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An experimental comparison of Extended Gaussian Image and Shape Distributions in 3D shape retrieval

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Abstract

The effective retrieval of three-dimensional shapes is a very crucial problem nowadays. It has to be not only efficient but also carried out in reasonable time. The last demand is especially difficult as 3D objects are usually built using lots of data (vertices, patches, etc.). That was the reason for minor interest dedicated few decades ago by scientists to them. At present, this problem became less important, thanks to the advances in computer hardware development. Now, one can find many new applications of 3D models, e.g. in CAD systems, entertainment, virtual reality, biometrics and image retrieval. In order to work with those objects three-dimensional shape descriptors are used. Those algorithms are created to represent objects independently of various problems concerning them, e.g. affine transformations, noise, occlusions. The result of experimental examination of two 3D shape descriptors is provided in the paper. The research was performed using the models from the „Princeton Shape Benchmark" database. This database is very popular in the task of experimental evaluation of 3D shape descriptors. In the paper two methods of that type are explored - Extended Gaussian Image and Shape Distributions – in the problem of 3D shape retrieval.

Keywords: Content Based Image Retrieval, 3D shape description, Extended Gaussian Image, Shape Distributions.

Eksperymentalne porównanie Rozszerzonych Obrazów Gaussa oraz Rozkładów Kształtu w wyszukiwaniu kształtów trójwymiarowych

Streszczenie

Skuteczne wyszukiwanie kształtów trójwymiarowych w multimedialnych bazach danych jest istotnym problemem. Musi być ono nie tylko efektywne, ale i wykonywane w rozsądnym czasie. Ten drugi warunek jest szczególnie trudny do spełnienia, ponieważ obiekty 3D są zazwyczaj skonstruowane z użyciem dużej ilości danych (wierzchołki, powierzchnie, itp.). Było to dawniej powodem mniejszego zainteresowania naukowców tym zagadnieniem. Obecnie, problem ten stał się mniej znaczący, dzięki postępowi technicznemu w dziedzinie sprzętu komputerowego. Możemy więc aktualnie znaleźć wiele zastosowań modeli 3D, np. w komputerowo wspomaganym projektowaniu, rozrywce, rzeczywistości wirtualnej, biometrii oraz wyszukiwaniu obrazów. Aby móc pracować z tego typu obiektami stosowane są deskryptory kształtu. Te algorytmy są tworzone po to, by reprezentować obiekty niezależnie od poszczególnych problemów ich dotyczących, np. przekształceń afinicznych, szumu, okluzji. W artykule przedstawiono wyniki porównania eksperymentalnego dwóch deskryptorów kształtu 3D. Badania wykonano z użyciem modeli z bazy „Princeton Shape Benchmark". Baza ta jest bardzo popularna w ocenie deskryptorów kształtu 3D. W artykule dwie metody tego typu są badane - Rozszerzone Obrazy Gaussa oraz Rozkłady Kształtu - w kontekście problemu indeksowania kształtów 3D.

Słowa kluczowe: Indeksowanie obrazów na podstawie zawartości, opis kształtu 3D, Rozszerzone Obrazy Gaussa, Rozkłady Kształtu.

1. Introduction

The recent noticeable progress in graphics hardware and software made possible more efficient and faster computation of large multimedia data. One of the most time consuming problems within this area is the processing of three dimensional objects in real time. This can be observed for example in virtual reality, entertainment and CAD systems. However, other applications of 3D objects can be easily found, e.g. biometrics and 3D model retrieval. Especially the first one is recently considered crucial, because of the rising importance of the biometric identification of persons in various aspects of criminality and terrorism. On the other hand, the second one is considered as the most time and resources consuming. The retrieval performed in multimedia databases – usually containing thousands of objects – is strongly dependent on the selection of the algorithms applied to it. Hence, the usage of appropriate methods is so significant. They have to be effective, however they cannot work too long. In order to satisfy those two requirements the 3D shape descriptors are used. They can be defined as algorithms for representation of 3D models independently of any problems that can occur in particular application. The three properties can be stated ([1]):

- Descriptive power;
- Conciseness and easeness of indexing;
- Invariance under transformations.

The first property means the ability of efficient finding the similar objects when using the particular 3D shape descriptor. The second one means that achieved description should be as compact as possible. Thanks to this the storage requirements and the time required for searching the database are smaller. The last property is connected to the robustness to any problems that may occur in particular application.

The algorithms for 3D shape description can be divided into four main groups, basing on the most important properties of the methods. Those are geometrical, structural, symmetrical and local descriptors ([2]). The first group is definitely the most numerous and includes for example: Extended Gaussian Image ([3]), Complex Extended Gaussian Image ([4]), Shape Distributions ([5]), Shape Histograms ([6]), three-dimensional moments ([1]) and spherical harmonics ([7]). An example of the structural approach is the Multiresolutional Reeb Graph ([8]). The Reflective Symmetry Descriptor ([9]) belongs to the symmetrical group. Finally, an example of the local approaches was presented in [10] and it was based on canonical geometric scale-space analysis and encoding the local shape information within the inherent support region of each feature.

In the paper two geometrical approaches were experimentally evaluated – Extended Gaussian Image and Shape Distributions. They will be described in two following sections. During the experiments the „Princeton Shape Benchmark" database ([11]), a benchmark for evaluation of 3D shape descriptors, was used. The first method – EGI – was preliminarily described and analysed by the Author in [12]. Here it is compared with another 3D shape descriptor.

2. Extended Gaussian Image

The description of the Extended Gaussian Image, provided in this section, is based on [3]. Roughly speaking, the Gaussian image of a model can be obtained by associating with each point on its surface the point on the Gaussian sphere, with the same surface orientation.

Firstly, the Gaussian curvature has to be defined as to be equal to the limit of the ratio of the two areas as they tend to zero ([3]):

$$K = \lim_{\delta O \to 0} \frac{\delta S}{\delta O} = \frac{dS}{dO}, \tag{1}$$

where for a small patch δO on the object, each point belonging to it corresponds to a point on the Gaussian sphere δS.

From the above we can obtain integrals ([3]):

$$\iint_O K dO = \iint_S dS = S, \tag{2}$$

where S is the area of the corresponding patch on the Gaussian sphere. We can rewrite the above relationship ([3]):

$$\iint_S 1/K \quad dS = \iint_O dO = O, \tag{3}$$

where O is the area of the corresponding patch on the object. The above relationship suggests the usage of the inverse of the Gaussian curvature in the definition of the Extended Gaussian Image of a smoothly curved object.

Considering the above, we can define a mapping that associates the inverse of the Gaussian curvature at a point on the surface of the model with the corresponding point on the Gaussian sphere. Let u and v be parameters used for identification of points on the original surface, and ζ and η - on the Gaussian sphere (e.g. longitude and latitude). We can define the Extended Gaussian Image as ([3]):

$$G(\xi,\eta) = \frac{1}{K(u,v)}, \tag{4}$$

where point with the coordinates (ζ, η) lies on the Gaussian sphere and has the same normal as point (u, v) on the original surface.

3. Shape Distributions

The description of the Shape Distribution, provided in this section, is based on [5]. The descriptor is built basing on 3D polygonal model of an object. The crucial stage of the method is the selection of the function (in fact, free to choose) that will be used for representation of an object. The authors of the whole approach proposed the following set of based on simple features geometrical functions ([5]):

- A3 – measures the angle between three random points on the surface of a model;
- D1 – measures the distance between a fixed point (centroid) and one random point on the surface;
- D2 – measures the distance between two random points on the surface;
- D3 – measures the square root of the area of the triangle between three random points on the surface;
- D4 – measures the cube root of the volume of the tetrahedron between four random points on the surface.

The most important advantages of the proposed above functions are simplicity and invariance to particular transformations of an object. Moreover they are robust to some small level of noise. Some exemplary graphical representations of D2 shape function for a few canonical shapes are provided in Fig. 1. As we can see they are clearly distinguishable.

After a selection of the shape function we can start the computation of the representation based on it. In general, N samples from the shape distribution are evaluated and a histogram is constructed. It preserves the information, how many of those samples fall into each of B fixed sized bins. From the histogram a piecewise linear function is reconstructed, with V equally spaced vertices, V has to be less or equal to B.

Basing on the discussion provided by the authors of the approach, the above parameters can be established as follows: $N = 1024^2$ samples, $B = 1024$ bins, and $V = 64$ vertices. That gives shape distributions with low enough variance and high enough resolution ([5]).

The generation of samples is following. All polygons are split into triangles. For each triangle its area is derived and stored along with the cumulative area of all triangles processed so far. Later, a triangle with probability proportional to its area is selected, by generating a random number between 0 and the total cumulative area and performing a binary search on the array of cumulative areas. For each that triangle, a point P on its surface is generated, using two random numbers r_1 and r_2 ranged from 0 to 1, using the formula:

$$P = (1-\sqrt{r_1})A + \sqrt{r_1}(1-r_2)B + \sqrt{r_1}\,r_2 C, \tag{5}$$

where A, B and C are the vertices of the selected triangle.

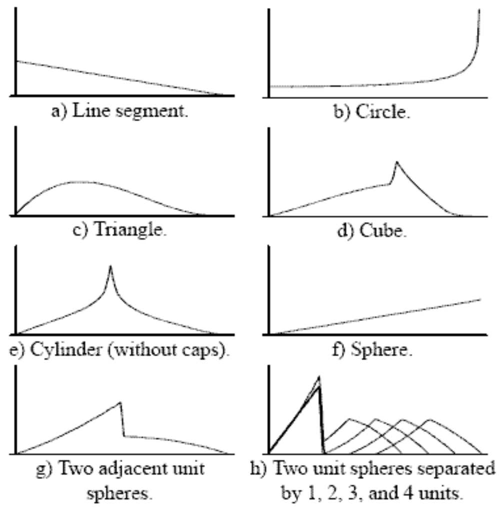

Fig. 1. Exemplary D2 Shape Distributions. In each case, the horizontal axis represents distance, and the vertical one - the probability of that distance between two points on the surface ([5])

Rys. 1. Przykładowe Rozkłady Kształtu dla funkcji D2. Za każdym razem pozioma oś reprezentuje odległość, a pionowa – prawdopodobieństwo dla tej odległości pomiędzy dwoma punktami na powierzchni ([5])

4. Experimental results

The two described three dimensional shape descriptors were experimentally compared using the models taken from the „Princeton Shape Benchmark" database ([11]). Several examples of objects from this database are presented in Fig. 2. In experiments 312 objects, belonging to 13 various classes were used. Each 3D model was represented using the tested algorithm and stored. The retrieval was performed using the Euclidean distance as dissimilarity measure and was considered successful if proper class was selected. Obviously, the template objects were taken before the tests were performed and were not used as test objects.

The results achieved by Extended Gaussian Image ([2]) are provided in Tab. 1. and for the Shape Distributions in Tab. 2. According to the discussion provided in [5] the D2 function was used as the best from the group proposed by authors.

As we can see from tables 1. and 2. the results of the two explored three dimensional shape descriptors are very similar. That concerns mostly the overall average retrieval result. In this case Extended Gaussian Image is slightly better since it achieves the efficiency above 60%.

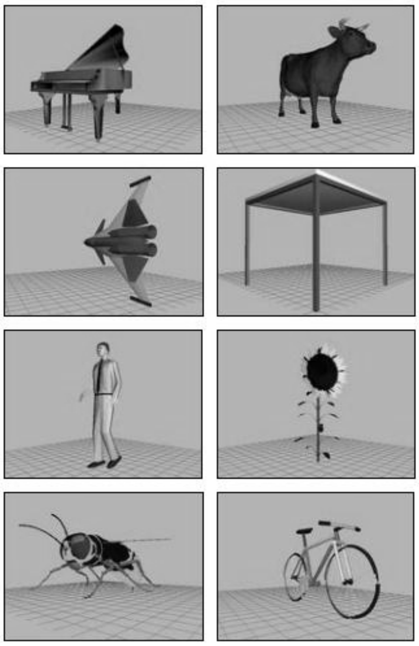

Fig. 2. Examples of 3D objects stored in the Princeton Shape Benchmark ([11])
Rys. 2. Przykładowe obiekty 3D z bazy Princeton Shape Benchmark ([11])

Tab. 1. Experimental results for retrieval of 3D objects using EGI
Tab. 1. Wyniki dla indeksowania obiektów 3D z użyciem deskryptora EGI

Class no.	Properly retrieved objects	Wrongly retrieved objects	Percentage of properly retrieved objects, %	Percentage of wrongly retrieved objects, %
1.	41	30	57,75	42,25
2.	23	12	65,71	34,29
3.	10	9	52,63	47,37
4.	17	15	53,13	46,87
5.	8	2	80,00	20,00
6.	18	18	50,00	50,00
7.	4	2	66,67	33,33
8.	2	1	66,67	33,33
9.	28	15	65,12	34,88
10.	7	3	70,00	30,00
11.	20	13	60,61	39,39
12.	4	4	50,00	50,00
13.	6	0	100,00	0,00
Overall	188	124	60,26	39,74

Tab. 2. Experimental results for retrieval of 3D objects using Shape Distributions
Tab. 2. Wyniki dla indeksowania obiektów 3D z użyciem Rozkładów Kształtu

Class no.	Properly retrieved objects	Wrongly retrieved objects	Percentage of properly retrieved objects, %	Percentage of wrongly retrieved objects, %
1.	56	15	78,87	21,13
2.	20	15	57,14	42,86
3.	16	3	84,21	15,79
4.	11	21	34,38	65,63
5.	3	7	30,00	70,00
6.	26	10	72,22	27,78
7.	3	3	50,00	50,00
8.	0	3	0,00	100,00
9.	12	31	27,91	72,09
10.	6	4	60,00	40,00
11.	18	15	54,55	45,45
12.	1	7	12,50	87,50
13.	3	3	50,00	50,00
Overall	175	137	56,09	43,91

The overall result for Shape Distributions is narrowly above 56%. Moreover, the achievements of the first approach can be considered more convincing. For class no. 13 the retrieval result was equal to 100%, for class no. 5 to 80%, and for other classes it was always higher or equal to 50%. The results of Shape Distributions were worse, when considering the particular classes. Although in three cases (classes no. 1, 3, 6) the retrieval efficiency exceeded 70%, in two cases it was completely unacceptable: for class no. 12 the retrieval rate was equal to 12,50 %, and for class no. 8 it was zero.

5. Conclusions

In the paper two 3D shape descriptors were discussed and experimentally explored. The first one, Extended Gaussian Image, is based on notions of Gaussian curvature and Gaussian sphere. The Gaussian Image for an object is obtained by associating with each point on its surface the point on the Gaussian sphere, with the same surface orientation. The Shape Distributions was the second 3D shape descriptor explored. In this case we are using a set of simple functions based on geometrical features of an object.

During the experiments 312 objects from 13 classes were used. They were taken from „Princeton Shape Benchmark” database ([11]). The results are quite close for the methods. The EGI achieved 60.26% average retrieval rate, and the SD – 56.09%. What is more important, the second algorithm was clearly worse, when considering particular classes. Above all, in the case of class no. 8 the retrieval rate was equal to 0%. This value was also very small for class no. 12. Hence, the Extended Gaussian Image can be considered as better from the two approaches, explored and presented in this paper.

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