A Robust 3D Shape Descriptor based on the Electrical Charge Distribution

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Abstract: Defining a robust shape descriptor is an enormous challenge in the 3D model retrieval domain. Therefore, great deals of research have been conducted to propose new shape descriptors which meet the retrieving criteria. This paper proposes a new shape descriptor based on the distribution of electrical charge which holds valuable characteristics such as insensitivity to translation, sale and rotation, robustness to noise as well as simplification operation. After extracting the canonical form representation of the models, they are treated as surfaces placed in a free space and charge Q is distributed over them. Following to calculating the amount of charge on each face of the model, a set of concentric spheres enclose the model and the total amount of distributed charge between the adjacent spheres on the model's surface generates the Charge Distribution Descriptor (CDD). A beneficial two-phase description using the number of Charged-Dense Patches for each model is utilized to boost the discrimination power of the system. The strength of our approach is verified using experiments on the McGill dataset. The results demonstrate higher ability of our system compared to other well-known approaches.

1 INTRODUCTION

Recent growth in the computer technology has resulted in an increasing number of 3D models. 3D scanners and cameras, 3D modelling software, mobile phones and etc. are among the new technologies which speed up the creation of these models. Nowadays, thousands of models are available in the domain-specific datasets. In addition, the rapid developments of the internet have hooked more attractions for retrieving 3D models based on their contents. On the other hand, due to the higher complexity of the models, annotating and retrieving these models using text-based retrieving systems is a non-trivial task. Consequently, researches have drawn a particular attention to the proposing new shape descriptors by which the models can be searched, indexed and retrieved in a beneficial manner.

During last decade, several shape descriptors for model retrieval have been introduced and some of them have a good retrieval quality (Kazhdan et al., 2003); (Chen et al., 2003); (Lian et al., 2010). But defining a robust shape descriptor to enhance the retrieval quality especially for non-rigid objects and partial matching is still a challenging area. A typical constructive shape descriptor should be invariant to the linear transformations such as the translation, scale and rotation. Moreover, robustness to noise, model deformations and simplifications are some other characteristics which result in boosting the retrieval ability.

In this paper, we propose a histogram-based shape descriptor based on the distribution of electrical charge which describes non-rigid objects effectively. It is insensitive to the linear transformations and some other modifications such as noise and simplification. A two-phase describing framework is utilized in order to defining models in a more distinguishable manner.

We organize the rest of the paper as follows: section 2 mainly dedicated to give a brief summary of the related works. The proposed approach is mainly discussed in the chapter 3. Experimental results are presented in section 4 and finally in section 5 we discuss our conclusion and the future works.

2 RELATED WORKS

Research on the 3D model retrieval started less than

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2 decades ago. Since then, dozens of techniques have been proposed most of which use shape descriptors to represent the models in an informative way. Based on the information used, they can be classified into 4 main categories namely statistic-based (Histogram-Based), Transform-based, Graph based and view-based approaches. A beneficial survey about the aforementioned approaches can be found in the works by Bustos et al and Tangelder and Veltkamp (Bustos et al., 2005); (Tangelder et al., 2008).
Since our proposed descriptor lies in the first category, in the sequel we provide a brief review of available methods of statistic-base category.

2.1 Histogram-based Descriptors

In these approaches, a histogram which accumulates the numerical values of a specific property is used to represent the model features. Shape Distribution, Shape Histogram, Extended Gaussian Images (EGI) and Electrostatic Fields are only to name a few of these techniques.

The Shape Distribution descriptor (Osada et al., 2001) contains a set of functions based on geometric measurements (e.g., angles, distances, areas, and volumes) using some random points on the surface of the 3D model. The accuracy of the appropriate histograms could be altered by changing the number of random points. Even though D2, one of their functions, had better retrieval quality than the other functions, generally speaking, none of the functions have enough ability for describing 3D models. This work was extended later by Ohbuchi et al (Ohbuchi et al., 2003) by using quasi-random sequence of numbers instead of pseudo-random sequences.

The shape histogram proposed by Ankerst et al (Ankerst et al., 1999) has been evaluated in the context of molecular biology and reached good accuracy and performance. They decomposed the 3D models using one of these three techniques: Shell model, Bin model and spider-web or combined model. Their technique is not invariant to rigid transforms and so they had to do pose-normalization as a pre-processing step. Also, since the approach proceeds with voxel data, 3D objects represented by polygonal meshes need to be voxelised prior to descriptor extraction.

The Extended Gaussian Image (EGI) is a spherical histogram in which bins accumulate the count of the spherical angles of the surface normal per triangle, usually weighted by triangle area (Zhang, et al., 2006). It is a histogram that records the variation of surface area with surface orientation. Later some extensions of the original EGI; Complex-EGI and Volumetric-EGI were introduced to enhance the original EGI especially for differentiate between convex and non-convex shapes without any pose normalization (Kang and Ikeuchi, 1997); (Horn, 1984).

Paquet et al (Paquet and Rioux, 1997); (Paquet et al., 2000) exploited both the geometric features and photometric properties such as cord, angle, colour, reflection and texture. Their techniques are easy to implement but since they only consider the global property of the model, their proposed approach is not very discriminative about objects details.

Recently, Mademlis et al employed electrostatic fields to 3D model retrieval (Mademlis et al., 2008). They considered the complete voxelised 3D model as a distribution of electric charge. Changing control parameters of descriptors enabled them to extract 24 histograms for each 3D model. Despite of robustness with respect to object's degeneracies and native invariance under rotation and translation, their descriptor is sensitive to non-rigid transforms.

Some other techniques have been proposed to use histograms for 3D model retrieval such as utilizing the Probability Distance Function (Akgul et al., 2009) and distance function by the 3D Poisson equation (Pan et al., 2011) which in addition to good retrieval ability, they are robust to shape perturbation and noise.

The main advantage of histogram-based approach is their simplicity of implementation. Almost all of the aforementioned methods are very straightforward to implement and understand. And if they are combined with the other methods as a pre-processing step or active filter they can improve their retrieval performance.

3 PROPOSED APPROACH

Our motivation for proposing the Charge Distribution Descriptor (CDD) comes from a famous fact in physics-electricity which says: "the electric charges on the surface of conductor tend to accumulate at the sharp convex areas and disappear at the sharp concavity areas".

We treat the 3D model as a conductor placed in a free space (the space with no electric charge). Then, a predefined electrical charge **Q** is distributed on the surface of the 3D models. The amount of distributed charges over each face of the model becomes the descriptor of that face. Figure 1 illustrates the 6 steps of our proposed approach.

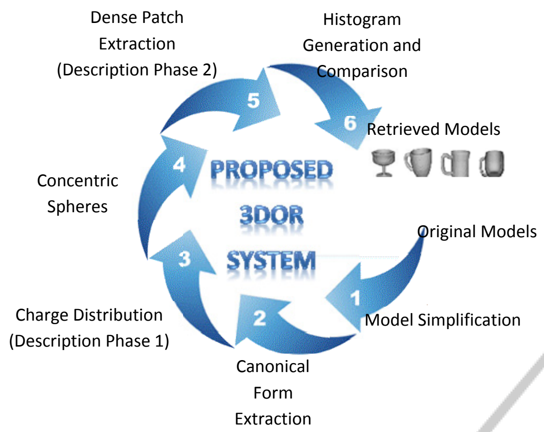

Figure 1: The proposed retrieval system.

To computing the charge distribution on the triangular faces of 3D models we employed the Finite Element Method (FEM) technique proposed by Wu and Levin (Wu and Levin, 1997). Using the Gauss's law and conservation-of-charge fact, they were able to calculate the charge distribution density on the any arbitrary surface.

Since the charge distribution is calculated regardless of coordinate systems, it is invariant to the translation and rotation transformations but it is not constant during resizing the models. So, we use the amount of distributed charge (instead of charge density) on the surface of each triangle. It is insensitive to scale transformation and simply is calculated via the underneath formula:

$$Chrgamnt_i = chrgDns_i * TriArea_i \quad , i=1,...,m \qquad (1)$$

where $TriArea_i$ and $ChrgDns_i$ are the area and charge density *of face i respectively and m* is the number of faces on the surface of each model.

Figure 2 shows four different coloured models based on their charge distribution; the redder areas indicate the surfaces holding more electrical charge. As displayed in this figure, the sharper points located in the convex areas have more electrical charge than the other parts and vice versa.

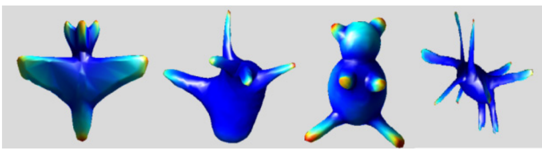

Figure 2: Four coloured models from the McGill dataset; the redder parts specify the denser faces.

3.1 Concentric CDD

In order to describe each model j, the N_s concentric spheres are drawn on the centre-of-mass of the model. The radii of the spheres monotonically increase to enclose the model entirely. The range of radii should meet the following criteria:

$$\min(d_j) < R_k < \max(d_j) \quad , j=1,2,...,m \qquad (2)$$

Here d_j is the distance of face from center-of-mass and *m* is the number of faces on each model. The sum of charge amount in each layer between two adjacent spheres is assigned to each layer and the N_s-1 dimensional feature vector describes the whole 3D model. Figure 3 shows three different sample models and their corresponding concentric spheres. (Here Ns=4).

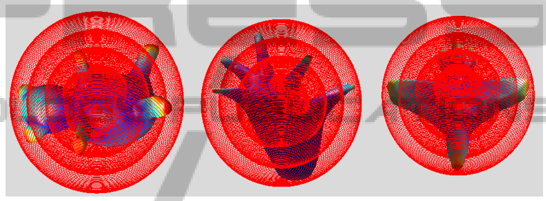

Figure 3: Three different models and their corresponding concentric spheres.

It is important to note that the deformation of models has significant effect on the amount of charge distributed on the model surface located between two adjacent spheres. To overcome this problem, we use the canonical form[1] representation by which non-rigid shape similarity problem can be mapped into an easier problem of rigid similarity. To this end, we utilize the Least-Square technique with the CAMCOF algorithm. Since both of SAMCOF algorithm and the geodesic distance extraction are time consuming tasks, we first simplify all of the models so that they have 2000 faces using the MeshLab (MeshLab1.1.0, 2008). Later on in this paper we show that the proposed descriptor is robust to model simplification (see figure 6).

After simplification, geodesic distance extraction and canonical form computation, the amount of charge on each face of the simplified models is computed. Figure 4 displays the results for three different poses of a spectacles model; although the poses are deferent but their canonical form presentations and distribution of charge are quite similar.

[1] The canonical form is a bending-invariant representation in which the geodesic distances are approximated by the Euclidian ones (Elad-Elbaz and Kimmel, 2003).

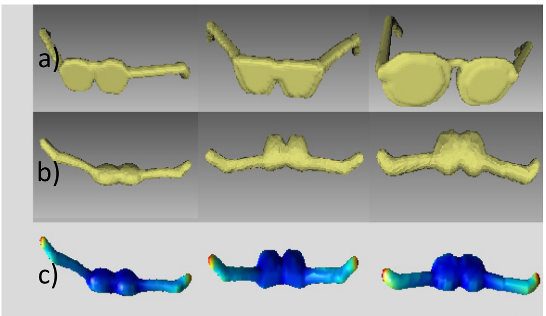

Figure 4: (a): Three different poses of a spectacle models, (b): corresponding canonical forms and (c): distribution of electrical charge.

3.2 Two-Phase Descriptor

In order to boost the retrieval quality, a two-phase shape description framework is leveraged. To this end, we extract the number of High-Density-Patches (HDP) on the surface of each charged model and utilize them to calculate the final dissimilarity between the pairs of models. Each HDP includes a local maxima point (a surface with higher electrical charge than its neighbours) and a set of adjacent faces on the model surface which have the charge density more than a pre-defined threshold τ. The threshold τ is experimentally selected as shown in Equation (3). Figure 5 shows some extracted dense patches on the models based on the density distribution:

$$\tau = 0.3*\max(ChrgDns_i)\ ,\ i=1,2,\ldots,m \qquad (3)$$

Here m is the number of faces for each model and $chrgDns_i$ is the charge density for face i.

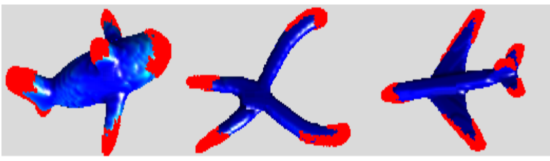

Figure 5: Extracted dense patches on the surface of three different models.

Testing our retrieval ability using the effect of the HDP numbers for each model, we concluded that, since the numbers of HDPs for most of the articulated models are not constant, retrieving the similar models based on the number of HDPs leads to the lower ability of finding the similar models. To solve this problem and balance the effect of HDP numbers during the matching phase we assigned a weight λ to each HDP which is defined using the formula (4):

$$\lambda = \frac{\max(ChrgDis) - \min(ChrgDis)}{\max(\#HDP) - \min(\#HDP)} \qquad (4)$$

After calculating the dissimilarity measure between each pair of models using the original CDD descriptor, the weight factor λ is applied to extract the final dissimilarity between two models i and j as follows:

$$\begin{aligned} Dis(i,j) &= chrgDis(i,j) + \\ &\left|\#HDP_i - \#HDP_j\right| * \lambda \end{aligned} \qquad (5)$$

Where *ChrgDis(.,.)* is the dissimilarity measure based on original CDD and $\#HDP_i$ is the number of High-Density-Patches on the model i.

4 EXPERIMENTAL RESULTS

We have tested our approach on the McGill dataset, which is publicly available on the internet. It consists of 458 models classified into 19 different classes. (256 articulated models in 10 classes and 202 non-articulated models in 9 classes). Beside of the retrieval quality of our descriptor, the robustness to the simplification and noise are studied.

4.1 Robustness against Simplification and Noise

As mentioned before, the introduced shape descriptor is invariant to the linear transformations. But we verify the robustness of it against some geometry operations. We use the pictorial presentation of models to show the effect of transformations in the distribution of electrical charge on the surface of the models. Figure 6 illustrates that the CDD descriptor proposed in this paper is remains stable after the simplification and noise; The original models in figure 6-(a) are simplified from 20K faces into 3K in 6-(b). In addition, a random noise is applied to the boundary of original models in figures 6-(c).

Comparing the distribution of the electrical charge for all of these modified models in figures 6 and 7 supports our claim that the CDD descriptor is invariant to the aforementioned transformations; the CDD descriptor's histogram of these modified models has small variations but they are still quite similar. The reason for insensitivity to noise and simplification can be explained as follows: as Wu

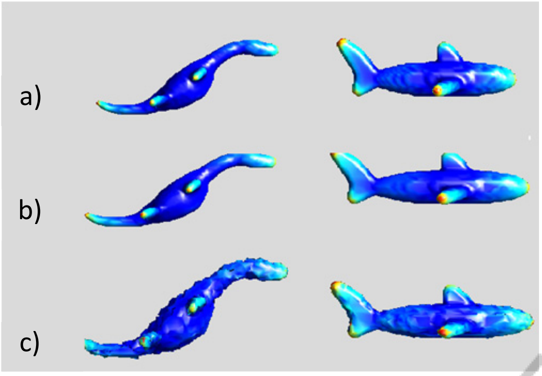

Figure 6: The original models and some modifications. (a): original models, (b): simplified models, and (c): noisy models.

and Levin charge on each face is contributed to by all other faces. So, the small boundary changes which are caused by noise and simplification have almost no meaningful effects on the density. It is a great advantage of our approach compared to the curvature-based approaches (e.g. mean-curvature and curvature-index); they are considerably affected by any surface perturbations.

4.2 Algorithm Parameters

We tested several different options for number of concentric spheres to enclose and describe the models and observed some evaluation factors for each one. The evaluation factors such as Nearest Neighbour (NN), First Tier (FT), Second Tier (ST), E-Measure, and Discounted Cumulative Gain (DCG) in the following table shows that 20 spheres is the best choice for the sphere counts.

4.3 Retrieval Ability

In order to verify the ability of our shape descriptor the Precision-Recall plot is employed to compare our system with 6 other well-known approaches. These approaches are MDS-CM-BOF (Lian et al., 2010), D2 (Osada et al., 2001), G2 (Mahmoudi and Sapiro 2009), GSMD (Papadakis et al., 2007), SHD (Kazhdan et al., 2003) and LFD (Chen et al. 2003). As mentioned in (Lian et al., 2011), the MDS-CM-BOF descriptor is one the state-of-the-art approaches which showed the great ability in the SHREC'11 contest. Furthermore, The LFD had the best quality comparing to the other 12 descriptors in (Shilane et al., 2004).

As depicted in figure 8, thanks to specific matching scheme (the Clock Matching scheme), the MDS-CM-BOF descriptor is the best one, and our approach ranked second. The figure shows that our approach provides the higher retrieving quality than other 5 approaches by far.

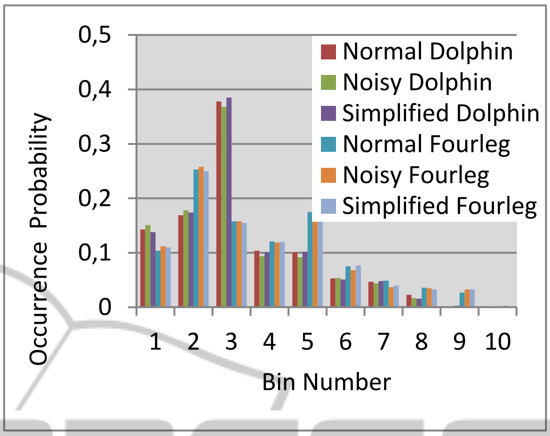

Figure 7: The CDD histograms of models in figure 6.

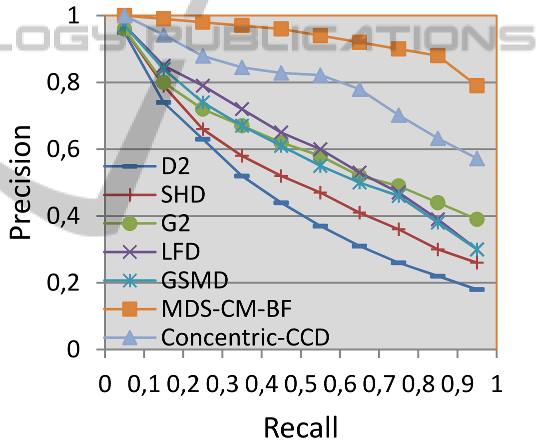

Figure 8: The Precision-Recall plot for our and 6 different other methods.

Table 1: Evaluation factors for different number of concentric spheres in the Concentric-CDD method.

Sphere Count	NN	FT	ST	E	DCG
5	0.7212	0.3414	0.4710	0.4012	0.6337
10	0.8563	0.4940	0.6359	0.4719	0.8172
20	0.8812	0.6052	0.7744	0.5019	0.8461
50	0.7375	0.4803	0.6433	0.4735	0.7968
200	0.4063	0.2641	0.3805	0.2879	0.5868

5 CONCLUSIONS

A robust shape descriptor introduced in this paper describes the 3D models based on the distributions of electrical charge over the triangular faces of each model. In addition to the distribution of charge, a beneficial two-phase description mechanism is also utilized in order to describe models in a more distinguishing manner; the number of High-Density-Patches on each model enabled us to boost the retrieval quality. Experimental results show that the proposed descriptor is invariant to the linear transformations as well as some geometry operations. In the next step of our work, we try to adjust our descriptor to support partial matching.

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