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Charge Density-Based 3D Model Retrieval Using Bag-of-Feature

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Abstract

As the number of 3D models is growing on the internet and other domain-specific datasets, the search and retrieval of such models are attracting a lot of attention. A shape descriptor it plays critical roles in the retrieval quality enhancement. In this paper we propose a new robust shape descriptor based on the distribution of charge density on the surface of a 3D model. After calculating the charge density for each triangular face of each model as local features, we utilize the Bag-of-Features framework to perform global matching using the local features. Our experiments on the McGill and PSB datasets show that the proposed descriptor is robust to a variety of modifications and transformations and offers a higher retrieving quality compared to other well-known approaches.

Categories and subject Descriptors (according to ACM CCS):I.3.5 [Computer graphics]: Computational Geometry and Object Modelling- H3.3 [Information Storage and Retrieval]: Information Search and Retrieval.

1. Introduction

The fast growth in technology during the last two decades has led to an enormous volume of multimedia information such as image, audio, video *etc*. in databases or over the internet. Following this growth, the question of "how do we generate 3D models?" has evolved into "how do we find them?" [FMK*03]. It means that the trend of research is going toward designing efficient systems to find a desired model in a large collection of 3D models.

To ease this task, many techniques have been proposed for content-based search and retrieval by leading researchers in which the main step is to describe the query and other available models in a useful and discriminative way. Many techniques have been proposed to represent the models using a numerical feature vector or an appropriate graph [OFCD01][DD01][TS04]. But still a great deal of research is being conducted to discover new descriptors to achieve a better result during the search process. Consequently, it is quite a challenging area to introduce new 3D shape descriptors, which are able to meet all of the retrieval criteria such as invariance against linear transformations, robustness against noise distortion and a good trade-off between the time and accuracy of the retrieving process.

In this paper we present a completely new shape descriptor which leverages a well-known fact from electrical physics about the tendency of charge density to accumulating at the sharp convexity areas on the surface of a solid. Using the Finite-Element-Method the charge density is calculated for each triangular face of the models to act as a local feature. Then models are described by the combination of these local features. The Bag-of-Features framework enables us to compare two models using the local features.

2. Related works

3D model retrieval has recently attracted lots of attentions. Hence, great deals of research have been conducted to introduce high quality shape descriptors to meet the retrieval requirements. For more details about these approaches we refer the readers to the survey paper by Tangelder and Veltkamp [TV08]. Since our proposed approach mainly uses the Bag-of-Features (BOF) framework, this section is dedicated to a brief background on BOF in the 3D Retrieval domain.

A typical content-based image retrieval system using the BOF framework has 3 major steps; (1): feature point selection, (2): visual dictionary building and (3): histogram generation.

In the 3D model retrieval domain, the BOF is employed to compare models using the local features. Several works have described models using the BOF framework.

The spin image [JH99] is used as a local descriptor along with the BOF framework in several works. In the work of Shan *et al*. a probabilistic framework is introduced in order to support partial matching [SSMK06]. They used

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the spin image as a descriptor and proposed the "shapeme" histogram projection algorithm which can match partial objects.

In the work of Ohbuchi *et al*. several depth-buffer images are extracted from different views of 3D models [OOFB08]. The SIFT descriptor is utilized to locate and describe salient points on each view and finally the BOF framework is leveraged for model histogram building and comparison. A similar approach is used in [LGSZ10]. Instead of the original models, the authors use the canonical form of models to extract the depth-buffer views. After simplification, the PCA and MDS are applied on the models to calculate the canonical forms. The main contribution of their work is the new matching scheme which they called Clock Matching. Their method achieved very good rank among the participants of the SHREC'11 contest.

Beside many advantages of BOF methods, they suffer from discarding valuable information. Because all of the spatial relationships among the feature points are discarded, their descriptive capability is severely constrained.

A few methods have been proposed to address this problem. An extension to BOF is presented in the work of Pengjie *et al*. [LMM11]. After extracting 20 Spatial Structure Circular Descriptor (SSCD) images from each 3D model, they applied some change in the original BOF to include the spatial information. To this end the shell-sector model combined with logarithmic shell radii is employed (6 shell bins and 20 sector bins). Finally the EMD distance measure is utilized to find out the similarity measurement between the models.

Recently in [BB10], an interesting method is proposed to consider the spatial relationship among the features. Instead of using a histogram for each feature, images are described as histograms of pairs of features and the spatial relations between them (visual expressions). The Multi-Scale Diffusion Heat Kernel is employed as a shape descriptor. The same "visual expression" technique is leveraged by Lavoué very recently [Lav12]. Firstly, some patches are defined associated with feature points uniformly sampled on the surface. Then, each patch is described by projecting the geometry onto the eigenvectors of the Laplace–Beltrami operator. A BOF framework augmented with the visual expression technique is employed to support partial matching in a spatial-sensitive manner.

As mentioned above, despite good retrieval quality, most BOF-based approaches do not consider the spatial relationships between the local features.

3. Proposed Approach

In this section, first we briefly introduce the background of charge-distribution, which is the cornerstone of our work and then its application in 3D model description will be presented.

3.1. Background

There is a famous fact in the physics of electricity which explains a natural phenomenon and says: "the electric charges on the surface of a conductor tend to accumulate at the sharp convex areas and disappear at the sharp concave areas".

We treat the 3D model as a conductor which is placed in a free space (a space with no any electric charge). So we distribute a predefined electrical charge Q on the surface of the 3D model. We expect that the density of distributed charge over each triangular face of a 3D model describes it properly.

It is important to remember that since the surfaces of 3D models are arbitrary, it is impossible to solve the charge density equation analytically; therefore the Finite Element Method (FEM) is leveraged to calculate the charge density of each triangular mesh. To do so, we employed the FEM technique proposed by Wu and Levin [WL97]. So, to see the details of calculating distributed charge density on the surface of 3D models, we refer the readers to the work of Wu and Levine [WL97]. By employing their approach, each triangular face has its own scalar charge density value which will be used as a descriptor for the faces.

Having the charge density for each triangle we start the process of model retrieval. Figure 1 shows four different coloured model samples based on their charge density distribution.

Figure 1, *Four coloured models from the McGill dataset; the redder parts specify the denser faces.*

3.2. Bag-of-Features Charge Density Descriptor (CDD)

In order to set up the BOF framework, we choose N random surface triangles on each of all M models in the dataset followed by clustering all of the M*N points into D clusters by the K-Means clustering algorithm. The cluster centres are considered as the visual words. For any model *i*, we select N sample points and create a feature vector based on the CDD descriptor at these points. The resulting vectors are compared to all of the words in the dictionary and the nearest ones are selected to construct a histogram which counts the number of occurrences of the visual words.

3.3. Some useful characteristics of charge distribution as a shape descriptor

The proposed shape descriptor has interesting properties which are very beneficial in the 3D retrieval domain. In the following we will briefly explain some of them.

- **Invariance to transformations:** Since the density is calculated regardless of the coordinate system and only depends on the total amount of distributed charge (Q) and the size of the model, it is completely robust to linear transformations such as translation and rotation. Invariance to scale can be easily achieved by placing models into the unit sphere.
- **Insensitivity to noise and simplification:** the global property of charge density leads to less sensitivity to

noise which is a great advantage compared to the curvature-based approaches which are considerably affected by any surface perturbations. The charge density is robust to simplification as well; although during the simplification process, the sizes of triangular faces are increased, the amount of distributed charge on the faces is changed by the same ratio. Consequently, the charge density of simplified faces remains the same. It leads to speed up the retrieving process by working on the simplified models. Figure 4 depicts the CDD descriptor histograms for the simplified and noisy models shown in Figure 2. The similarity of the CDD descriptor histograms supports our claim that the CDD descriptor is invariant to the aforementioned transformations.

Figure 2, *The original models and some modifications. (a): original models with 20K faces, (b): simplified models with 5K faces, and (c): noisy model.*

4. Experimental Results

We applied our proposed method to the models in two publicly available standard datasets, the McGill and PSB datasets.

Firstly, we examined the effects of several parameters for our algorithm. After finding the best parameter values, we experimentally evaluated our algorithm using the McGill and PSB datasets; the precision-recall curve is utilized in order to compare our algorithm with some other well-known approaches.

4.1. Algorithm Parameters

We tested some parameters of the algorithms namely the dictionary size and the number of feature points for the BOF-CDD algorithm for which some evaluation factors such as Nearest-Neighbour, First-Tier, and DCG are observed. After analysing the effect of different parameters, the dictionary size and the feature point count are set to 20 and 1000 respectively. Figure 3 depicts that the choice of 1000 seems to be the best one for the feature point count per model.

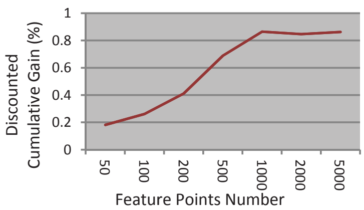

Figure 3, *The relation between the DCG and number of feature points in BOF-CDD (Dic. size=20)*

4.2. Time Complexity

Our CDD shape descriptor was implemented in MATLAB and some of its critical parts were written in C++, connected to MATLAB using the MEX interface. Since the proposed shape descriptor is robust against simplification, all of the models are down-sampled into 5000 triangular faces before any computation. The total process for simplification, charge distribution and feature extraction for each model takes an average of 4.2 seconds. And the average time for search a query on the McGill dataset and retrieve models on a 3GHz PC with 4GB RAM is 6.1 seconds.

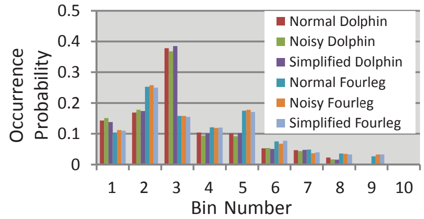

Figure 4, *The CDD histograms of models in Figure 2*

4.3. Comparing with Other Approaches

Aiming for evaluating our approach, we applied the proposed approach to the McGill and PSB standard datasets and compared the retrieval ability of our system with some other well-known approaches.

These approaches include MDS-CM-BOF [LGSZ10], D2 [OFCD01], SilPH [AS12], CM-BOF [LGS10], GSMD [PPPT07], SHD [KFR03] and LFD [CTSO03]. The LFD has the best retrieval ability compared with the other 12 descriptors in [SMKF04]. In addition, the MDS-CM-BOF descriptor is one the state-of-the-art approaches which thanks to the beneficial matching scheme (the clock matching) achieved a very good ranking among the participants of SHREC'11 contest.

Figures 5 and 6 depict the precision-recall comparison of our approach with the aforementioned methods using the McGill and PSB datasets respectively. As shown in Figure 5, our method distinctly outperforms 5 other methods, but the MDS-CM-BOF descriptor is still the best one by far. It is because of their interesting matching approach, Clock-Matching, which compares all possible pairs of relevant views to find the similarity measurement. The curve in Figure 6 illustrates that the retrieval quality of our approach on the PSB dataset is the best compared to other approaches especially for the lower amount of recall values.

5. Conclusion and Future Works

This paper presented a new shape descriptor based on the distribution of the electrical charge density on the surface of triangulated models. The Finite Element Method is employed to calculate the charge density. And the BOF framework is utilized to perform shape matching on the McGill and PSB standard datasets. Several parameters of the proposed algorithm were studied to boost the retrieval quality.

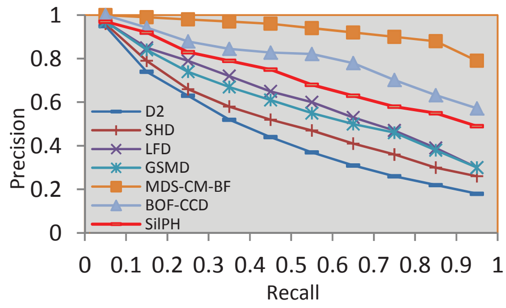

Figure 5, *The Precision-Recall plot for our and 6 different other approaches on the McGill dataset*

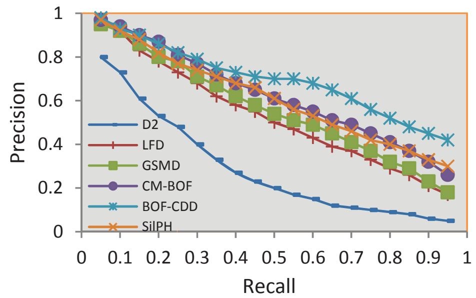

Figure 6, *The Precision-Recall plot for our and 5 other approaches on the PSB dataset*

In addition to higher retrieval ability, our experiments show that the proposed descriptor is invariant to the rotation, translation, simplification, deformation and noise distortions. In the next step we will try to improve our method so that it performs the matching of the models based on some available parts of a desired model to support partial matching.

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