Semantic Relation Driven SVM-Based Function Recognition for 3D Shape Components

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1 Introduction

The semantic knowledge of 3D shapes could reflect the human's perception of shape functions and the knowledge on functional description plays a very important role in shape analysis and understanding. Therefore, functional recognition of 3D shape becomes a hot issue that needs to be solved urgently. And the component-based function recognition technique is one of the main solutions. Feng et al. [1] proposed a junction-aware shape component descriptor to obtain functional semantics. Léon et al. [2] presented a high-level signature method to capture the functional semantics of shape component. Laga et al. [3] proposed the component-aware similarity measure approach. The above methods make full use of the function relations between shape components to achieve the task of function recognition. To further improve the accuracy of functional recognition, the methods combining semantic information with the structure of components are proposed recently. For example, the modal function transformation based on shape matching pairs of shape components [4] and a rule-based expert system for inferring functional annotation [5] were proposed. And the compositional model combining shape and appearance [6] also have good performance for functional recognition. However, they show unsatisfactory results for these shapes, which have large geometric and topological variations. So, it is necessary to propose a new approach to improve the accuracy of function recognition of 3D shapes.

In this paper, we present a semantic relation driven SVM-based 3D shape components function recognition approach(SDFR) to solve the problem of reorganizing functional components under large scale deformations. The main contributions of the proposed approach are as follows. (1) The shape segmentation

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scheme based on approximate convexity decomposition is proposed to identify shape components with independent semantics. (2) A semantic calculation method based on component context relations is proposed to qualitatively measure semantic relations between the obtained shape components, which has stability for shapes with large geometric and topological variations. (3) The functional classification method using SVM is performed to achieve the task of shape recognition. In a word, SDFR integrates the advantages of semantic information and shape structure to improve the accuracy of function recognition for 3D shapes, especially for shapes with large-scale deformation.

The rest of the paper is structured as follows. Section 2 presents the framework of SDFR. Section 3 illustrates the implementation of SDFR. Section 4 presents experimental work to demonstrate our approach. The last section concludes the paper.

2 The Overview of SDFR

Let $\{S_1, S_2, \ldots, S_n\} \in S$ denotes the three-dimensional shape set, $\{p_1, p_2, \ldots, p_m\} \in P$ denotes the independent component set for $S_i(S_i \in S)$, and $\{c_1, c_2, \ldots, c_m\} \in C$ denote the corresponding component label of functional category. The aim of proposed SDFR is to retrieve the shape component which has the same functional category with p_t, and p_t is one of components for test shape S_t. Figure 1 shows the framework of SDFR and it consists of three steps.

Specifically, the shape segmentation scheme based on approximate convexity decomposition is presented and it uses the contour dissimilarity and boundary attributes of convexity to effectively divide each 3D shape into multiple combinations of components with different function semantics, i.e. $\cup_{i=1}^{N} p_i = S_i(S_i \in S)$. Then, for $\forall p_i(p_i \in S_p)$ and $\forall p_j(p_j \in S_q)$, the semantic calculation method based on context relations of the obtained components is proposed to quantify the semantic similarity between p_i and p_j, which could maintain stability for shape components with large scale deformation. Finally, according to the obtained semantic similarity of shape components, the function recognition method using SVM is adopted to determine the functional label for each component.

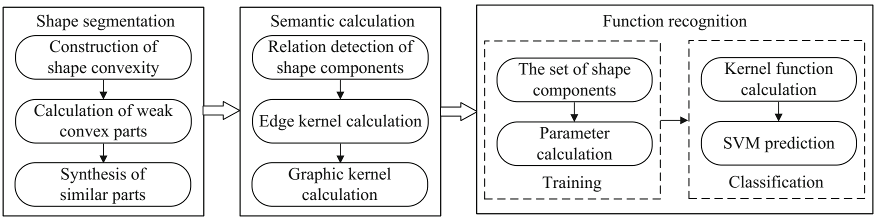

Fig. 1 The framework of SDFR method

3 The Implementation of SDFR

In this section, we elaborate the critical steps in the process of SDFR implementation. The proposed method is to address the problem of automatic recognition in the presence of significant geometric and topological variations of 3D shapes.

3.1 Shape Segmentation of 3D Shapes

In the light of the visual perception characteristics of human for the complex shapes, 3D shapes can be decomposed into multiple combinations with different semantic components and to achieve this task [7], the approximation convexity decomposition technology can be adopted to complete shape segmentation [8, 9]. On this basis, the segmentation scheme contains construction of shape convexity, calculation of weak convex parts and synthesis of similar parts.

Firstly, S_i is divided into the approximate bump set by using the over-segmented method. Based on the extracted bumps from the set, the shape convexity is constructed and the initial block set $BS = \{BS_1, BS_2, \ldots, BS_n\}$ is captured by using the graph-based clustering method.

Secondly, the convex rank for $BS_i (BS_i \in BS)$ is computed using (1):

$$R(BS_i) = |VI(BS_i)|/|BS_i|^2 \tag{1}$$

where $VI(BS_i)$ is the set of all pairs of points in BS_i that are in a line-of-sight, *i.e.* $(i, j) \in VI(BS_i)$ $(i \in BS_i, j \in BS_i)$. The weakly convex set $W = \{W_1, W_2, \ldots, W_m\}$ is obtained by descending $R(BS_i)$ and the weakly convex parts with similar visible properties are merged to inform a new set $W = \{W_1, W_2, \ldots, W_{m'}\}$.

Finally, the geometrical features of the parts are described using the contour dissimilarity and the boundary attributes of the convex set, and the weak convex components with similar geometric features are synthesized. The contour dissimilarity of parts can be computed using EMD, shown in (2).

$$dist(W_i, W_j) = E(h_i, h_j) \tag{2}$$

where h_i and h_j are histogram of shape diameter function for W_i and W_j, respectively.

The boundary attributes can be computed by the convexity of the seams, shown in (3).

$$\begin{aligned} VS_{i,j} &= \{(\boldsymbol{\omega}_p, \boldsymbol{\omega}_q) : \boldsymbol{\omega}_p \in W_i, \boldsymbol{\omega}_q \in W_j, (\boldsymbol{\omega}_p, \boldsymbol{\omega}_q) \in NG_k, \theta(\mathbf{n}_p, \mathbf{n}_q) \le \pi\} \\ AS_{i,j} &= \{(\boldsymbol{\omega}_p, \boldsymbol{\omega}_q) : \boldsymbol{\omega}_p \in W_i, \boldsymbol{\omega}_q \in W_j, (\boldsymbol{\omega}_p, \boldsymbol{\omega}_q) \in NG_k, \theta(\mathbf{n}_p, \mathbf{n}_q) > \pi + \varsigma\} \end{aligned} \tag{3}$$

In (3), $VS_{i,j}$ and $AS_{i,j}$ denote the convex seam and concave seam between W_i and W_j, respectively. ω_p denotes the sampling point with direction $-\mathbf{n}_p$ in D_i. $\theta(\mathbf{n}_p, \mathbf{n}_q)$ denotes the angle between $\mathbf{n}_p$ and $\mathbf{n}_q$, ζ denotes the adjustment threshold, and NG_k denotes the neighbor graph combined by seams. W_i and W_j are merged when they satisfy the distance condition, shown in (4).

$$|NS_{i,j}|/|AS_{i,j}| \geq \eta, dist(W_i, W_j)/\max(dist(W_i, W_j)) \leq \sigma \tag{4}$$

where η and σ are merge thresholds. Then the independent component set P for shapes can be obtained.

3.2 Semantic Calculation of Shape Components

When the geometrical features and topological structure of 3D shapes change greatly, we find that the semantic relations of the shape part maintain relatively stable and this can be applied to the problem of functional classification.

Given graph $G(V, E)$ denotes component relations of 3D shapes, V denotes the nodes of shape component, and E denotes the different type relations among the nodes. Then the problem of functional classification is changed to the problem of graphic kernel calculation and obtained graphic kernel $\boldsymbol{\Psi}$ quantifies the semantic similarity of the function of the shape components.

Combining geometric features of component with context relations between nodes, $\boldsymbol{\Psi}$ is computed by using (5)

$$\psi^l(G_p, G_q, p_A, p_B) = \begin{cases} \psi_N(p_A, p_B) \times \sum\limits_{\substack{p_s \in AN_{Gp}(p_A) \\ p_{s'} \in AN_{Gq}(p_B)}} \psi_E(e, e')\psi^{l-1}(G_p, G_q, p_s, p_{s'}), & l > 0 \\ \psi_N(p_A, p_B), \quad l = 0 \end{cases} \tag{5}$$

In (5), l denotes the length of graph path, G_p and G_q are the relation graph for shape S_p and S_q, respectively. $p_A \in G_p$, $p_B \in G_q$, $AN(x)$ denotes all adjacent nodes for x in G, e and e' are the edges which connect between p_A and p_s, p_B and p_s. Ψ_N denotes the node kernel, which reflects the similarity geometric characteristics of the two components, and it is calculated by using shape description operator based on Euler distance, shape size based on unit sphere and the principal direction feature based on PCA. Ψ_E denotes the edge kernel, which reflects the context of different nodes, shown in (6).

$$\boldsymbol{\Psi}_E(\boldsymbol{e}_p, \boldsymbol{e}_q) = \boldsymbol{R}(\boldsymbol{e}_p, \boldsymbol{e}_q) \tag{6}$$

Which $e_p \in E_p$ and $e_q \in E_q$, R denotes the context relation between e_p and e_q, *i.e.* if there is the relation between e_p and e_q, $R(e_p, e_q)$ is 1, otherwise is 0.

The contextual semantic relations between shape parts are divided into two sorts: the basic relations and the derivation relations. The basic relations mainly contain inclusion relation, symmetry relation, horizontal support relation, side connection relation and adjacency relation. The definitions are shown as follows.

Definition 1 Inclusion relation. If the overlap of bounding boxes of p_1 and p_2 is over 50%, then there is the inclusion relation between them, denoted as $IN(p_1, p_2) = 1$.

Definition 2 Symmetry relation. If there are rotational symmetry, translation symmetry or reflection symmetry between p_1 and p_2, then there is the symmetry relation between them, denoted as $SYR(p_1, p_2) = 1$.

Definition 3 Horizontal support relation. If the contact surface of p_1 is perpendicular to the gravity vector of p_2, there is the horizontal support relation between them, denoted as $HR(p_1, p_2) = 1$.

Definition 4 Side connection relation. If the normal of contact area of p_1 is perpendicular to the symmetrical spindle of p_2, then there is the side connection relation between them, denoted as $SCR(p_1, p_2) = 1$.

Definition 5 Adjacency relation. If p_1 and p_2 have a common vertex or the bounding boxes of them are overlapping, then there is the adjacency relation between them, denoted as $AR(p_1, p_2) = 1$.

Based on the above the basic relations, the derivation relations are designed to capture the underlying context semantic information, which are shown as follows.

Rule 1 If $SYR(p_1, p_2) = 1$ and $SYR(p_2, p_3) = 1$, then $SYR(p_1, p_3) = 1$.
Rule 2 If $HR(p_1, p_2) = 1$ and $SYR(p_2, p_3) = 1$, then $HR(p_1, p_3) = 1$.
Rule 3 If $SCR(p_1, p_2) = 1$ and $SYR(p_2, p_3) = 1$, then $SCR(p_1, p_3) = 1$.

3.3 Function Recognition Using SVM

Since the methods using SVM are better than many traditional classification methods in the terms of controlling over-fitting, the efficiency of calculation and classification accuracy, function recognition using SVM could be used to establish functional semantic classifiers and it contains two steps, training and classification. In the training phase, we set $\boldsymbol{\Psi}$ as the kernel function, and use it to calculate the support vectors and the optimal parameters. In the testing phase, we segment the 3D shape to obtain the set of shape components, calculate the Kernel function, and predict the function labels of shape components by using the optimal parameters.

4 Experiments Results and Discussion

We used the experimental data from Princeton University database [10] and the COSEG dataset [11], which contain four types of 3D shapes (candlesticks, birds, planes, and ants). Experiments were performed using Matlab platform. For each type of shapes, half of the samples in the data set were randomly selected as the training set and the other half were the test set. In the experiments, the normal adjustment parameter ζ was 0.05, the weak convex component merging thresholds and η and σ were 0.8 and 0.15 respectively.

Since that functional recognition depends on the high-level semantics of shape classification, we use the classification error rate to verify the accuracy of function recognition for each components of 3D shapes. The lower the index of the classification error rate, the higher the accuracy of the function recognition.

Figure 2 shows the comparison results of classification error rates using by semantic corresponding method GCFR [3] and the proposed method, which show that SDFR obtains the lower classification error rates for each shape component of each shape. The main reason is that the semantic calculation method based on the context relations could improve the recognition accuracy of the functional semantic classification.

To further measure the effect of functional recognition, we computed the component matching accuracy. For any type of shapes, the artificial label of component can be marked as its corresponding to the matrix, denoted as $M = m_{ij}$ $(i, j = 1, \ldots, N)$. N is the total number of components contained in this shapes. If the component j has the same functional label as the component i, then $m_{ij} = 1$, otherwise $m_{ij} = 0$. $AC(p,q) = \Sigma_{i \in p} m_{i\varphi(i)}/N_{\mathrm{p}}$ measures the component matching accuracy of the shape class. Where p and q represent the two shapes, respectively. For component i in p,

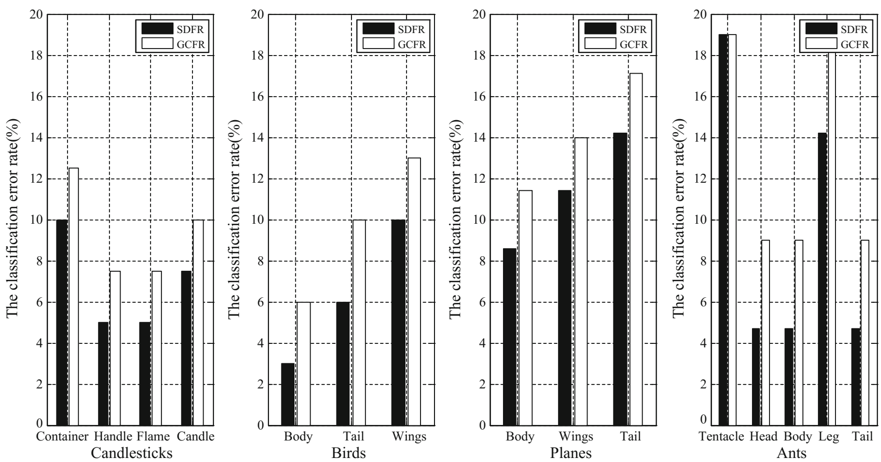

Fig. 2 Comparisons of classification error rates using by GCFR and SDFR

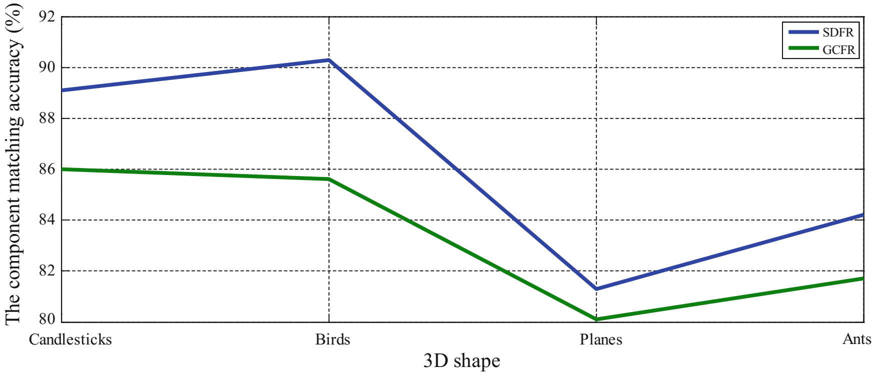

Fig. 3 Comparisons of matching accuracy of shape components

$\varphi(i)$ is the component of q that has the same functional label as i, and N_p is the total number of components in P. If the functional labels of all the components in p are the same as the functional labels in q, the value is 1, and if no function label is classified correctly, the value is 0. Figure 3 shows the average matching accuracy of the components obtained using the proposed method and GCFR. It can be seen that the matching accuracy obtained by using SDFR method is higher than that of GCFR.

5 Conclusions

The diversity of geometrical features and topologies of different 3D shapes leads to the identification of shape components with different apparent is a challenging problem. The semantic relations between shape components contain potential structural information, which could provide valuable observations for statistical methods. On this basis, we change the recognition problem into the prediction problem, and propose the SDFR method. The innovations of this method are shown as follows. (1) The shape segmentation based on approximate convexity decomposition is proposed, which decomposes the shape into shape components with different semantics. (2) A semantic calculation method based on context relations is proposed to quality the functional similarity. (3) SVM classifier with functional semantic similarity as kernel function is constructed to effectively predict the functional semantics of different shape components. The experimental results show that the method has good recognition effect and high recognition accuracy.

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