algorithms can process this problem, including spectral clustering, fuzzy clustering, core extraction and Poisson equation. Here we use Poisson equation to generate segmentation result.

As for Poisson equation based mesh segmentation, it first computes shape signature for each face by Poisson equation. The Poisson equation is to place a set of particles at the internal point and let them move in a random walk until they hit the boundary and so get the mean time required for a particle to hit the boundaries. So Poisson signature is a kind of structure related shape attribute that can be used for mesh segmentation. Furthermore, Poisson equation is independent of the coordinate system over the entire domain as well. So the shape signature based on Poisson equation is robust under rotation, noise-distortion, shape crash and rigid transformation. Therefore, the signature can be used in definition of graph node attribute and further use for graph matching based part annotation. Poisson signatures for some models can be shown in fig.3.

![Fig. 3: Poisson signatures for 3D models (The signature is significantly different for part)](image_url)

With the defined signature by Poisson equation and structure ontology, we can easily construct K-way segmentation. Firstly, it extracts a core face by Poisson signature. Secondly, it performs K-1 binary segmentation by geodesic distance and Poisson signature to get other K-1 parts. And the remained faces will construct a core part for input 3D model. Finally, it uses graph cut to refine the segmentation boundary. More details about the mesh segmentation by Poisson equation can be found in the reference[13].
6 Semantic Rules Based Part Annotation

After K-way decomposition, the input model has been decomposed into K meaningful parts, denoted by set $PS = \{ps_1, ps_2, \ldots, ps_i, \ldots, ps_K\}$. Only the semantic concept for core part is known, so we need to recognize part semantic for other K-1 parts. A general method is to use graph matching to generate part correspondence between input 3D model and example defined in structure ontology. So the annotation for example can be transferred to input 3D model. These methods, like Earth Mover Distance, Bipartite graph matching,...[22], may produce incorrect result due to model pose or geometry signature. Taken for an example, the matching result by using bipartite graph may have result that the part “leg” for input model is matched to the part “arm”. Obviously, it gives a wrong part semantic description.

For this reason, we formulate a distinctive part annotation algorithm, which is deduced from semantic rules. For different semantic classes, the semantic rules are defined by the geometry attributes. So the part semantic can be recognized by geometry attribute. Different semantic class may require different semantic rules associated with geometry attributes. As an example, this section describes how to recognize part semantic for Human class by defined rules. This section gives more details about rules 4 and 5.

1) Recognition of Part ”Head”

The recognition of Part “Head” is performed by self-dissimilarity analysis. For each part, we want to find the other part that is most similar with it. So the self-dissimilarity value for “head” part will be highest because all other parts are very different with it. On the contrary, the part for “arm” or “leg” will be low. The Fig.4 visualizes the self-dissimilarity distribution for human. As shown in the following figure, the head is independent of other parts. The white color means high value for the $sys_i$ and the black color low. The highest $sys_i$ can be recognized as part “Head”.

The self-dissimilarity for each part is computed by average Poisson signature. For each part $ps_i \in PS$, the average Poisson signature $ws_i$ is computed by the following equation:

$$ws_i = \frac{\sum w_j}{|ps_i|}$$  \hspace{1cm} (1)

here $w_i$ is the value of Poisson signature for each face. For each part, its average Poisson signature is further normalized by the following equation:

$$ws_i = \frac{ws_i}{\max(ws_j)}$$  \hspace{1cm} (2)

Based on the above shape measures, we can define self-dissimilarity $sys_i$ for each part:

$$sys_i = \min(\text{fabs}(ws_i - ws_j)), \hspace{1cm} j = 2, K - 1, j \neq i$$  \hspace{1cm} (3)

The above equation is a description of self-dissimilarity for part set. So we can recognize part ”head” by the following equation:

$$p_i \in \{"Head"\}, \hspace{1cm} \max_{i=1,\ldots,K}(sys_i)$$  \hspace{1cm} (4)

2) Recognition of Parts ”Arm” and ”Leg”
After recognition of Part "Head", the remained problem is how to recognize "Arm" and "Leg". Most often, the body of human has the semantic character that its length will be larger than width. So we can use geometry attribute geodesic distance to measure this semantic character. The Fig. 5 shows a geodesic distance description for human instance. The red and blue line denotes the length and width of body respectively. Obviously, the length of red line will be larger than that of blue line. So the semantic recognition of "Arm" and "Leg" can be performed by geodesic distance analysis.

To do this, we first select one face \( f_i \in p_{\text{head}} \) randomly. Suppose two parts \( p_1, p_2 \in \{ "Arm", "Head" \} \). The two faces \( f_j \in p_1, f_k \in p_2 \) are selected randomly as well. The geodesic path from \( f_i \) to \( f_j \) must pass the part "Torso", and let line segment belonging to this part be \( \text{geod}_1 \). Similarly, we have distance \( \text{geod}_2 \). The distance \( \text{geod}_1 \) and \( \text{geod}_2 \) is an approximation to the length and width of body. So based on the semantic character of Human, it can define the equation (5).

\[
\begin{cases} 
  p_1 \in \{ "Arm" \}, & \text{geod}_2 > \text{geod}_1 \\
  p_2 \in \{ "Leg" \}, & \text{Otherwise}
\end{cases}
\]

Fig. 4: Self-dissimilarity distribution for Human
Fig. 5: Geodesic distance distribution for Human

Finally, we can summarize the process of part annotation as Table 2.

| Step 1: Let the part set be \( TS = PS \) |
| Step 2: Annotate core part as “body”, remove it from set \( TS \) |
| Step 3: Compute the \( \text{sys}_s \) for each part in set by equation (3) |
| Step 4: Recognize part “Head” by the equation (4), remove it from set \( TS \) |
| Step 5: select one face randomly for remained parts in \( TS \), and compute its geodesic distance to \( f_i \in p_{\text{head}} \) |
| Step 6: Get the line segments in the part “Torso” and sort them in ascendant |
| Step 7: Judge the “Arm” and “Leg” by equation (5) |

| Table 2: Part semantic recognition for human class |

7 Experiments and Discussions

This section gives some experiment results to verify the proposed framework. The testing models are mainly from segmentation Benchmark[28]. The benchmark comprises a data set with 380 surface meshes and provides plenty of segmentation result by different algorithms. However,
it does not provide the semantic representation for each category. We select some categories, including human, pliers, chairs and animals et al in our experiment. For each semantic class, we first select one model to generate its structure ontology. Then the structure ontology is used to verify the proposed framework. Each kind of structure ontology concludes a segmentation result associated with part annotation, as shown in Figure 6. The corresponding semantic rules are defined as well. Based on the definition of structure ontology, each definition has a core part. Mostly, the definition of center part has a meaningful semantic. For example, the center part of pliers denotes the slip point; the center part of chair denotes the cushion and so on. In experiments, we first make comparison with some existing segments and verify that shape attributes are not enough for consistent segmentation. Then some part results are shown to verify semantic rules based part annotation. Finally, some limitations of the proposed framework are discussed.

7.1 Consistent segmentation

With the above definition of structure ontology, we can show some experiment results with the proposed framework. The first experiment is to show the consistent segmentation of a set of models. As a comparison, we also show some results from existing algorithms, including feature point and core extraction and shape diameter function. To simplify the representation, we use FPCE and SDF to denote the above two algorithms respectively. The FPCE algorithm tries to extract feature points for each meaningful part by using multidimensional scaling. However, it can not get correct part count. So the segmentation results of such models will not be inconsistent. For example, two semantic legs will be considered as a part in segmentation. The kernel idea of SDF is to use a new shape measure called shape diameter function for segmentation. Actually, the shape diameter function has some advantages to capture the topology structure feature for 3D shapes, which will be very helpful for segmentation. However, it is still not enough to generate a consistent segmentation. For example, the legs of some models have been split into two parts, while others have been split into three or four parts. Similar problems also appear in shoulders. As shown in Fig.7. On the contrary, the structure ontology is defined prior to mesh segmentation in our proposed framework, so the defined structure ontology can be used in segmentation. It makes the results be more consistent even for different poses and component percentage.

![Structure ontology for some semantic classes](image)

Fig. 6: Structure ontology for some semantic classes
7.2 Part semantic recognition

Next, we will show more experiments for other semantic classes. For other semantic classes, the required semantic will be different with human classes. For example, the semantic class "Pliers" and "Chair" only uses symmetry in semantic rules. While for animals, the medial axis distance is required to recognize "Tail" and "Head". Some experiments are shown in Fig. 8. These models can be annotated correctly. For semantic class "Animals", the instance "Horse" and "Cat" are different, but have common structure. So they can share structure ontology.

7.3 Limitation

The proposed framework is to output consistent segmentation and part annotation. This framework also exist some limitations that need to be improved. Firstly, current framework can not distinguish part semantic like "left arm" and "right arm". While for some modeling applications, it may be necessary for further distinguishing these part semantics. Secondly, it uses Poisson equation based segmentation for any other semantic class. The Poisson signature is a kind of volume based geometry signature. So it can not process some models like "mug". Actually, the proposed framework is independent of segmentation algorithms. So these problems may be resolved by other segmentation algorithms. We can improve the definition of structure ontology, which can select best segmentation algorithms for specified semantic class.
8 Conclusion

This paper addresses the problem about how to recognize part semantic automatically. It proposed a unified framework for mesh segmentation and part annotation. The proposed framework defines structure ontology to bridge the semantic gap between geometry data and high level semantic. So it can avoid inconsistent segmentation problem that exists in previous algorithms. Furthermore, it can recognize part semantic automatically by the mapping between geometry data and high level semantic.

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