3D Model Retrieval using Density-based Silhouette Descriptor

Qi Tang and Xin Yang
Institute of Image Processing and Pattern Recognition, Shanghai Jiao Tong University, Shanghai, China
Key Laboratory of System Control and Information Processing, Ministry of Education of China, Shanghai 200240, China

Keywords: Shape Matching, Retrieval, Silhouette, Probability Density Function, Kernel Density Estimation, Invariance.

Abstract: In this paper we present a new content-based retrieval descriptor, density-based silhouette descriptor (DBS). It characterizes a 3D object with multivariate probability functions of its 2D silhouette features. The new descriptor is computationally efficient and induces a permutation property that guarantees invariance at the matching stage. Also, it is insensitive to small shape perturbations and mesh resolution. The retrieval performance on several 3D databases shows that the DBS provides state-of-art discrimination over a broad and heterogeneous set of shape categories.

1 INTRODUCTION

With an increasing number of 3D repositories available on the Internet, effective retrieval from large databases has become a hot spot (Marini et al., 2007; Li et al., 2012). Text-based systems, requiring manual annotation of the shapes, is severely limited in describing complicated 3D models (Tangelde and Veltkamp, 2008). Content-based systems, on the other hand, only require a shape descriptor that can automatically extract shape features (Min et al., 2004).

Among many content-based systems, Silhouette descriptor (SIL) (Vranic, 2004) and Density-Based Frame (DBF) (Akgul et al., 2009) have high retrieval accuracy on a large number of databases. By introducing DBF into SIL, we proposed a new shape descriptor, density-based silhouette descriptor (DBS). It uses multivariate probability density functions to describe the feature distributions of a given 3D object's 2D silhouettes. Like DBF, DBS is computationally efficient and enjoys a permutation property that guarantees invariance to a certain class of 3D transformation at the shape matching stage. Similar to SIL, DBS is relatively insensitive to small shape perturbations and mesh resolution. Consequently, DBS can be adapted to a broad and heterogeneous set of shape categories.

The rest of this paper is organized as follows: Section 2 describes the steps of DBS and its invariance properties in detail. Following that, Section 3 undertakes an exhaustive campaign of retrieval experiments and illustrates the effectiveness of DBS on several 3D model databases. We draw conclusions in Section 4.

2 DENSITY-BASED SILHOUETTE

Let $P_i, i = 1,2,3$ be the model's one projection and $f(\bullet|P_i)$ be the probability density function of feature distribution on projection P_i. Let S be the random feature defined on the model's 2D silhouettes and take values within R_S. The source set $\{s_k^i \in R_S\}_{k=1}^{K_i}$ is feature values, computed on the projection P_i, and is used to estimate the probability function. Furthermore, we specify a finite set of N evaluation points, $\{t_n \in R_S\}_{n=1}^{N}$, called target set. Thus, for an object O, its density-based silhouette descriptor of feature S is

$$\begin{aligned} f_{S|O} &= [f_S(t_1|P_1),\ldots,f_S(t_N|P_1),f_S(t_1|P_2),\ldots, \\ &\quad f_S(t_N|P_2),f_S(t_1|P_3),\ldots,f_S(t_N|P_3)] \end{aligned} \tag{1}$$

Density-based Silhouette consists of four main stages (see Figure 1):

1. In the silhouette extraction stage, we extract 2D silhouettes from a given 3D model and demonstrate DBS's insensitivity towards low mesh resolution.
2. In the feature calculation stage, we choose silhouette features that are easy to compute and locally discriminative.
3. In the target selection stage, we choose an appropriate target set over which the probability density function is evaluated.
4. In the matching stage, we estimate $f(\bullet|P_i)$ at the designated targets t_n, using KDE technique coupled with the fast Gauss Transform (FGT) (Yang et al., 2003).

Tang Q. and Yang X. (2013).
3D Model Retrieval using Density-based Silhouette Descriptor.
In *Proceedings of the 2nd International Conference on Pattern Recognition Applications and Methods*, pages 267-270
DOI: 10.5220/0004201602670270
Copyright © SciTePress

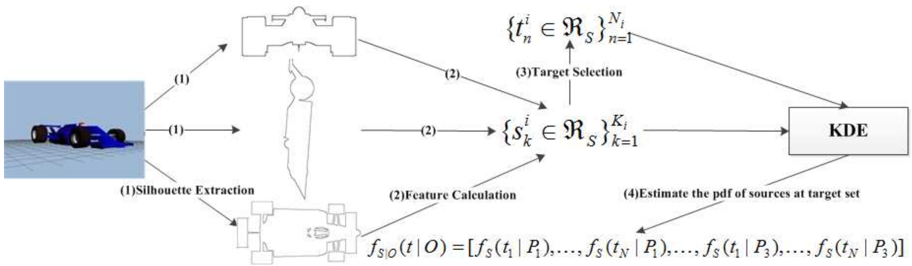

Figure 1: The design process of the density-based silhouette.

2.1 Silhouette Extraction

In (Vranic, 2004), the author gives details about the silhouette extraction. The projection of a 3D model is formed through the union of projections of all triangles in the mesh-model.

We use ”centaur0” from TOSCA (Bronstein et al., 2006) to demonstrate DBS's insensitivity towards mesh resolution, see Figure 2:

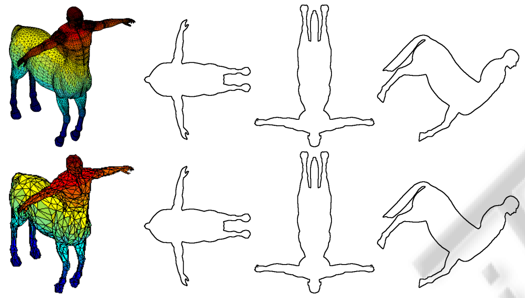

Figure 2: DBS's insensitivity towards low mesh resolution.

The model on the first row has 31532 faces and 15768 vertices, but the model on the second row only has 1996 faces and 1000 vertices. However, their 2D silhouettes change very little.

2.2 Local Silhouette Features

1. Zero-order Features
   We use the radial distance R and the unit radial direction $\vec{R}$ as zero-order features to describe the basic information of a silhouette. The two features may not be effective all by themselves, but they can be very useful in computing other features.
2. First-order Features
   The unit tangent direction $\vec{T}$ and the distance D_T standing for the distance between the tangent direction and the origin are considered as the first-order features.
3. Second-order Features
   The differential $d\vec{T}$ of the tangent field, denoted as $\vec{SI}$ and its distance, D_{SI}, from the origin are considered as the second-order features.

We can construct a feature $(R,\vec{R},D_T,\vec{T},D_{SI},\vec{SI})$ to give a thorough characterization of the model's 2D silhouettes. However, the dimension of this feature vector is too high, which brings in problems such as pdf estimation accuracy, high computation time and huge storage size. Thus, we adopt the strategy in (Akgul et al., 2009) using multivariate pdf-based descriptor with manageable dimension:

- R-descriptor, $f_{R|O}$, represent the probability description of $(R,\vec{R})$.
- T-descriptor, $f_{T|O}$, represent the probability description of $(T,\vec{T})$.
- SI-descriptor, $f_{SI|O}$, represent the probability description of $(SI,\vec{SI})$.

Density-based silhouette descriptor is a combination of the three descriptors,

$$DBS = a_1 * f_{R|O} + a_2 * f_{T|O} + a_3 * f_{SI|O}, a_1 + a_2 + a_3 = 1 \quad (2)$$

2.3 Target Selection

For scalar features, we use R as an example. For a database containing M models, we find $R_{min_i}{}^m$ $(m = 1,\dots,M)$ for each model's projection P_i^m and construct a vector $R_{min} = (R_{min_1}{}^1, R_{min_2}{}^1, R_{min_3}{}^1, \dots, R_{min_1}{}^M, R_{min_2}{}^M, R_{min_3}{}^M)$. $R_{lower} = \frac{min(R_{min})+median(R_{min})}{2}$ and R_{upper} can be obtained in the same way. Note that too small or too large values can be eliminated. The interval $I_R = R_{upper} - R_{lower}$. We choose the target points of R by partitioning the interval into N_{I_R} equally spaced subintervals and by taking the middle points.

For directional vector $\vec{R}$, $\vec{T}$ and $\vec{S}$, the corresponding target points should lie on the unit circle. In the every quadrant, we partition the unit circle into N_C subintervals uniformly and take the middle point of every arc. This leads a uniform partitioning of the circle and guarantees invariance to a certain class of 3D transformation in the matching stage. Consequently, the total number of the target points should be $N = 4 * N_I * N_C$.

Science and Technology Publications

2.4 Kernel Density Estimation

We prefer the nonparametric KDE methodology with a Gaussian kernel, as it is flexible and computationally efficient, to describe the probability density functions. For a random feature S,

$$f_S(t_n|P_i) = ((2\pi)^{\frac{m}{2}}|H|)^{-1}\sum_{k=1}^{K_i} w_k e^{-\frac{1}{2}(t-s_k^i)^T H^{-2}(t-s_k^i)} \tag{3}$$

where $n = 1,\ldots,N$, $i = 1,2,3$

Source set $\{s_k^i \in R_S\}_{k=1}^{K_i}$ are feature values computed on the 2D silhouettes. K_i is the total points of the silhouettes extracted from projection P_i.

Target set $\{t_n \in R_S\}_{n=1}^{N}$ are the pdf evaluation points.

Bandwidth H models the degree of uncertainty about the observation and controls the smoothing behavior of the KDE. Appropriate bandwidth is essential for applications using KDE scheme. Computation of the bandwidth can be seen in (Akgul et al., 2009).

2.5 Invariance of DBS

The "continuous PCA" (Vranic, 2004) is one of universal tools for pose normalization. However, the method does not align all models in an ideal way. As there are $3! = 6$ possible coordinate axis relabeling and $2^3 = 8$ possible polarity assignments, the admissible transformation is $6*8 = 48$. Each transformation corresponds to one shape descriptor, but DBS can deduce the other 47 descriptors from any descriptor. We use R-descriptor as an example.

P_1 represents the x-projection, P_2 represents the y-projection, and P_3 represents the z-projection. When we change x axis with y axis, the new R-descriptor is

$$\begin{aligned} f'_{R|O} = & [f_R(t_1|P_2),\ldots,f_R(t_N|P_2),f_R(t_1|P_1),\ldots, \\ & f_R(t_N|P_1),f_R(t_1|P_3),\ldots,f_R(t_N|P_3)] \end{aligned} \tag{4}$$

When we change the polarity of x axis,the new projections can be seen in Figure 3.

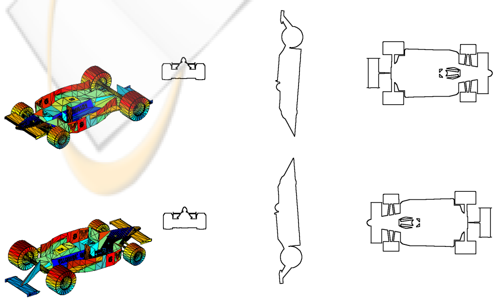

Figure 3: The effect of the change of x axis polarity on the model's 2D silhouettes.

As the target set is concentric circles which is symmetric with respect to x axis and y axis, the new R-descriptor can be obtained simply by permuting the component of vector $f_{R|O}$ (Akgul et al., 2009), The other descriptors can be obtained in the same way.

3 EXPERIMENTAL RESULTS

3.1 Databases and Evaluation Tools

We test the retrieval potential of DBS on two 3D databases selected from different domains.

Princeton Shape Benchmark (PSB) (Shilane et al., 2004) consists of a training set (907 models in 90 classes) and a test set (907 models in 92 classes). In general, PSB meshes have low resolution and they are non-regular, non-smooth, and contain degeneracies such as non-manifold, non-connected triangles of varying size and shape.

GWSB2010 (Vanamali et al., 2010) contains 3168 models in 43 classes. The reason to choose this benchmark as testing environment is that it has very large number of 3D models, which greatly challenges the 3D shape retrieval research community.

In order to make a thorough evaluation of a 3D shape retrieval algorithm, we employ a number of common evaluation measures (Shilane et al., 2004) used in the retrieval community: Precision-Recall curve, Nearest Neighbor (NN), First-tier (FT), Second-tier (ST), E-measure (E), Discounted Cumulative Gain (DCG) and Normalized DCG (NDCG).

3.2 Selection of Coefficients of DBS

As there are three coefficients in DBS, we fix one coefficient and observe the changes of the other coefficients on the retrieval result of DBS.

$$DBS = a_1 * f_{R|O} + a_2 * f_{T|O} + a_3 * f_{SI|O}, a_1 + a_2 + a_3 = 1 \tag{5}$$

From Table 1 we see that $DBS = 0.25 * f_{R|O} + 0.45 * f_{T|O} + 0.35 * f_{SI|O}$ performs the best. The reason for SI-descriptor playing a less important role in DBS is that the computation of SI-feature is not as accurate as the computation of T-feature. This is also the reason that we do not use higher-order features.

3.3 Retrieval Comparisons and Performance Analysis

In this section, we first compare the retrieval performance of DBS against some other representative 3D

Table 1: DCG (Percent) Performance of DBS with different coefficients on PSB test.

a2/a3	0.0	0.1	0.2	0.3	0.4	0.5
0.0	61.2	62.7	64.0	65.1	65.5	65.7
0.1	62.5	63.9	65.2	66.1	66.6	66.6
0.2	63.6	64.9	66.1	66.9	67.3	67.1
0.3	64.4	65.7	66.7	67.5	67.6	67.4
0.4	65.1	66.2	67.1	67.7	67.6	67.1
0.5	65.5	66.5	67.2	67.4	67.3	66.4
0.6	65.6	66.6	67.0	67.1	66.4	
0.7	65.6	66.2	66.6	66.3		
0.8	65.3	65.7	65.9			
0.9	64.8	64.9				
1.0	63.9					

Table 2: Retrieval statistics (Percent) of state-of-art 3D shape descriptors on PSB test.

Descriptor	NN	DCG	NDCG
DBS	70.5	67.8	8.7
CRSP	67.9	66.8	7.1
DSR	66.5	66.5	6.6
DBF	68.6	65.9	5.7
SWD	46.9	65.4	4.9
LFD	65.7	64.3	3.1
DBI	60.9	61.4	-1.6
REXT	60.2	60.1	-3.7
SIL	55.7	59.7	-4.3
RISH	55.6	58.4	-6.4
3DHT	58.8	57.7	-7.5
SHIST	54.6	54.5	-12.6

model retrieval algorithms on PSB. The other statistics given in Table 2 are taken from the study in (Akgul et al., 2009).

From Table 2 we see that though PSB is one of the most challenging databases, DBS is among the top cluster. The reason is that low resolution and degeneracies can be avoided in computing DBS and these are main characters of models in PSB.

The other statistics in Table 3 are taken from the study in (Vanamali et al., 2010). From Table 4 we see that DBS can also perform well on a large database. Compared to SIL, DBS has a better performance.

4 CONCLUSIONS

In this work, we have introduced a new 3D shape descriptor, Density-Based Silhouette descriptor. The new descriptor inherits advantages from both DBF and SIL and shows high retrieval accuracy on several 3D databases with varying mesh resolution, semantic content and classification granularity. On PSB, one of the most challenging database, its DCG is nearly two percent higher than DBF's. On GWSB2010 which has more than 3000 models, DBS also has a high retrieval accuracy. The retrieval experiments on two databases show that DBS can be adapted to a broad and heterogeneous set of shape categories.

Table 3: Retrieval statistics (Percent) of state-of-art 3D shape descriptors on GWSB2010.

Descriptor	NN	FT	ST	E	DCG
DSR472	87.1	49.8	63.9	35.6	83.1
LFD	86.4	48.0	61.3	33.6	81.6
DBS	80.9	41.5	56.0	30.1	78.2
SIL300	80.7	41.2	54.8	30.0	78.0
DSR438	80.9	40.7	53.2	30.6	77.0
RSH136	78.3	38.5	50.8	27.5	75.8

REFERENCES

Akgul, C., Sankur, B., Yemez, Y., and Schmitt, F. (2009). 3d model retrieval using probability density-based shape descriptors. *IEEE Trans on Pattern Analysis and Machine Intelligence*, 31(6):1117–1133.

Bronstein, A., Bronstein, M., and Kimmel, R. (2006). Efficient computation of isometry-invariant distances between surfaces. In *SIAM J. Scientific Computing*, volume 28, pages 1812–1836.

Li, B., Godil, A., Aono, M., and Bai, X. (2012). Shrec'12 track: Generic 3d shape retrieval. *Eurographics Workshop on 3D Object Retrieval*.

Marini, S., Paraboschi, L., and Biasotti, S. (2007). Shape retrieval contest 2007: Partial matching track. In *Proc. SHREC in Conjunction with Proc. Intl Conf. Shape Modeling and Applications*, pages 13–16.

Min, P., Kazhdan, M., and Funkhouser, T. (2004). A comparison of text and shape matching for retrieval of online 3d models. In *Proc. European conference on digital libraries*, pages 209–220.

Shilane, P., Min, P., Kazhdan, M., and Funkhouser, T. (2004). The princeton shape benchmark. In *Proc. Shape Modeling Int'l*, pages 167–178.

Tangelde, J. and Veltkamp, R. (2008). A survey of content based 3d shape retrieval methods. *Multimedia Tools and Applications*.

Vanamali, T., Godil, A., Dutagaci, H., Furuya, T., Lian, Z., and Ohbuchi, R. (2010). Shrec'10 track: Generic 3d warehouse. *Eurographics Workshop on 3D Object Retrieval*.

Vranic, D. (2004). *3D Model Retrieval*. PhD dissertation, Univ. of Leipzig.

Yang, C., Duraiswami, R., Gumerov, N., and Davis, L. (2003). Improved fast gauss transform and efficient kernel density estimation. In *Proc. Int'l Conf. Computer Vision*, volume 1, page 464.