SHREC'08 Entry: Hybrid IIT-NCSR-Demokritos

Panagiotis Papadakis, Ioannis Pratikakis, Stavros Perantonis, Theoharis Theoharis, Georgios Passalis

SHREC'08 Entry: Hybrid_IIT-NCSR-Demokritos

Panagiotis Papadakis* Ioannis Pratikakis† Stavros Perantonis‡
Computational Intelligence Laboratory
Institute of Informatics and Telecommunications
National Center for Scientific Research "Demokritos", Athens, Greece

Theoharis Theoharis§ Georgios Passalis¶
Computer Graphics Group
Department of Informatics and Telecommunications
National and Kapodistrean University of Athens,Greece

ABSTRACT

In this paper, we present an overview of the 3D object retrieval method that we employed in our participation to the Generic Models track of SHREC 2008 organized by the AIM@SHAPE network of excellence. The proposed methodology is detailed in [2]. Our method is based on a hybrid scheme where 2D features as well as 3D features are extracted from a 3D model which has been previously normalized for rotation using two alternative alignment techniques. The alignment methods that are used are CPCA and NPCA. The 2D features are Fourier coefficients extracted from a set of depth buffers and the 3D features are spherical harmonic coefficients extracted from a spherical function-based representation of a 3D model.

Index Terms: H.3.3 [Information Search and Retrieval]: —

1 INTRODUCTION

The 3D object retrieval methodology that we employ is based upon a hybrid shape descriptor. Based on the previous work of Passalis et al. [3], we extract 2D features from a depth-buffer based representation of a model and 3D features (spherical harmonic coefficients) from a spherical function based representation as in the work of Papadakis et al. [1]. In the hybrid scheme, the two kinds of features are linearly combined to produce an integrated hybrid 3D shape descriptor. Invariance to similarity transformations is achieved using CPCA and NPCA [1], where the two methods are employed in parallel to alleviate the rotation invariance problem, for both 2D and 3D features. In the following, we briefly describe the stages for the extraction of the hybrid shape descriptor.

2 POSE NORMALIZATION

First, we normalize each 3D model for translation by computing its centroid using CPCA [4] and translating the model so that the centroid coincides with the origin.

We address the rotation invariance problem, by following the same approach as in [1] where two alignment methods are used, namely CPCA and NPCA. This is a meaningful choice, since by using CPCA and NPCA we consider both the surface area distribution and the surface orientation distribution that both characterize the rotation of a model's surface. As discussed in [1], there exist cases where one method performs better than the other.

*e-mail: ppapadak@iit.demokritos.gr
†e-mail: ipratika@iit.demokritos.gr
‡e-mail: sper@iit.demokritos.gr
§e-mail: theotheo@di.uoa.gr
¶e-mail: passalis@di.uoa.gr

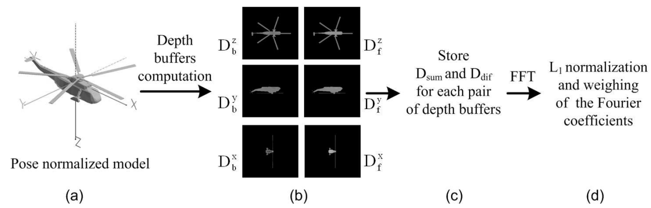

Figure 1: Consecutive stages for the extraction of the 2D features.

Scaling invariance is achieved by normalizing the features to their unit L_1 norm since the selected 2D and 3D features are proportional to the models scale. Therefore, by normalizing the scale of the features we are in fact normalizing the scale of the corresponding model.

3 FEATURE EXTRACTION

3.1 2D feature extraction

Based on the work of [3], we use a depth buffer-based representation of a 3D model to compute a set of 2D features. In Figure 1, the main steps (a)-(d) for the extraction of the 2D features are shown.

From a pose normalized 3D model, we acquire a set of six depth buffers by projecting the model to the faces of a cube which is centered at the origin and whose size is proportional to the model's scale. For each set of parallel depth buffers, we compute the difference D_{dif} between the front D_f and back D_b depth buffer to capture the model's thickness. To avoid information loss, the sum D_{sum} of the front and back depth buffer is also computed. In the following, we compute the Discrete Fourier Transform of each D_{dif} and D_{sum} buffer and normalize the coefficients to their unit L_1 norm.

Finally, two weighting schemes are applied to the coefficients. First, the coefficients are weighed inversely proportionally to their degree since lower frequencies are considered to have more information compared to higher frequencies, which are more sensitive to noise and after the coefficients are weighed proportionally to the ranks of the principal directions that are encoded by the respective depth buffer.

The final 2D feature set is the concatenation of the coefficients of the six depth buffers. The 2D features set of model i that is aligned either by CPCA or NPCA, is denoted as $2Df_i^j$ where $j \in \{CPCA, NPCA\}$.

3.2 3D feature extraction

Based on the work of [1] we extract the 3D features using a spherical function-based representation of the 3D model and compute the spherical harmonics transform for each spherical function. In Figure 2, the main steps (a)-(e) for the extraction of the 3D features are shown.

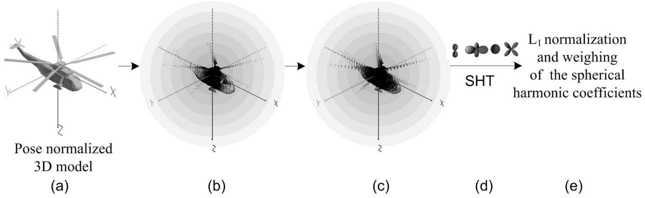

Figure 2: Consecutive stages for the extraction of the 3D features.

First, we represent the surface of a 3D model using a set of spherical functions, by projecting approximately equidistant parts of the 3D model to concentric spheres of increasing radius. This is done by computing the intersections of the surface of the model with rays emanating from the origin at the (θ, φ) directions, where θ corresponds to the longitude and φ to the latitude coordinate. In the following, we modify the spherical functions to include every point that is closer to the origin than the furthest intersection point on the corresponding ray. Thus, we obtain a volumetric representation of the 3D model and for each spherical function we compute the spherical harmonics transform [1], store the spherical harmonic coefficients and normalize them to their unit L_1 norm.

Finally, spherical harmonic coefficients are weighed inversely proportionally to their degree similarly to the 2D features set.

The final 3D feature set is the concatenation of the spherical harmonic coefficients of the N spherical functions. The 3D features set of model i that is aligned either by CPCA or NPCA, is denoted as $3Df_i^j$ where $j \in \{CPCA, NPCA\}$.

4 Similarity Measure

The 2D and 3D features are computed for two alternative rotation normalized versions of a model. Thus, the final hybrid 3D shape descriptor $\mathbf{s}_i$ of a model i is the concatenation of the 2D and 3D features for each aligned version of the 3D model, resulting in $\mathbf{s}_i = (2Df_i^{CPCA}, 2Df_i^{NPCA}, 3Df_i^{CPCA}, 3Df_i^{NPCA})$. To compare the descriptors $\mathbf{s}_1$ and $\mathbf{s}_2$ of two models we compute $Dist(\mathbf{s}_1, \mathbf{s}_2) = dist_{2Df} + dist_{3Df}$, where $dist_{2Df}$ and $dist_{3Df}$ is the distance between the 2D and 3D features, respectively, denoted as $dist_{2Df} = min_j(L_1(2Df_1^j, 2Df_2^j))$ and $dist_{3Df} = min_j(L_1(3Df_1^j, 3Df_2^j))$, where $j \in \{CPCA, NPCA\}$, L_1 is the Manhattan distance and $dist_{2Df}$, $dist_{3Df}$ are normalized to $[0,1]$.

5 SHREC 2008 evaluation results

Since our method does not employ any form of learning it is comparable with the following methods: YamanasA_UL, YamanasB_UL, Napoleon_UL and CCECg_UL. We submitted one runfile, i.e. one parameter setting of our method, to give a view of the performance of our method in a general rather in a particular context. Therefore, in order to ensure a fair comparison, our method should be compared against the others by computing the average performance from the set of runfiles of each participant.

Under the previous premises, our method exhibits the 2nd best overall performance among the participants for the 1st query set. Regarding the evaluation using the 2nd query set, we believe that it is inappropriate to draw conclusions regarding the overall performance of any method regardless of its ranking. The reason for this is that a large portion of the 2nd query set comprises models that belong to the smallest classes within the test dataset, in contrast to the 1st query set which is more representative of the content of the dataset. In particular, the sum of all relevant models for the 1st query set is 1876 whereas for the 2nd query set it is 892. This means that the evaluation using the 1st query set is statistically much more significant than the evaluation using the 2nd query set that cover less than half of the content of the test dataset (1814 models). Inevitably, this rises the question of what would be the performance of the participating methods in a 3rd query set that would cover that part of the dataset that is not covered by the 2nd set.

Our method shows inferior performance in the 2nd query set. However, this should not be considered as a disadvantage, since we want our method to exhibit top discrimination power overall for the plurality of models within a dataset, which is demonstrated from the evaluation of the 1st query set.

In Figure 3, we show a set of example queries and the respective top 10 retrieved models using the proposed hybrid method.

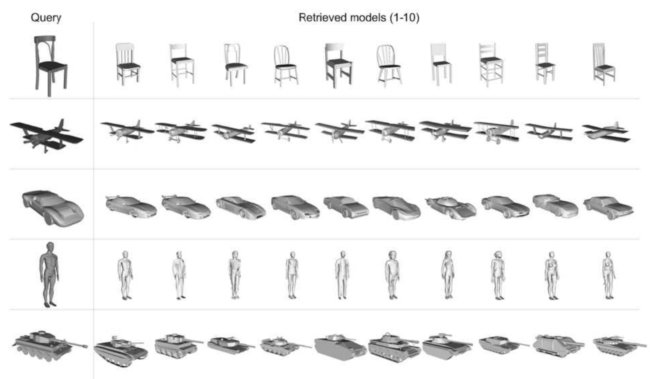

Figure 3: Example queries and the respective top 10 retrieved models using the proposed hybrid method.

Through the opportunity to participate in the track, we would also like to demonstrate a prototype 3D model search engine (CIL3D) which uses the proposed hybrid method and is publicily available through the internet, by following the next link: http://emedi3.emedi.iit.demokritos.gr/cil3d/

Currently, CIL3D enables content-based 3D model search within the Princeton Shape Benchmark dataset. Please note that CIL3D should not be used to verify the retrieval results of our participation in SHREC 2008, since the search engine employs a lossy compression scheme for the hybrid features and in some cases the retrieval results may not exactly match those that are evaluated in the track.

Last but not least, we would like to congratulate the winner of the track Kunio Osada (Univ. of Yamanashi) and thank Ryutarou Ohbuchi (Univ. of Yamanashi), organizer of the track, for giving the opportunity to evaluate the effectiveness of 3D shape retrieval algorithms within generic 3D model datasets.

6 Acknowledgement

This research was supported by the Greek Secretariat of Research and Technology (PENED ”3D Graphics search and retrieval” 03 ΕΔ 520).

References

[1] P. Papadakis, I. Pratikakis, S. Perantonis, and T. Theoharis. Efficient 3D shape matching and retrieval using a concrete radialized spherical projection representation. *Pattern Recognition*, 40(9):2437–2452, 2007.

[2] P. Papadakis, I. Pratikakis, T. Theoharis, G. Passalis, and S. Perantonis. 3D object retrieval using an efficient and compact hybrid shape descriptor. In *Eurographics Workshop on 3D Object Retrieval, Crete, Greece*, April 15, 2008, to appear.

[3] G. Passalis, T. Theoharis, and I. A. Kakadiaris. Ptk: A novel depth buffer-based shape descriptor for three-dimensional object retrieval. *Visual Computer*, 23(1):5–14, 2007.

[4] D. V. Vranic. *3D Model Retrieval*. PhD thesis, University of Leipzig, 2004.