Shape Topics:
A Compact Representation and New Algorithms for 3D Partial Shape Retrieval

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Abstract

This paper develops an efficient new method for 3D partial shape retrieval. First, a Monte Carlo sampling strategy is employed to extract local shape signatures from each 3D model. After vector quantization, these features are represented by using a bag-of-words model. The main contributions of this paper are three-fold as follows: 1) a partial shape dissimilarity measure is proposed to rank shapes according to their distances to the input query, without using any time-consuming alignment procedure; 2) by applying the probabilistic text analysis technique, a highly compact representation "Shape Topics" and accompanying algorithms are developed for efficient 3D partial shape retrieval, the mapping from "Shape Topics" to "object categories" is established using multi-class SVMs; and 3) a method for evaluating the performance of partial shape retrieval is proposed and tested. To our best knowledge, very few existing methods are able to perform well online partial shape retrieval for large 3D shape repositories. Our experimental results are expected to validate the efficacy and effectiveness of our novel approach.

Keywords: *Shape representation, partial shape retrieval, a bag-of-words model, probabilistic text analysis.*

1. Introduction

Large 3D shape repositories are becoming available at present. In computer vision, pattern analysis, computer aided design, manufacturing, molecular biology and a number of other disciplines, part-based 3D model retrieval is extremely valuable. One typical example is to create new shapes by cutting and pasting existing shape parts [1]. However, most existing methods for shape analysis are based on global shape similarity functions. Very few methods support efficient 3D partial shape retrieval from large databases. This paper aims to develop a new method for 3D partial shape retrieval.

The key technical challenge is how to achieve high efficiency while retaining accuracy. In this paper, we investigate methods for partial shape similarity measure without the need of an alignment-verification procedure. This is fundamentally different from most existing approaches for 3D shape matching.

Our approach is based on the concept of Spin image signatures. We start by using a Monte-Carlo approach to sample mesh geometry and bases points of spin images. It is robust and insensitive to differences in mesh resolution and tessellation. Using vector quantization [2], spin image clusters (shapemes) are generated. A bag-of-words model is used to represent features. With an analogy to document analysis, such clusters correspond to words, 3D models match with documents, shape repository is mapped to corpus. As a result, statistical text analysis techniques [3, 4] are easily incorporated into our framework.

The first contribution of this paper is that we propose a partial shape dissimilarity measure based on Kullback-Leibler divergence. With this measure, the constraint that the partial query shape should be properly embedded in the retrieved global shapes is implicitly modeled.

Second, with the assumption that each 3D model can be represented by a mixture of latent topics, we propose a highly compact representation “Shape Topics”. It is based on latent Dirichlet allocation [3]. Again, the dissimilarity measure under this shape representation is proposed. Tremendous gain in efficiency is achieved with moderate degradation in performance.

Third, a performance evaluation method is proposed for partial shape retrieval. By generating random shape patches automatically, the influence of the difference in the selected partial shape is averaged out on a large shape repository.

This paper is organized as follows: We review related work in Section 2. Starting with a conceptual overview of our approach, details of feature extraction and representation are introduced in Section 3, followed by dissimilarity measure and "Shape Topics" signature in Section 4. Experimental results are presented in Section 5. Finally, we conclude this paper in Section 6.

2. Previous Work

Designing discriminating global 3D shape descriptors is an active research area [5]. Recently, a publicly available shape benchmark is released and the performance of some global shape descriptors are reported [6]. We shall use the same benchmark for performance evaluation.

Local 3D shape descriptors are the foundations of our work [7, 8]. We adopt spin images [7], because "3D shape contexts" is not suited for bag-of-words paradigm and "harmonic shape contexts" is computationally expensive [8].

The 2D descriptor "shape contexts" is proposed and an iterative shape matching method using thin-plate spline is studied in [9]. Similar matching by alignment methods are applied to 3D shape and a review can be found in [10]. A different approach to partial shape matching is to simplify the dissimilar parts of the global shape [11]. These methods are computationally expensive in general.

Two efficient 2D shape matching methods are proposed in [2]. One is "representative shape contexts", and the other is "Shapeme". The former is readily available for partial shape matching but is still too slow to apply to our problem. The latter is vector quantization. However, the distance definition is only appropriate for global shape similarity measure.

A recent proposed method [12] circumvents this problem by segmenting 3D shapes in the database into parts and maintaining a "shapeme" feature for each part. Partial shape matching can be handled by two steps: First, the optimal binary composition of parts' feature is calculated for each database shape, to approximate the query shape feature. Second, similarities between the query shape feature and the composite parts-features of database shapes are calculated for nearest neighbor shape recognition.

In this paper, a suitable dissimilarity measure is proposed for direct 3D partial shape retrieval without segmentation. To further reduce the time and storage complexity of online retrieval, we propose a highly compact signature "Shape Topics". It is based on probabilistic semantic analysis technique [3]. Related papers on image analysis include [13, 14, 15]. Spatial layouts are incorporated [15] to generalize the bag-of-words model. Though helpful in object recognition, fixing the spatial configuration may be harmful to partial shape matching: separating a part from a global shape would break up many interconnections.

3. Basic Procedures of Our Approach

The ultimate goal of this paper is to develop a highly compact shape representation which also supports efficient partial shape retrieval. To see why this is possible, we give a simple example to illustrate the concept.

Suppose we have a 3D model of a man. It has non-zero *posterior* probability distribution on four topics: head, torso, arm, and leg. If a partial shape having a subset of the four topics is entered as the query, finding the global shape under this compact semantic representation is very easy.

We seek to achieve this high-level description step-by-step in this section. From bottom to top, large quantities of low level features are condensed and intrinsic structures are revealed, which leads to high efficiency.

In this section, we introduce how features are extracted and represented in our method. Since dissimilarity measure and Shape Topics are the main focus of this paper, they will be discussed thoroughly in Section 4.

3.1. Feature Extraction

The first step of this process is to extract and represent low-level features. As mentioned in Section 2, spin images [7] are chosen for the local shape descriptor in this paper. A brief introduction is given below.

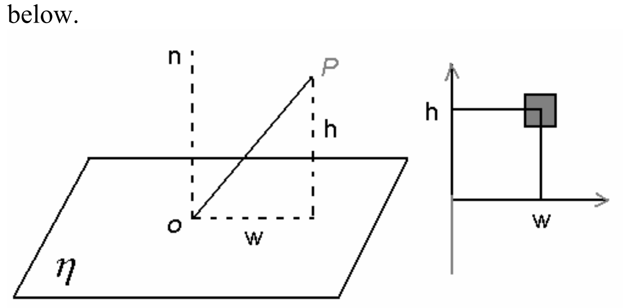

Figure 1: An illustration of spin image descriptor.

As shown in Fig. 1, $\boldsymbol{O}$ is the basis point of spin image descriptor, $\boldsymbol{n}$ is the mesh normal at the basis. Plane η is perpendicular to $\boldsymbol{n}$, and passes through $\boldsymbol{O}$. For each point $\boldsymbol{P}$ on the meshes, we calculate the vertical distance h and horizontal distance w to the plane. If $|h| < H$ and $|w| < W$, then the corresponding bin (shown in gray) on the spin image is added by one, where H and W are the vertical and horizontal support range of the spin image. When all points on the meshes are visited, the spin image signature at $\boldsymbol{O}$ is generated.

The original paper [7] uses mesh vertices to generate spin images. However, in the shape benchmark [6], many 3D models have both large and tiny triangles. To account for this, we use a Monte-Carlo strategy to sample N points on the meshes [16]. The importance of each triangle is proportional to its area. After this process, sample points are distributed on the meshes uniformly.

Spin image characterizes the local shape around its basis, within the support range. It is also invariant to rotation and translation. We use the same Monte-Carlo approach to select M bases uniformly on the mesh, and calculate the corresponding spin images using the N point samples.

In this paper, $M = 500$ is fixed for a global shape. For partial shape retrieval, spin image signatures are calculated only for bases within the selected region, which speeds up the feature extraction procedure. In image analysis, the bases of a local descriptor are often picked using an interest point detector and the support range for each basis is decided by scale-space extrema [17]. On 3D shape, there is a lack of distinctive local structure, such as textons in images. Therefore, improper bases selection and scale decision may deteriorate the performance of local shape descriptor. Since scale is not the main focus of this paper, we test the performance of partial shape retrieval with a fixed global scale. Multi-scale representation or scale selection on 3D shape will be a direction for future research.

Therefore, we set the support range of spin image descriptors to a fraction of the global shape size:

$$H = W = 0.4R$$

R is the root mean square of the distances from points on the meshes to the shape centroid, which can be computed using an analytical formula. To ensure the sampling density on the surface is equal for each scale-normalized 3D model, the number of sample points on a mesh is set as follows:

$$N \propto S / R^2 \tag{1}$$

S is the sum of the areas of all triangles on a 3D model. The average N is 50,000 for the shape repository [6].

3.2. Feature Representation

Now each 3D model is represented with a number of spin images. Without compression, restoring all spin images of all 3D models in the PSB benchmark [6] needs gigabytes of memory, which prohibits efficient partial shape retrieval. We use a k-means algorithm to agglomerate 1500 clusters from these spin images, and represent each spin image with the index of its nearest cluster. The number of clusters is chosen based on previous results [13, 14, 15] and is shown empirically good for our task. The clusters are referred to as "shapemes" in [2], but we treat each cluster as a word. This allows effective text analysis technique to be incorporated into our framework [3, 4]. Finally, by discarding the information of bases position, each 3D model is represented by a histogram counting word frequencies.

4. Dissimilarity Measure and Shape Topics

4.1. Dissimilarity Measure

In our 3D shape retrieval system, the feature of the query shape is extracted online, and compared with those in the database. The retrieval results are ranked according to the dissimilarity measure. How to choose the dissimilarity measure is a key problem and we investigate this issue in this subsection.

In text retrieval, vector space model [18] is a well founded method which is shown to be excellent. A cosine similarity measure is used between the word histogram of the query and a document in the database, with various weighting strategy. However, the symmetric nature makes it not suited for our purpose.

Suppose a partial shape query have two topics, head and torso. It is a good candidate to be a part of a man's 3D model. However, the man's model (suppose which has four topics) could not be a part of the query shape. This example shows the dissimilarity measure should be asymmetric.

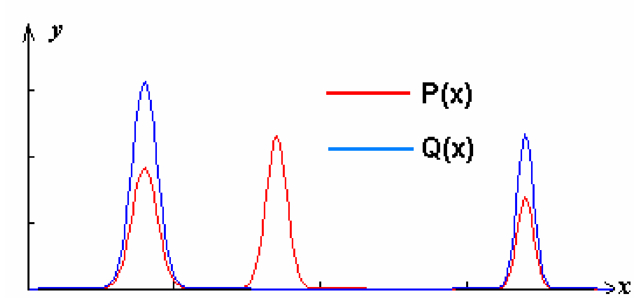

Figure 2: The asymmetric property of KL divergence.

Suppose another partial shape have three topics, head, torso and wing. It is a good candidate to be a part of a bird's 3D model, but not a man's. The cosine similarity measure will give the same value for the two partial shapes against a man's model, which is undesirable.

Motivated by the two conceptual examples, we propose Kullback-Leibler divergence as a suitable dissimilarity measure for our problem, owing to the sparseness of word histograms and topic histograms (shown later). As illustrated by Fig.2, the two distributions are sparse, i.e. approaching zero outside the modes. In cases for any position x within a mode of Q, it is also within a mode of P, the divergence $KL(Q(x) \| P(x))$ is small (Fig.2). Otherwise, the divergence is large. Roughly speaking, the KL divergence is small *iff* all the modes of Q are *within* the modes of P. More details can be found in [19].

This property is desirable since for a good match, we expect the word distribution of a partial shape query to be within the global shape. If the query shape has modes outside the global shape, the large dissimilarity measure will penalize such a match.

In our problem, we normalize the word distribution that sums to one, and use the following dissimilarity measure:

$$D_{dissimilarity} = KL((1-\varepsilon)Q + \varepsilon I \,\|\, (1-\varepsilon)P + \varepsilon I), \quad (2)$$

where Q, P are the word distributions of the query and a global shape in the database. I is a uniform probability distribution and ε is a small number. ε provides a tradeoff between two forces: one is the distinction between the common parts of P, Q, and the other is to penalize Q out of P. When ε is very small, the latter force is dominant.

In document analysis, it is assumed that different words have different discriminative power. The idea is simple: Words that frequently appeared in a corpus are less distinctive, and vice versa. To account for this, a widely used strategy is to weigh each word channel with the inverse document frequency (idf) [18]:

$$w = \log N - \log n, \quad (3)$$

where N is the number of documents in the corpus, n is the number of documents that a word appears. For our method, we compare shape retrieval with and without idf-weighting to word histograms. The two approaches have nearly identical performance. Perhaps, this is because shape words are generated by clustering, but not via a frequency-based selection of spin images. For simplicity, idf-weighting is not used in this paper.

4.2. Shape Topics

Using the dissimilarity measure that is introduced, matching word distributions is a practical way for 3D partial shape retrieval. However, unlike a fixed size dictionary in natural language processing, visual words in image analysis and shape words in this paper would increase endlessly with the growth of the database. Can we obtain a more parsimonious shape representation to account for this? Recent advances in probabilistic text analysis give appropriate answer to this question.

We shall briefly introduce the idea of latent Dirichlet allocation [3]. It is a generative hierarchical Bayesian model. The process of generating a document in a corpus can be described as follows. The length of the document L is sampled from a Poisson distribution. The parameter θ is sampled from a Dirichlet distribution:

$$\theta \sim Dirichlet(\alpha) \quad (4)$$

The above two processes are done once for a document. The following process repeats L times. For each word in the document, a topic t_l is sampled from the distribution:

$$t_l \sim Multinomial(\theta) \quad (5)$$

Then a word is generated from a multinomial distribution

$$w_l \sim Multinomial(t_l, \beta) \quad (6)$$

When the number of topics is fixed, the maximum likelihood estimates of the parameters of these distributions are leant using a variational EM method in an unsupervised manner. Automatically deciding the topic number is possible by Bayesian model selection using a Markov Chain Monte Carlo approach [4]. We found that the performance of partial shape retrieval is relatively insensitive to the topic number. So, it is fixed manually in this paper.

For a new document, The Dirichlet *posterior* γ_i is estimated using a variational approach for each topic i. $\gamma_i - \alpha_i$ approximates the number of words generated from the topic i, where α_i is the prior parameter of the *i-th* topic.

Then each 3D model can be represented by the histogram $\{\gamma_i - \alpha_i\}$ over topics. After normalization, this shape signature is referred to as Shape Topics.

The dissimilarity measure is similar to that of the word histograms, except for a logarithm warping:

$$D_{dissimilarity} = KL(\tilde{Q} \| \tilde{P}) \quad (7)$$

$$\tilde{q}_i = \log(\gamma q_i + \delta) \quad (8)$$

$$\tilde{p}_i = \log(\gamma p_i + \delta) \quad (9)$$

where q_i and p_i are the *i-th* component of the shape topic signature, γ is a scaling factor and δ is a shift factor which is slightly larger than 1.0.

Note that the topics learned do not correspond to human perception naturally. Modeling object categories in the generative graphical model is possible [13]. However, we argue that generative models are good at explaining the data, while discriminative approaches are better in classification generally. We use multi-class support vector machines to map objective "Shape Topics" to subjective object categories, which will be discussed in Section 5.

5. Experimental Results

In our partial shape matching system, an interested patch on a 3D model can be selected using a mouse, as shown in Fig. 3. The spin images whose bases within the interest region are calculated as the search key. After vector quantization, the resulting word histogram or "Shape Topics" of the query is compared to those of the database model's. The output of our retrieval system is a ranking list of models, with decreasing similarity to the query.

However, the position, size and shape of the selected region affect the retrieval results seriously. To account for this, we propose the following method to evaluate the performance of a partial shape retrieval system.

For each 3D model, a point is selected randomly on the meshes as the interested center. The spin image bases on this model are sorted by their distances to the interested center. A fixed percentage of the spin images nearest to the interested center are selected as the search key. In this manner, the effect of position and shape of the selected region can be averaged out by computing the statistics over all 3D models in the database.

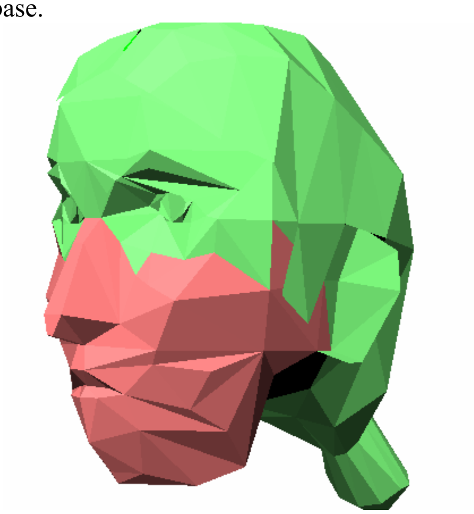

Figure 3: A 3D model and the selected partial shape (in red).

To compare with other 3D shape retrieval algorithms tested on the Princeton Shape Benchmark [6], we use five statistics, "nearest neighbor (NN)", "first tier (FT)", "second tier (ST)", "E-measure (E-M)", "discounted cumulative gain (DCG)" and the "precision-recall plot" to measure the quality of the retrieval results. Details about the statistics can be found in [6].

We tested our algorithms on the 907 3D models of the "testing part" of the benchmark. These models belong to the 92 classes with the finest classification granularity. It is hard to achieve good classification performance under this strict setting.

Note that direct comparison between our algorithm and global 3D shape retrieval algorithms is unfair and perhaps meaningless. There are two main reasons. First, only partial information on the query shape is used. Second, 3D models in different categories may have similar patches to the partial shape query. However, encouraging results are obtained.

5.1. Partial Shape Retrieval with Word Histogram

The first experiment is based on word histogram, a 1500 dimensional shape descriptor. We selected 20% spin images nearest to an interested center as the search key. Parameter ε in Eq.2 is set as: $\varepsilon = 0.13$. Each query takes about 1.60 sec, with 1.01 sec for spin image generation, 0.34 sec for vector quantization, 0.25 sec for dissimilarity calculation and ranking (on a PIV 2.4GHz CPU with 256M memory).

\	NN	FT	ST	E-M	DCG
KL	0.971	0.262	0.335	0.175	0.594
L2	0.802	0.221	0.275	0.139	0.533
VSM	0.510	0.221	0.305	0.165	0.534

Table 1: The retrieval statistics with different (dis)similarity measures.

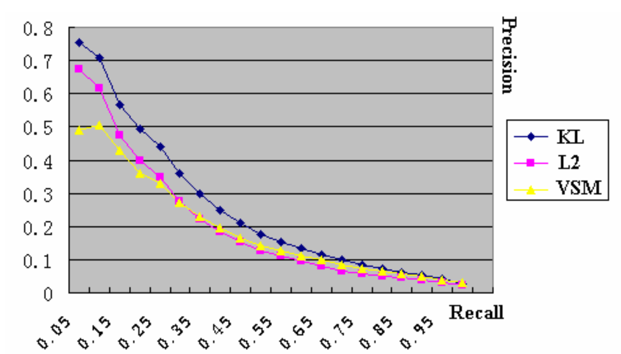

Figure 4: The precision-recall plot with different (dis)similarity measures.

Table 1 shows the retrieval statistics under three different (dis)similarity measures: the proposed distance measure on word histograms (KL), L2 Norm (L2) and vector space model (VSM) with tf-idf weighting [18]. The global shape of the query patch is included in the retrieval results. We can see that KL is significantly better than the other distance measures: Only KL has a very high nearest neighbor accuracy, indicating that the global shape can be successfully found from a randomly selected small portion of it. Fig. 4 shows the corresponding precision-recall plot.

Though tested on different shape benchmark, it is interesting to compare our result to that of [12]. First note that their "Bayesian optimal" similarity measure is very similar to the vector space model, expect using a different idf-weighting (without taking logarithm). Second, their task is to recognize an instance of partial shape by nearest neighbor search, while our task is to retrieve shapes in the same class of the query. In their report (see table 1 in [12]), segmenting 30 shape parts raises the nearest neighbor recognition accuracy from 78.5% (HP-1, without segmentation) to 91.1% (HP-30). In our experiments, as shown in table 1, the nearest neighbor accuracy for the propose KL dissimilarity is 97.1% (without re-sampling the spin image basis and geometry of shapes), compared to the 51% of the vector space model. This suggests that by adopting a suitable dissimilarity measure, similar (or even better) performance can be achieved with far better efficiency both in time and storage, compared to [12].

5.2. Partial Shape Retrieval with Shape Topics

The second experiment is to study the performance of "Shape Topics", as shown in Table 2. The topic number is fixed to be 40 in this paper. The parameters in Eq.7-9 are set as: $\delta = 1.03$, $\gamma = 40.0$. Neither ε in word histograms nor γ, δ in Shape Topics is performance sensitive: a broad range of values yield similar outputs.

Note that "Shape Topics" is a highly compact shape representation. A 3D model has non-zero *posteriors* in 4.65 topics on average. Only 14 bytes storage requirement is needed to archive the indices and values of theses non-zero *posteriors* for a 3D model. To our knowledge, this is a tremendous save up in space over all previous 3D shape descriptors. As a result, the comparison time for the query feature with all features in the database is greatly reduced. Therefore, "Shape Topics" is readily for partial shape retrieval on very large 3D shape repositories. This is a major advantage over previous approaches on scalability.

Fig. 5 shows the precision-recall plot of the "Shape Topics (ST)" method, in comparison with "word histogram (WH)" method. Note "WH" is just the "KL" in Figure 4, but whether the descriptor is based on words or topics is our emphasis here. Again, the task is to retrieve global shapes based on the selected 20% part of the query shape.

\	NN	FT	ST	E-M	DCG
ST	0.614	0.223	0.301	0.163	0.537

Table 2: The retrieval statistics of "Shape Topics".

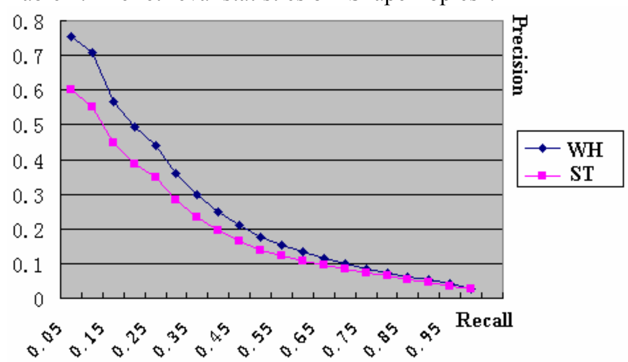

Figure 5: The Precision-recall plot for "Shape Topics (ST)", in comparison with "Word Histogram (WH)".

From Table 2 and Fig.5, we can see that after a dimension reduction from 1500D to 40D, the retrieval performance only degrades gracefully. In comparison with Table 1, the retrieval performance of "Shape Topics" is even better than the L2 and VSM distance measure on word histograms in terms of DCG measure.

To see the characteristics of partial shape retrieval using "Shape Topics", we show two examples in Fig. 6 and Fig. 7. Some retrieved shapes are not good under global similarity measure, but they share a similar part with the query.

Note that "Shape Topics" is faster than "word histogram" for online 3D partial shape retrieval. The extra time for "Shape Topics" is to make inference about the *posteriors* over topics from word histograms. This process happens only once for the query shape. It takes less than 0.05 sec. on our PC, while the time for feature comparison with all 3D models in the database is reduced greatly.

5.3. Global Shape Retrieval with Shape Topics

Although "Shape Topics" is a highly parsimonious shape representation, we find that it is even better than some global 3D shape descriptors with nearly 10 times of storage requirements. To see this, we use 100% of spin images on the query shape. To be consistent with tests on existing global shape descriptors, we remove the query shape out of the retrieval results. The retrieval statistics are shown in Table 3. We use the symmetric KL divergence here, i.e.

$$D_{dissimilarity} = KL(\tilde{Q} \| \tilde{P}) + KL(\tilde{P} \| \tilde{Q}) \quad (10)$$

Performance of global shape descriptors are referred to [6]. It is shown that "Shape Topics" is better than "D2" [16], a widely used global shape descriptor.

\	NN	FT	ST	E-M	DCG
Global	0.314	0.168	0.248	0.155	0.444

Table 3: The statistics of "Shape Topics" for global shape retrieval (The query is removed form the retrieval results).

The results of global shape retrieval are shown in Fig. 7. Fig. 6 is referred to for a comparison between global shape retrieval and partial shape retrieval.

5.4. 3D Model Classification using Shape Topics

It is not hard to establish the mapping from Shape Topics to 3D model categories. We train multi-class SVMs with radial basis kernel function to infer category label for a "Shape Topics" distribution. We choose the classification file with the "coarse2" granularity [6]. There are the same 7 categories in both the training and testing part of the benchmark. The parameters of SVMs are decided using cross validation. We obtain a 55% correct classification rate in the "testing part". Note the sub-categories of the "training/testing part" of the 7 classes are different. This perhaps leads to the correct rate underestimated.

6. Conclusion

In this paper, we investigate the problem of efficient partial 3D shape retrieval. First, a Monte-Carlo method is used to select interested points and to sample geometry, which makes our approach robust to irregular mesh tessellation. Using vector quantization, each 3D model is represented as a bag-of-words. Second, the asymmetric KL divergence is proposed for dissimilarity measure and demonstrated to be effective for partial shape retrieval. Finally, we show that a compact signature "Shape Topics" can be obtained using probabilistic semantic text analysis. Extensive Experiments validate the effectiveness of our approach.

Acknowledgements

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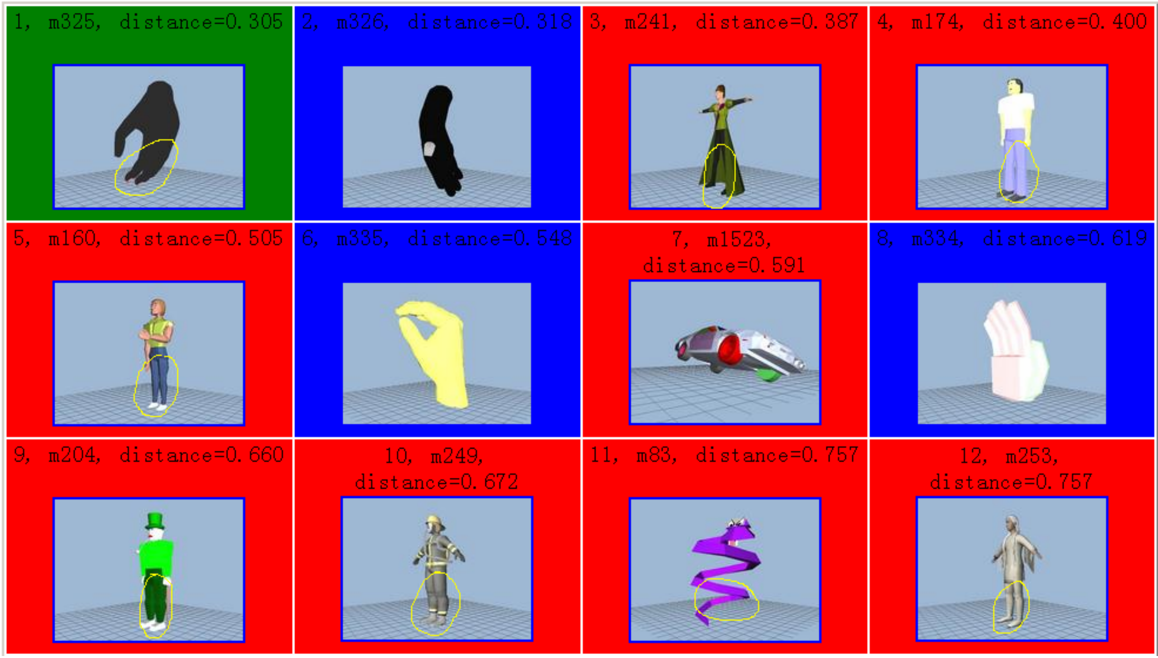

Figure 6: An example of partial shape retrieval using Shape Topics. 20% spin images of the query shape nearest to an interested point is selected as the search key. We use the utility of the Princeton Shape Benchmark [6] to generate the retrieval results. Green margin corresponds to the query shape, blue margin to retrieved shapes in the same category as the query, red margin to retrieved shapes in different categories from the query. To see the difference of "Shape Topics" with previous global 3D shape retrieval approaches, we intentionally choose this example which is not good in terms of global similarity measure. However, most of the high ranking "false matches" have parts similar to the partial shape query. We mark these parts with yellow circles. Therefore, in terms of partial similarity measure, "Shape Topics" does a good job.

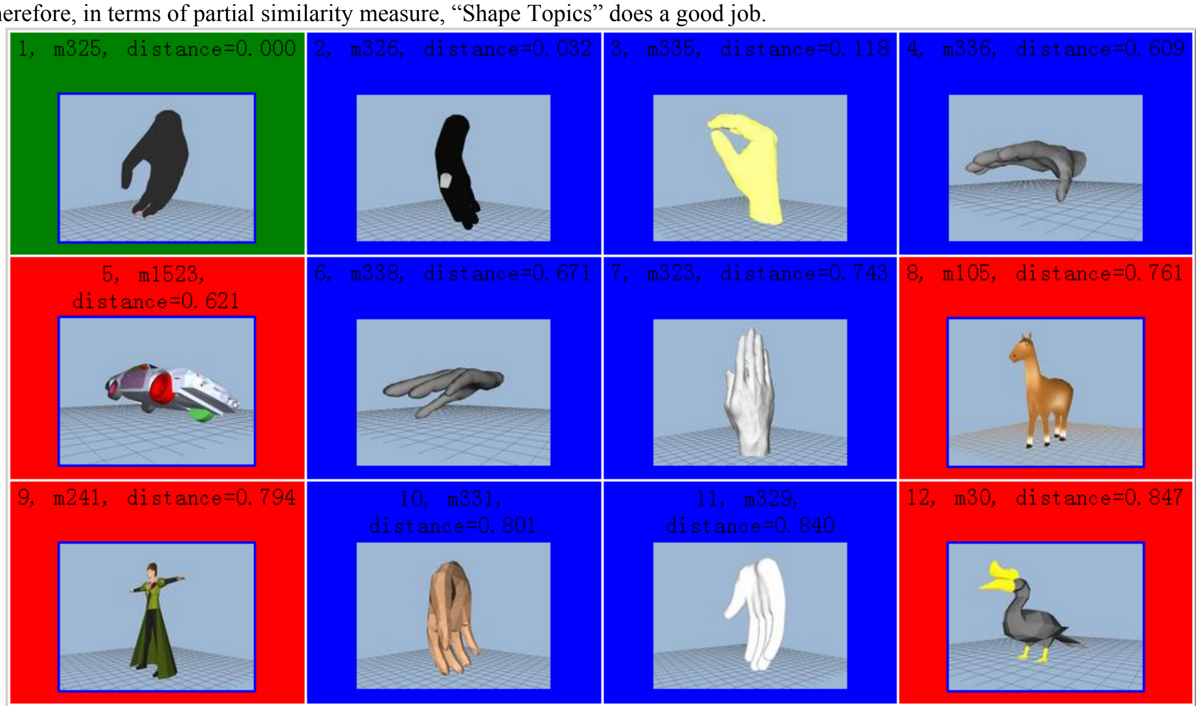

Figure 7: An example of global shape retrieval using Shape Topics. 100% spin images of the query shape are selected as the search key. Note the query model is identical to that in Fig. 6. To make the retrieval results comparable to that in Fig. 6, we use the same asymmetrical dissimilarity measure. However, not only fingers, but also palm and wrist are included in our search key. The new introduced topics remove most of the non-hand shapes in Fig.6 from the high-ranking list. Seven out of eleven retrieved shapes are in the same category as the query.