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On the Effectiveness of Various Techniques of Searching in 3D Mesh Objects in Databases

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Abstract: The article compares some algorithm for object comparison, that can be used for searching 3D objects in database. There are tested: basic D2, TH, and EGI algorithms. The algorithms use histograms as descriptors of 3D shape. The techniques were tested using cultural heritage objects and objects from Shape Princeton Benchmark. Additional test use the same object represented with different accuracy.

The tests give us conclusions about the restricted usefulness of the algorithms and suggest the important parameters for searching in database.

Keywords: 3D mesh, 3D representation, database, object comparison, cultural heritage

1. Introduction

The number of databases with 3D objects grows. The objects are designed by artists, by engineers, or obtained by 3D scanners. The databases with 3D objects use mainly text description for searching. The searching technique is useful for many purposes, but it has two important limitations: the descriptions are added by human operators, that is inconvenient for databases with many objects, and the descriptors uses only an information previously considered. Shape descriptors, generated automatically can give us full information about the object shape and does not need any human activity.

The efficiency of used descriptors should depend on the kind of compared objects – differs between a groups of different objects.

2. Algorithms

There are many techniques for 3D objects comparison and there are no any leading algorithm. The main scheme of many algorithms is as follows: calculate descriptor for each object, store descriptors, and compare descriptors.

In EGI (Extended Gaussian Image) algorithm [18] a descriptor is given as a histogram of surface orientations. The evolution of EGI gives CEGI [7, 8, 17] – Complex Extended Gaussian Image, where the descriptor of surfaces orientation is a histogram of complex values. Multi-Shell Extended Gaussian Image (MSEGI) eliminates the major drawback of EGI – the lack of any direct distance information [15].

Descriptors calculated using spherical projection representation and a spherical harmonic transform becomes a popular method [4, 5, 9, 11]. The technique in brief:

1. the objects are translated and rotated, to obtain the same position and orientation;
2. spherical functions are calculated for the objects;
3. spherical harmonic transform is calculated for the spherical functions;
4. created descriptors are compared (see: the main scheme of the algorithm).

Some authors presented other methods – for example: wavelets [6], and surface partitioning spectrum (SPS) [13].

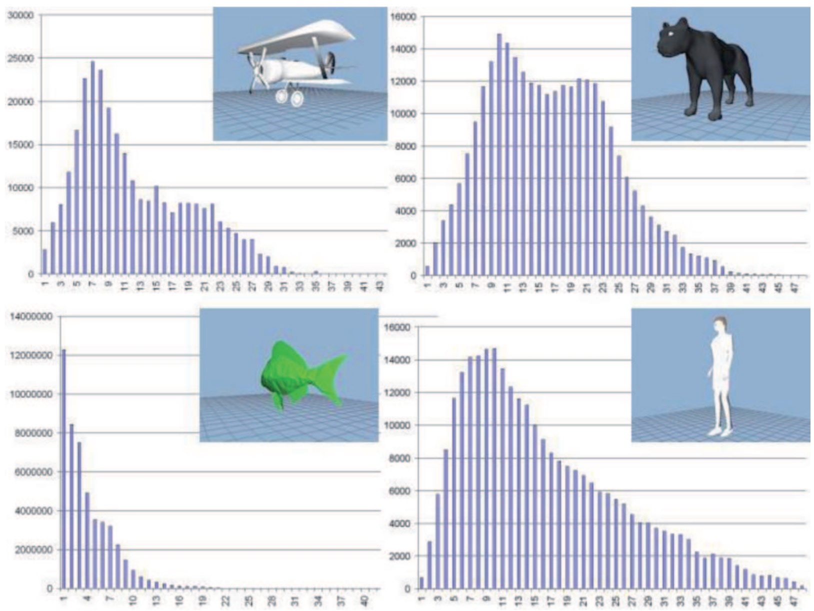

Fig. 1. D2 histograms for four objects (from the Shape Princeton Benchmark database)

In the article three algorithms are presented: D2, TH and EGI. The D2 [1, 2, 12, 13] algorithm bases on a distance histograms.

The histogram is built in five steps:

1. Rescale all models to the same size. The method is rotation-invariant, but not scale-invariant. In fact, rescaling is made with limited accuracy.
2. Set the number of points for the histogram. The number of the points should be the same for all histograms used in comparison.
3. Select the random points on the object surface with constant density (the number of points selected on a single triangle of the mesh depends on the triangle area).
4. Calculate all distances between the points.
5. Calculate histogram of distances (using EMD – Earth Mover's Distance).

The algorithm is very simple and universal. There are also some variants of the algorithm with histograms of (only) interior sections, or of sections that intersect the surface of the object. In the article only the base algorithm was tested.

One of the variants of the D2 algorithm is TH (thickness histogram) algorithm. The TH algorithm is very similar to the D2 algorithm, but it uses histogram of the cross product of line segment (between points) and normal vector to the surface.

In the first series of tests was also used another variant of D2 algorithm in which the distances were measured not between two points on the surface, but between a point on the surface and the centre of mass.

EGI (Extended Gaussian Image) algorithm [17, 18, 19] uses mapping on Gaussian sphere – such mapping is called Gaussian image of the (mapped) object. Algorithm is as follows:

1. Prepare set of normal vectors (points on the Gaussian sphere with a constant density).
2. Rotate object (use the same main axis for all objects). If the comparison method is invariant to the sphere rotation, the point could be omitted.
3. For all triangles of the object mesh:
   (a) Calculate normal vector;
   (b) Find normal vector from the Gaussian sphere, the most close to the calculated normal vector for a triangle;
   (c) Add the triangle area to the histogram. (The histogram is built for surfaces orientation, each value is related to the normal vector from the Gaussian sphere).

Normalize the histogram.

1. Note: in the CEGI algorithm, the value (**P**) (for normal vector on the Gaussian sphere – $\hat{\mathbf{n}}_k$) – is a sum of for all N$_k$ triangles with the proper orientation ($\hat{\mathbf{n}}_k$), where triangle areaa ($A_{l,\hat{\mathbf{n}}_k}$) is the magnitude and a normal distance (d$_{l,k}$) is the phase.

$$\mathbf{P}_{\hat{\mathbf{n}}_k} = \sum_{l=1}^{N_k} A_{l,\hat{\mathbf{n}}_k} e^{jd_{l,k}}$$

3. Tests: beads

The first group of tested object constitutes of beads from a necklace. The necklace is an archaeological finding of the Lusatian culture, and comes from the archaeological collection of the Museum of Gliwice. The beads are an example of the cultural heritage objects.

The beads can be divided into four categories:

1. 'smooth' beads (without visible ornaments);
2. beads with visible ornaments;
3. beads with 'weak' ornaments;
4. a four-horn bead.

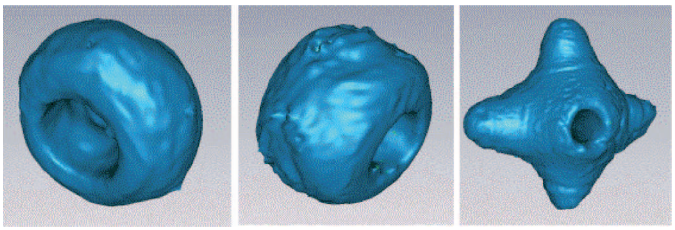

Fig. 2. Examples of the beads (from left): a smooth bead, a bead with ornaments and the'four-horn' bead

The first question was how important is the influence of randomly generated points (in D2 algorithm) on the output. To the first test were used three beads called: A (a smooth one), B (with ornament), and C (the four-horn bead), with 500 points.

	A	A	A	B	B	B	C	C	C
A	0	0.04765	0.06252	0.24126	0.23723	0.25656	0.9832	0.93364	0.98290
A	0.04765	0	0.08250	0.23581	0.24360	0.25868	0.99236	0.94187	0.99735
A	0.06252	0.08250	0	0.24746	0.25254	0.2793	0.89445	0.84797	0.88571
B	0.24126	0.23581	0.24746	0	0.10420	0.06333	1	0.95425	0.98520
B	0.23723	0.24360	0.25254	0.10420	0	0.0930	0.90927	0.86476	0.89620
B	0.25656	0.25868	0.2793	0.06333	0.09330	0	0.99193	0.94652	0.97712
C	0.9832	0.99236	0.89445	1	0.90927	0.99193	0	0.07664	0.05318
C	0.93364	0.94187	0.84797	0.95425	0.86476	0.94652	0.07664	0	0.087
C	0.9828	0.99735	0.88571	0.9852	0.8962	0.97712	0.05318	0.087	0

Tab 1. Normalised distances between the beads using 500 points and D2 algorithm

The data presented above (Table 1) are normalised – maximal value was set to 1. The normalisation was used for better comparison of results of D2 algorithm with different number of points. The results are characterised by a cubic growth with number of points.

	A	A	A	B	B	B	C	C	C
A	0	0.00191	0.00754	0.25282	0.25317	0.25266	0.91054	0.90249	0.90407
A	0.00191	0	0.00712	0.25292	0.25327	0.25276	0.91160	0.90346	0.90489
A	0.00754	0.00712	0	0.25425	0.25461	0.25410	0.91677	0.90808	0.91003
B	0.25282	0.25292	0.25425	0	0.00328	0.00130	1	0.99264	0.99411
B	0.25317	0.25327	0.25460	0.00328	0	0.00259	0.99760	0.99025	0.99172
B	0.25266	0.25276	0.25410	0.00130	0.00259	0	0.99948	0.99212	0.99359
C	0.91054	0.91160	0.91677	1	0.99760	0.99948	0	0.01338	0.00928
C	0.90249	0.90346	0.90808	0.99264	0.99025	0.99212	0.01338	0	0.00534
C	0.90407	0.90489	0.91003	0.99411	0.99172	0.99359	0.00928	0.00534	0

Tab 2. The same objects compared using D2 algorithm and 100 000 points. Normalised results

We can see that two histogram of the same object differs, because of random generation of points, but the differences between the same objects histograms are much smaller than between histograms of different objects.

For 100 000 points, the influence of randomness on the output is smaller. Figs. 3, 4 and 5 illustrate relations between distances – distances between the histograms of the same objects are relatively (in relation to the distances between histogram of different objects) smaller, and decrease with number of used points.

The Figs. 3-5 show the worst distances from three tests, and illustrate differences between two forms of the D2 algorithm, and TH algorithm. The best results (for number of points bigger than 5000) gives the base D2 algorithm. TH (thickness histogram) seems to give the worst results, but the closer look to the data suggests that the problem lies in bigger differences between classes – the differences between beads from three classes and the 'four-horn' bead become close to maximal reached value, while differences between objects within the first three classes were significantly smaller.

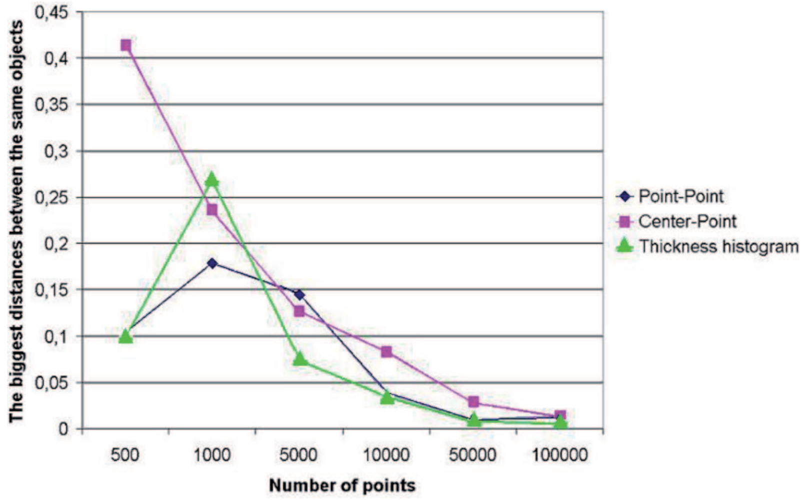

Fig. 3. The relation between the number of points used to calculate histograms, and the biggest distance between independently calculated histograms of the same object

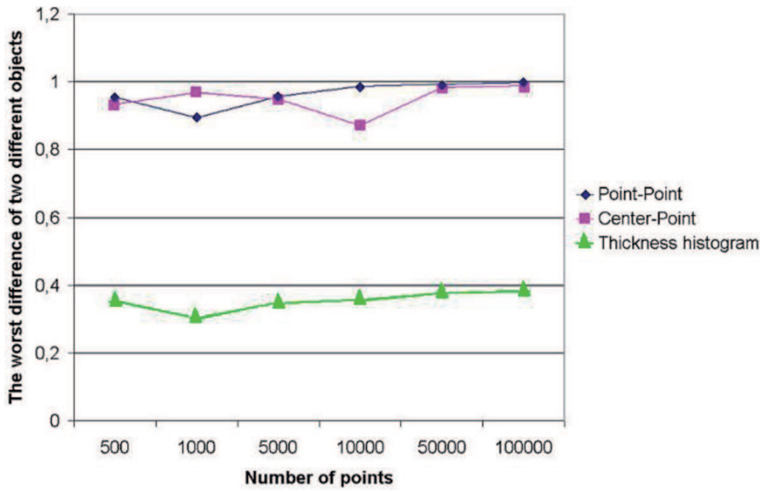

Fig. 4. The relation between the number of points used to calculate histograms, and the smallest (worst) distance between the different objects

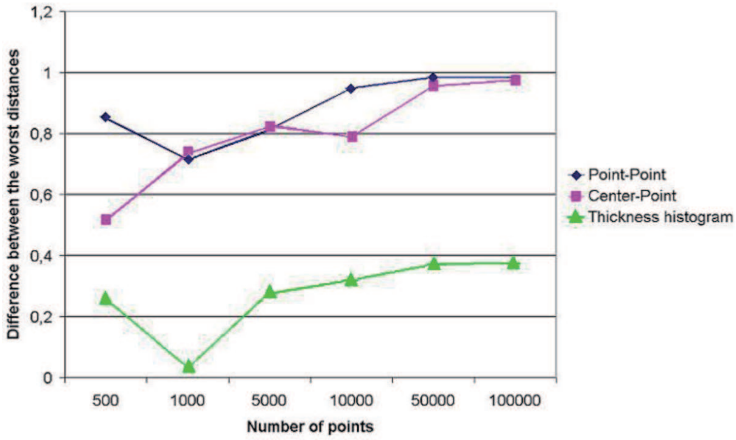

Fig. 5. The relation between the worst distances (the greatest distance between the same objects, and the smallest distance of the different objects) and number of points

It is important to remember that the time complexity of the D2 algorithm (base version) and TH algorithm is cubic. The time complexity is linear for the variant of D2 algorithm with distances from the centre of mass and points on the surface (see Fig. 6).

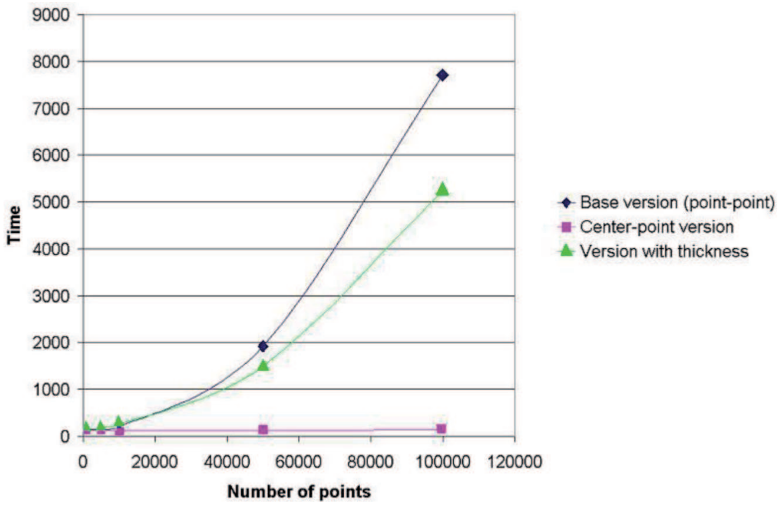

Fig. 6. Time complexity (time in seconds) of the D2/TH methods

The choice of the algorithm to calculate distance between histograms is not very important – EMD, Euclides and Cumulative Euclides gives similar results (the worst results gives the Manhattan distance between histograms, see Fig. 7), while analysis of EMD algorithm suggests the algorithm is only slightly affected by the size of the objects.

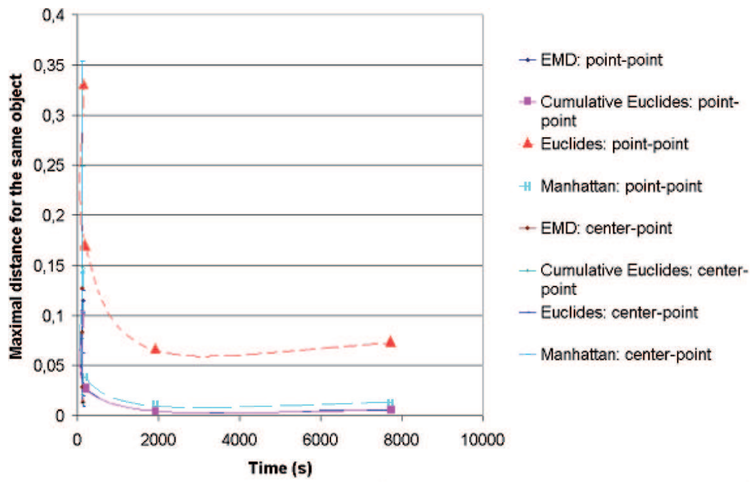

Fig. 7. Comparison of the maximal distances between the same objects using different methods

EGI algorithm gives not any proper results – distances between objects within a class was similar to the distances between objects in different class (even for the 'four-horn' bead). Probably problem lies in the number of used vectors on Gaussian sphere (128), and used algorithm for descriptor comparison (EMD).

4. Tests: Shape Princeton Benchmark

The results of the first tests series suggests possibility of the using D2/TH algorithm for objects classification in the database (see Tables 1-2 and interpretation of Fig. 5). The next test was performed using a bigger database – The Shape Princeton Benchmark. The database contains 1815 objects (3D meshes), while the objects contain from 16 to 316498 triangles.

On Fig. 8 we can see that the objects in the database are divided into groups. In the each group objects seems to be similar.

The groups are visible on Figs. 8-10, but closer look suggests that it is not easy to use the TH algorithm to classify objects into groups (Fig. 11 for one of the objects).

The Fig. 11 illustrates part of the distances (from Fig. 10) – the distances calculated for one object (no 64, chosen randomly). The nearest distances are between object number 64 (fish) and a few oblong articles, especially swords and knifes (see Fig. 12).

The distances calculated using the D2 algorithm are similar. For the presented data it seems to be impossible to find method for proper classification of the database. (Remark: because of the database size the distances were calculated only for limited number of points – the maximal used number of points was 6000.)

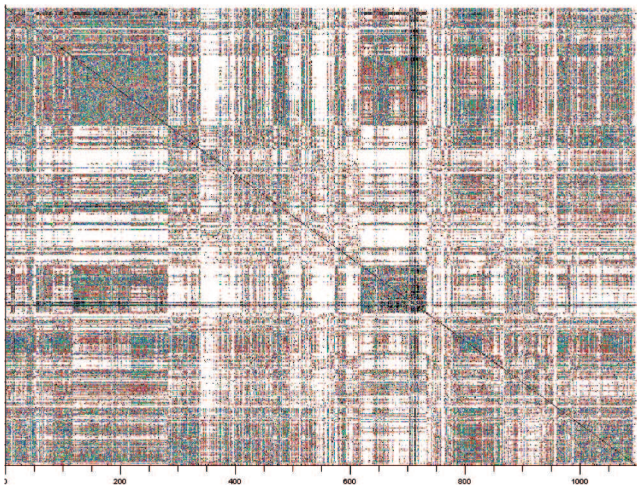

Fig. 8. Table of distances between objects (first 1097x1097 objects – the size was reduced because of limitations of visualization tools). The result was achieved using 1500 points on the each mesh surface and TH algorithm. Objects are closer to each other, if the pixel represents their distance is darker – white places represent maximal distances

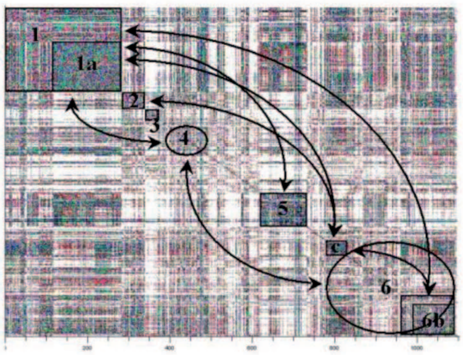

Fig. 9. The groups visible in the Fig. 8, and relation between them: 1) – live creatures; 1a) humans (and humanoids), 2) parts of a human body (faces, hands), 3) heads, 4) buildings; 5) oblong articles, e.g. knife, pistol, guitar, etc...; 6) furniture, 6b) plants, 6c) chairs

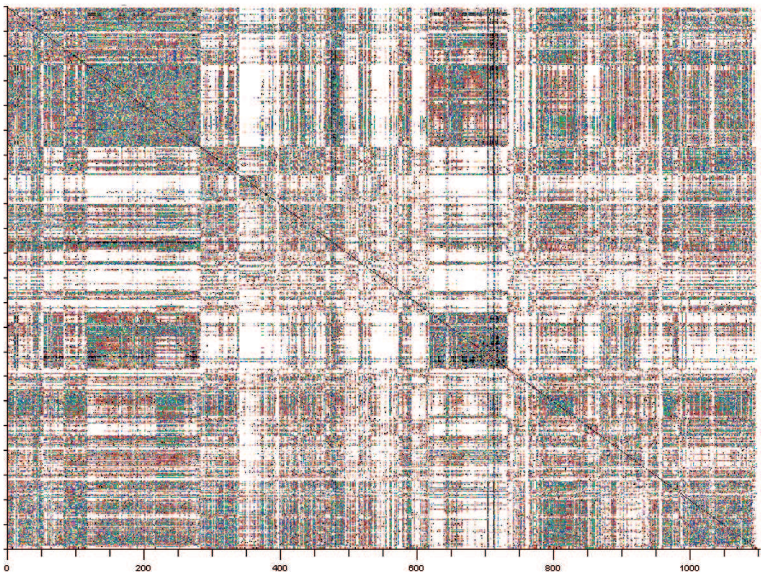

Fig. 10. The results for 6000 points (on each object surface)

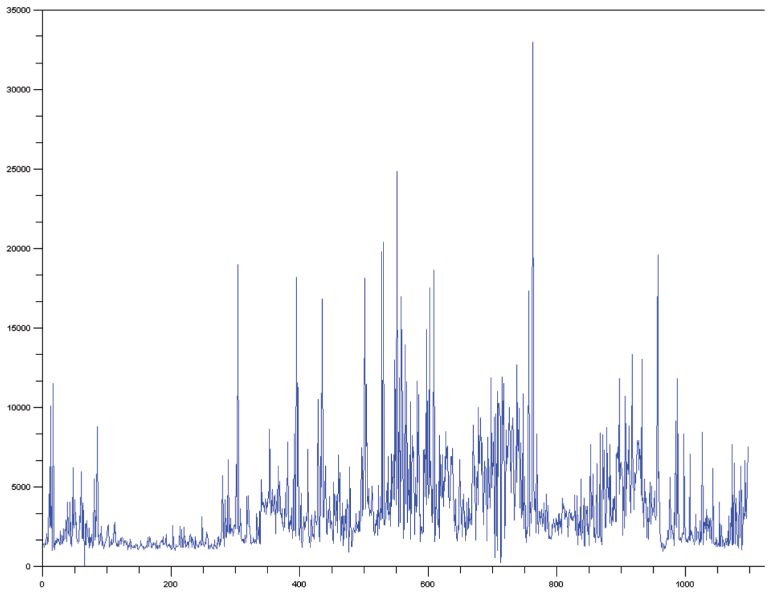

Fig. 11. Distances for the object no. 64 (fish) – the closest is the object no 712 (knife, distance: 243), while objects no 703 (sword, distance: 529), 707 (sword, distance: 988) are closer than the closest object in the neighbourhood of object 64 – 72 (dolphin, distance 1129)

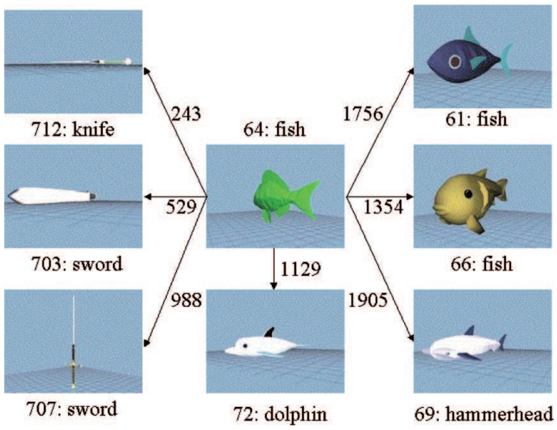

Fig. 12. The closest objects to the fish (no. 64) – on the left, the closest in the whole database (no. 712, 703, 707), and the closest in the 'fish' group – on the right (objects no. 61, 66, 69, 72)

The output was similar for the EGI algorithm – there were not visible any classes, but the algorithm suggested similarities that differ from D2-similarities. For example – the fish (object no. 64) was more similar to the dolphin (no. 72 – distance 0,29…) than to the swords (no. 703, distance: 0,73…; no. 707, distance: 0,66…), but the most similar to the knife (no. 712, distance: 0,08…; see also Fig. 13).

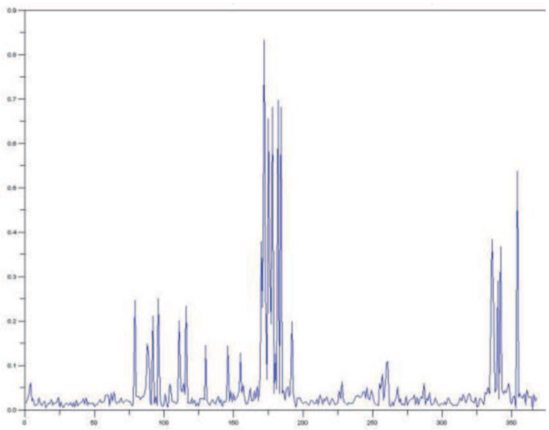

Fig. 13. Distances from the object no. 64 (attention: the number of objects is reduced) – the output differs from the fig. 12, but there are visible similarities for group of objects

5. Tests: the same object with different resolutions

The goal for the third series of tests was to check if the resolution of the object affects the results.

To check it, the test was performed with a series of meshes of the same object (part of the Goethe's face) with different resolutions. The meshes were: Goethe1a – 54391 triangles; Goethe2a – 40821 triangles; Goethe3a – 43239 triangles; Goethe4a – 20410 triangles; Goethe5a – 10204 triangles; Goethe6a – 5102 triangles. The object was compared with the four other objects (Fig. 14).

There are differences between histograms of the "Goethe" meshes, because of the differences between random point positions (see first series of tests results) and because of the difference in files (the change of resolution means differences between surface representations).

For the TH algorithm the goal of the test (i.e. the finding of the number of points for which the distances between objects are proper) was not met. Even for 12000 points (the highest number in tests) some Goethe's faces were closer to the other objects (especially to the object called "Abel", in fact a human bust) than to the other Goethe's faces.

The results for D2 algorithm and 5000 points (or more) are proper (Fig. 15).

Probably the worse results of TH algorithm was caused by the influence of surface changes (triangles inclination is important for TH algorithm) made by resolution reduction.

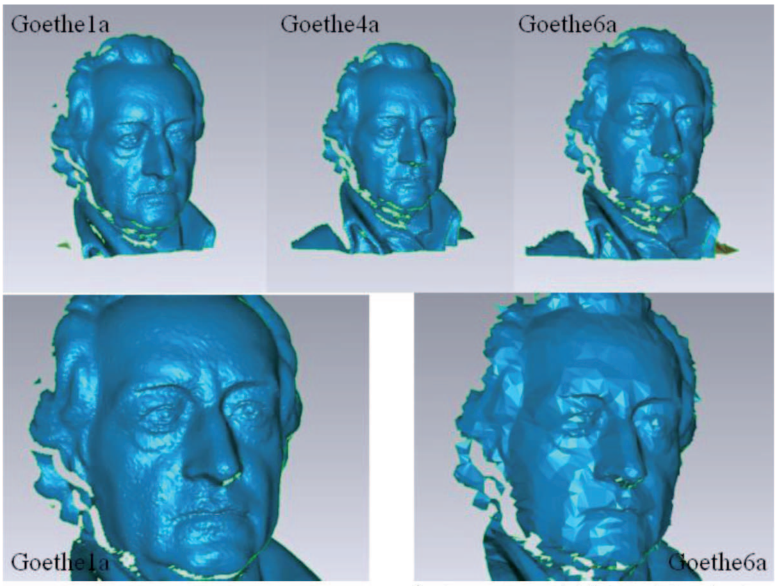

Fig. 14. Meshes: Goethe1a (the finest one), Goethe4a (middle) and Goethe6a

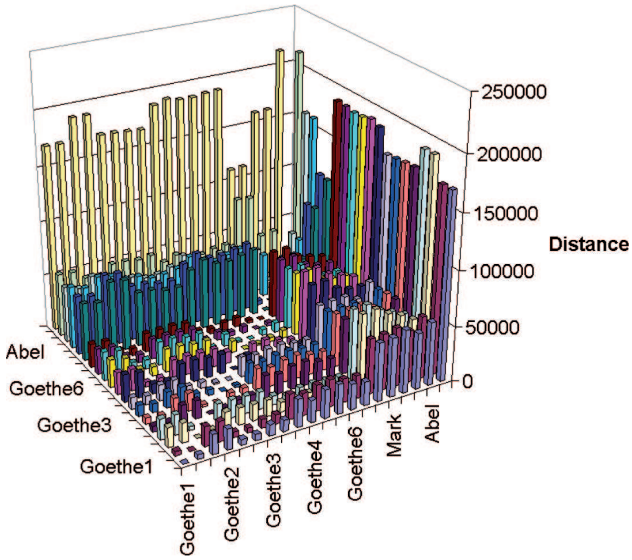

Fig. 15. The comparison for 5500 points and D2 algorithm. All the Goethe's faces are close to each other

EGI algorithm also is well suited to the change of mesh quality – distances between Goethe's faces significantly differs from the other objects (Fig. 16).

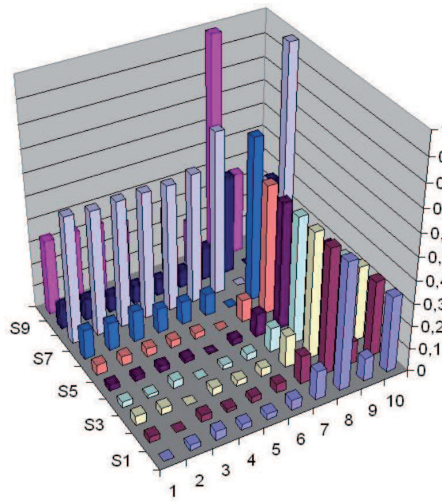

Fig. 16. The comparison for EGI algorithm. Objects 1-6 are Goethe's faces. The other objects have number 7-10

6. Summary

The base D2 algorithm is slightly better (that shows third series of tests) in objects identification than TH algorithm. The number of points used for applications depends on the number of triangles in meshes and should be determined experimentally – the presented tests are not sufficient to establish rule between adequate number of points and number of triangles.

The results of EGI algorithm was not so impressive. The problem with EGI algorithm may be caused by lack of the proper algorithm for calculation of the distance between EGI's descriptors. Because the EGI algorithm differ, both descriptors may be used to find similar objects.

There is no simply algorithm for objects (3D meshes) classification using D2 or TH algorithms. This problem needs further intensive exploration. The problem for finding part of the object in the database causes similar difficulties.

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O efektywności algorytmów wyszukiwania siatek 3D w bazie danych

Streszczenie

Artykuł prezentuje wyniki trzech serii testów, które przeprowadzono dla sprawdzenia możliwości wykorzystania algorytmów D2, TH i EGI w zastosowaniu do rozpoznawania przestrzennych modeli obiektów dziedzictwa kulturowego w bazie danych takich obiektów.

Algorytm D2 opiera się na porównywaniu histogramów długości połączeń między punktami na powierzchni obiektów. Dla każdego obiektu, po jego przeskalowaniu (sprowadzeniu do wspólnych wymiarów) wyznaczamy zadaną liczbę punktów na powierzchni. Punkty są wyznaczane losowo, przy czym zakładamy stałą gęstość rozkładu. Histogram długości tworzony jest dla wszystkich par punktów.

W pierwszej serii testów wykorzystano także wariant algorytmu D2, który opiera się na histogramie odległości punktów powierzchniowych od środka ciężkości obiektu.

Algorytm TH (ang. thickness histogram) stanowi wariant algorytmu D2 i opiera się na histogramie iloczynów wektorowych odcinków łączących punkty powierzchniowe (wyznaczane jak w przypadku algorytmu D2), oraz normalnych do odpowiadających im powierzchni.

W przypadku EGI (ang. Extended Gaussian Image) wyznacza się powierzchnię obiektu odpowiadającą danej orientacji – stanowi to odpowiednik histogramu dla określonej liczby orientacji (wektorów normalnych, wyznaczonych na sferze gaussowskiej).

We wszystkich wariantach algorytmów porównanie histogramów wykonywane jest za pomocą metody EMD (ang. Earth Mover's Distance), której zaletą jest odporność na drobne błędy w przeskalowaniu obiektów (dla algorytmów D2 i TH). W przypadku pierwszej serii testów porównano także inne techniki wyznaczania odległości między histogramami (odległość euklidesową, zsumowaną euklidesową, oraz Manhattan) – odległości euklidesowa i zsumowana euklidesowa nie wykazały jednak znacząco lepszych wyników pracy niż EMD, która powinna cechować się większą odpornością na błędy przeskalowania obiektów, odległość zaś Manhattan okazała się miarą znacząco gorszą.

W pierwszej serii testów przeanalizowano odległości wyznaczone dla trzech koralików pochodzących z naszyjnika będącego znaleziskiem archeologicznym, pochodzącym z kręgu kultury łużyckiej. Testy wykazały, że wszystkie trzy warianty algorytmu D2 pozwalają poprawnie rozpoznać rozpoznawać obiekty, przy czym wykorzystanie odległości od środka ciężkości prowadzi do ograniczeń dokładności (co częściowo rekompensuje niższą złożonością obliczeniową, rosnącą liniowo wraz z liczbą punktów). Wyniki testów algorytmu TH sugerowały możliwość wykorzystania go dla realizacji zadania klasyfikacji. Testy wykazały także, że jakość odpowiedzi (tj. różnica między najgorszymi spasowaniami obiektu ze swoimi kopiami i z obiektami innymi, pozwalająca na określenie wartości progowej dla rozpoznania obiektu) rośnie wraz z liczbą wykorzystanych punktów powierzchniowych. W przypadku algorytmu EGI nie osiągnięto podobnych wyników – wszystkie rodzaje koralików różniły się w podobnym stopniu.

Drugą serię testów przeprowadzono na danych pochodzących z bazy Shape Princeton Benchmark, a ich celem było sprawdzenie możliwości wykorzystania algorytmu TH dla podziału bazy danych na klasy. Uzyskane wyniki nie potwierdziły takiej możliwości, choć przeglądy bazy (rys. 8-10) wskazały na pewne rozróżnienie grup obiektów. Należy jednak zauważyć, że ze względu na rozmiar bazy (1815 obiektów) i jej zróżnicowanie (złożoność od 16 do 316498 trójkątów) ograniczono liczbę wykorzystanych punktów do maksymalnie 6000. Analiza możliwości klasyfikacji przy wykorzystaniu technik TH i D2 wymaga więc dalszych prac. Podobne wyniki uzyskano przy pomocy algorytmu EGI, przy czym listy najbardziej podobnych obiektów różniły się w przypadku algorytmu EGI i D2, co może sugerować wykorzystanie złożenia obu algorytmów do stworzenia bardziej złożonego deskryptora.

Celem trzeciej serii testów była weryfikacja wpływu jakości reprezentacji siatki na uzyskane wyniki. Testy potwierdziły, że algorytmy D2 i EGI poprawnie radzą sobie z różnicami między różnymi reprezentacjami tego samego obiektu (różniącymi się liczbą trójkątów, a co za tym idzie także cechującymi się pewnym zróżnicowaniem kształtu), podczas gdy algorytm TH okazał się wrażliwy na takie zmiany, co przy testowej liczbie punktów (maksymalnie 12000) czyni go nieprzydatnym dla porównań. Przypuszczalnym powodem takiego zróżnicowania jest większy, w przypadku algorytmu TH, wpływ nachylenia trójkątów powierzchni na uzyskane rezultaty.

Artykuł kończy podsumowanie, ukazujące jednocześnie kierunki dalszych potencjalnych prac – analizy technik klasyfikacji przy wykorzystaniu większej liczby punktów dla utworzenia histogramu oraz do testów porównań fragmentów powierzchni z kompletnymi obiektami.