*Regular Paper*

# Content based retrieval of 3D shape based on shape orientation

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In this project, we realized a 3D shape retrieval web system based on the analysis of shape orientation. We considered the spatial orientation of the polygon surfaces of a shape as important information and characterize this information by setting view planes. We then analyzed these view planes by multiresolution wavelet analysis (MWA), a powerful tool used in signal processing, and lowered the high resolution to low frequency domains because the high resolution contains too much information, which must be reduced in order to capture the main components. This method utilized shape orientation attribute, characterized this signal and extracted one shape descriptor. We conducted some experiments on Princeton Shape Benchmark, and found that this method achived higher retrieval performance than some previous methods. Here we present this new 3D shape retrieval web system and also discuss the internet application of this system.

## 1. Introduction

In the past twenty years, the use of multimedia information has expanded quickly in a number of fields such as image, audio, video, 3D model. The content of each multimedia information was produced with a great effort or in a long time by human. These multimedia information are important resources for us, and should be treated carefully and considered to reuse them. But it is not easy for human to reuse them because it is difficult for us to find an interest content in the enormous number of multimedia data. It is also difficult to give the multimedia data the sufficient text annotation. Therefore, researchers have made considerable efforts to make computers learn to understand, index, and retrieve images, audios, videos representing a wide range of concepts. The 3D model, as a relatively new form of multimedia, is rapidly increasing in many applications such as computer games, computer aided design, virtual reality environments, biology, e-business, and so on. 3D model data have a higher dimension than other multimedia data and represent more complex human intelligence. Consequently, it is becoming challenging to recognize, match, and then retrieve them. Therefore the computer graphics community has shown considerable interest in content based 3D shape retrieval.

Content based 3D shape retrieval can be described as the Figure 1. Given a query shape, a shape retrieval algorithm searches the similar shapes to the query shape, which belong to the same class in a database.

Content based 3D shape retrieval does not depend on the name or text annotation of 3D shape, but only 3D shape data. Consequently, it is necessary to develop an algorithm to help computer recognize the query shape and the other shapes in the database, and then compare them automatically. This algorithm could extract the main feature of 3D shape, store it in the disk, and match 3D shapes by virtue of comparing features. This process is very like that human see objects. For example, when he sees a tea cup in his office, he can recognize the tea cup, and remember it in his memory, when he goes home, he can find that a cup at his home is similar with the cup he saw in his office. Although it is easy for human to do these tasks, it is difficult for computers to finish this process. It is the key of content based 3D shape retrieval to catch the important feature representing itself, and the feature can be compared efficiently. The feature is also called the shape descriptor, that is, the feature could describe one 3D shape by only using the numbers computers could utilize.

When some shape descriptors were proposed by researchers, one problem appeared. Researchers began to argue that his own shape descriptor is better than others. It is difficult to infer or prove mathematically which algorithm of 3D shape retrieval is better. Under this situation, one shape benchmark, Princeton Shape Benchmark[1)] was proposed in 2004.

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The only way of the comparison between the shape retrieval algorithms is to adopt the same shape benchmark to evaluate the performance of one shape descriptor on evaluation parameters. These evaluation parameters include quantitative statistics, and time cost and storage cost. The quantitative statistics includes Nearest Neighbor, First Tier, Second Tier[2], E-Measure[3),4], and Discounted Cumulative Gain (DCG)[5].

## 2. Previous Work

3D shape retrieval has attracted the attention of researchers in computer graphics since 1999 according to our survey. You can also see the survey[6][7] and find the latest method until this year in[8]. At that time, researchers have caught the core of 3D shape retrieval, shape description. An earlier research was conducted by Ankerst et al.[11]. They used shape histograms decomposing shells and sectors around a model's centroid and did some experiments on 3D protein structures. Although they achieved good results only on protein structures, a relatively simple 3D shapes, this research is also thought as the important research on 3D shape retrieval because they supplied a good idea for analyzing 3D shape by hisotgrams. Vranic et al.[12] proposed to compare the distances ray casting from center to the surface, called spherical extent function. Hilaga et al.[13] constructed skeletal and topological structure of a 3D shape, and this method is robust in objects owning clear subparts, for example, animals and humans, however, it is sensitive at region boundaries. They conducted some experiments on 230 models and gave results represented using similarity matrix. The insufficiency of this method is that it has heavy time cost on constructing topology and comparing two topologies. The experiments in a linux system(Intel P2 400M) showed that topology can be computed in approximately 15 seconds on 10,000 vertices, and the average time of computing one similarity between two arbitrary shapes is 50 miliseconds, that is, if you search one shape in a database with 1000 shapes, it will cost about one minute, and some uers can not accept so long time. Morover, many objects have not clear topology, for example, boxes.

Statistics on the global geometric property of a 3D shape has been applied to shape matching. Osada et al.[16] matched 3D models with shape distributions on the Euclidean distance histograms of two arbitrary points of the surface. Another method developed by Ohbuchi et al.[23] extends the the shape function by considering the inner product of the normals of sampled point pairs. Liu et al.[25] presented a novel 3D shape descriptor for effective shape matching and analysis that utilized both local and global shape signatures, and term their descriptor "generalized shape distributions " because it is an extension of shape distributions[16]. Ohbuchi et al.[17] perform the shape analysis by using the moments of inertia about the principal axes of the model. These methods have a common limitation that they are capable of only capturing similar gross shape properties, and are powerless to capture the detailed shape properties.

Several methods have been used to characterize the intrinsic attributes, such as the distances to the center[14][18][20], and the curvature[10], of 3D shapes, and to project them onto a sphere to form spherical functions. Since the spherical function has 2.5 dimensions, processing is easier than that in 3D space. The spherical harmonics are first introduced in the 3D model retrieval by Vranic et al. in[14]. Kazhdan et al.[18] applied the invariance properties of spherical harmonics and presented an affine invariant descriptor based on spherical harmonics. Vranic et al.[20] improved this method by combining it with[14]. Novotni and Klein[21] presented a 3D Zernike descriptor by computing 3D Zernike descriptors from voxelized models as natural extensions of spherical harmonics based descriptors. However, for these methods, which are dependent on spherical functions, the small change in position of the sphere center can result in a significant noise in the feature descriptor.

Light Field Descriptor[19], produced projections of a 3D shapes from many viewing angles, and then encoded these projections as the feature by Zernike moments and Fourier descriptors. The LFD represents a visual perception similar to that of humans, however this descriptor must produce approximately one hundred projections, and has significant time cost. Therefore, the LFD is not applicable to the real-time retrieval. Podolak et al.[26] describe a planar reflective symmetry transform that captures a continuous measure of the reflectional symmetry of a shape with respect to all possible planes. The symmetry transform is useful for shape matching. Bespalov et al.[9] presented several distinctive benchmark datasets for eval-


**Fig. 1** 3D Shape Retrieval

uating techniques for automated classification and retrieval of CAD objects.Laga et al.[24] and Liu et al.[31] suggested using discrete spherical wavelets or continuous spherical wavelets to analyze the spherical functions defined by the sampling of the distances between surface and the center of mass of an object. Since the spherical function has a shortage that it is sensitive to the choice of the spherical center, and from a mathematical viewport, spherical wavelet transform has not yet been well defined up to now, the two descriptors have not achieved satisfactory results on shape retrieval.

After researchers found that histograms of Euclidean distances could not be used to pose-changing shapes such as bending or stretching, geodesic distances over the surface of the shape gained the attention. Tung and Schmitt[27] used the geodesic distances to construct an augmented multiresolution Reeb graph for 3D shape retrieval. Jain and Zhang[28] computed the spectral embeddings given by eigenvectors and eigenvalues of a geodesic distances matrix. These descriptors have an advantage in that they are invariant to non-rigid transformations. However, the computation of geodesic distances brings a big burden because the time cost is very high. The more recent work is that Ben-Chen and Gotsman[29] proposed a descriptor for characterizing shape using conformal factors. This descriptor is also invariant to pose changes, and is easy to compute. However this descriptor is subject to the constraint of the manifold mesh. Experiments of these descriptors were conducted on the McGill database[30], which was designed to test methods invariant to pose changes.

## 3. Shape Normalization

Before matching 3D shapes, one 3D shape needs preprocessing, called shape normalization that normalizes one shape into a canonical coordinate frame. Shapes have variable spatial positions, directions, different scales, and even reflection or symmetry. However, these shapes may be variations of the same shape, and these should be recognized as the same one. For example, a fish, can locate at arbitrary position in a river, can face east or west, can grow from a small fish to a big one, and two eyes are symmetric.

As preprocessing, normalization of each shape should be handled with before feature computation, and each shape is aligned in the same canonical coordinate frame (See Figure 2 ).

## 4. Multiresolution Wavelet Analysis on Shape Orientation

We have known that the previous methods[12)18)20)24] and our previous method SHX[47]. These methods have two common shortages: 1)use spherical function; 2)characterize the distances from the center to surface. These functions are based on spherical center, but the center is easy to change, and it is not stable.

In the section, I present our novel 3D shape descriptor by performing multiresolution wavelet analysis on shape orientation, named "MWA"[48]. I consider the spatial orientation of the polygon surfaces of a shape as important information and characterize this information by setting view planes. I then analyze these view planes by multiresolution wavelet analysis[32], a powerful tool used in signal processing, and lower the high resolution to low frequency

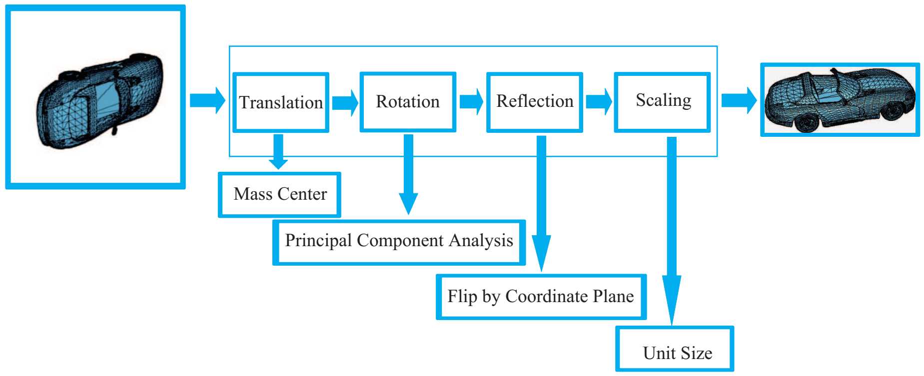


**Fig. 2** Shape Normalization

domains because the high resolution contains too much information, which must be reduced in order to capture the main components. I compare the proposed descriptor to the previous methods, on Princeton Shape Benchmark, and analyze the performance of the proposed descriptor from several aspects. The proposed descriptor improves the retrieval performance.

### 4.1 Sampling shape orientation from view planes

I place six view planes to the six faces of the bounding cube, and then decompose each view plane into some view points by a single resolution $N \times N$ horizontally and vertically. The decomposition is uniform in the horizontal and vertical directions.

The orientation of a face on the surface of a 3D shape can be described with the normal vector from inside to outside. I sample the face orientation by casting a perpendicular ray representing the view direction from a view point. The sampled face is the first one which the ray hits. Suppose that the vector $L$ and $V$ represent the orientation of the face normal and the view direction respectively. The value of inner product $(L, -V)$ is assigned to the view point O as the sampling value $O_{x,y} = (L, -V)$. Therefore, the sampling value is in the range of $[0, 1]$. The orientation matrix $O$ from a view plane is as follows.

$$O = \begin{pmatrix} O_{0,0} & \cdots & O_{0,N-1} \\ \cdots & O_{x,y} & \cdots \\ O_{N-1,0} & \cdots & O_{N-1,N-1} \end{pmatrix} \quad (1)$$

### 4.2 Multiresolution Wavelet Analysis

The orientation function $O(x, y)$ described in the above Equation 1 is decomposed from the high scale $s + 1$ to $s$ by the Daubechies wavelet[33], and multiresolution analysis can be realized. The initial scale is the orientation function $O(x, y)$ with an initial resolution $N \times N$, $N = 2^s$, which is decomposed iteratively by the following equations:

$$O_{\varphi}(s, m, n) = \frac{1}{2^s} \sum_{x=0}^{2^s-1} \sum_{y=0}^{2^s-1} O(s+1, x, y)\varphi_{s,m,n}(x, y) \quad (2)$$

$$O^i_{\psi}(s, m, n) = \frac{1}{2^s} \sum_{x=0}^{2^s-1} \sum_{y=0}^{2^s-1} O(s+1, x, y)\varphi^i_{s,m,n}(x, y) \quad (3)$$

where $O_\varphi$ defines the approximation of the $s + 1$ scale function $O$ at the scale $s$ by the scale function $\varphi$, and $O^i_\psi (i = \{H, V, D\})$ are the details in the horizontal, vertical, and diagonal directions, respectively.

### 4.3 Feature Vector and Similarity Metric

I use the wavelet coefficients (See Figure 3) of the final two scales as the feature vector $V$. Note that for the six view planes, there are six groups of wavelet coefficients and these groups of coefficients compose the feature vector $V$. Since the wavelet coefficients are close to the visual perception of human, we adopt the $L_1$ norm as the dissimilarity metric.

$$D = |V_1 - V_2| \quad (4)$$

### 4.4 Comparison with Other Retrieval Methods on Princeton Shape Benchmark

I evaluated the proposed retrieval method, MWA descriptor, on the Princeton Shape Benchmark, which contains a collection of generic 3D models, and has been distributed via website. I computed the quantitative statistics on seven recommended parameters, namely, Computation Time, Storage Size, and five

**Fig. 3** Feature vectors of shapes

The left column is composed of shapes. On the right column, a part of the feature is shown as wavelet coefficients of front view plane at two lowest scales. Whiteness means the large value of coefficients.

tools for evaluating retrieval precision, Nearest Neighbor, First Tier, Second Tier, E-Measure, Discounted Cumulative Gain (DCG), in order to evaluate the retrieval results. The statistics are summarized by averaging these five tools over all shapes in the data set. See Table 1 and Table 3.

Here, I investigated the retrieval precision of the following previous methods SHX, SHD, SWD, SD, and SSS. See the Table 2 for the detailed values of parameters.

(1) **Shape histograms on Shells and Sectors (SSS)** (Spatial Databases 1999)[11].
(2) **Shape Distributions (SD)**(ACM Trans. on Graphics 2002)[16].
(3) **Spherical Harmonics Descriptor (SHD)** (ACM Trans. on Graphics 2003)[18].
(4) **Spherical Wavelet Descriptor (SWD)** (IEEE SMI 2006)[24].
(5) **Spherical Healpix Descriptor (SHX)** (Journal of Information Processing Society of Japan 2008)[47].

Here we show the storage size of MWA feature vector and the average computation time on Princeton Shape Benchmark in Table 3.

The storage size of a feature vector is measured by bytes. The average computation time, which is shown in the above Table 3, is obtained on a PC with a Pentium 2.0 G processor

**Table 1** Quantitative Statistics on MWA method.

| Method | Nearest Neighbor | First Tier | Second Tier | E-Measure | DCG |
|---|---|---|---|---|---|
| MWA | 58.0% | 31.7% | 41.3% | 24.5% | 58.4% |

**Table 2** Quantitative Statistics on other methods.

| Methods | Nearest Neighbor | First Tier | Second Tier | E-Measure | DCG |
|---|---|---|---|---|---|
| SHX | 57.8% | 31.1% | 41.1% | 23.7% | 58.6% |
| SHD | 55.6% | 30.9% | 41.1% | 24.1% | 58.4% |
| SWD | 46.9% | 31.4% | 39.7% | 20.5% | 65.4% |
| SD | 31.1% | 15.8% | 23.5% | 13.9% | 43.3% |
| SSS | 22.7% | 11.1% | 17.3% | 10.2% | 38.6% |

**Table 3** Storage size and average computation time of MWA.

| Method | Storage Size (bytes) | Average Computation Time (seconds) |
|---|---|---|
| MWA | 1920 | 0.84 |

and 512 M of memory running Windows XP, and averaging the computation time over all 3D shapes. This condition is the same as that on which other methods runs. Here, I also investigated the storage size and average computation time of the previous methods SHX, SHD, SWD, SD, and SSS. See the Table 4 for the detailed values of parameters.

## 5. A 3D Shape Retrieval Web System

A 3D model retrieval web system was developed, and implemented as a proof-of-concept. In this system, the retrieval method - MWA is embeded for supplying the search method because the MWA method has the relative balance on the retrieval precision and retrieval time.

### 5.1 User Interface

It is a difficult problem how to supply users a good interface for searching the interesting 3D shape. In text retrieval[34)], users input several keywords memorized in their brains to search the related news, articles, papers, blogs, and so on. They can find their contents they wanted. In the server side, a web crawler[35)36)37)] has indexed all the visited pages automatically and supply billions of links to contents similar to all the sorts of keywords. By virtue of page parsing, the relations between keywords and contents are built. Image or video retrieval is more complex than text retrieval because computer or algorithm simulate the ways than human understands one image or video. Image retrieval[38)39)40)] commonly adopt one semantic classification to index all the images in the internet, extract the features of all the images, and create the semantic keywords to images or examples of images to help users to find their interesting images.[41)] realized one 3D shape retrieval system by virtue of 3D shape sketch interface[42)], and users can draw their 3D shapes freely, and search these sketches in the prepared 3D shape databases. But it needs a long time to draw a complex object, and only specialists can express their interesting objects by drawing freely. In this system, we will realize the retrieval by examples showed in Figure 4. Users supply their interesting examples to this system, and system will search similar objects to the input in the 3D shape database by computing the feature of input, and comparing this feature with features in the feature database.

### 5.2 Search Engine

Search engine is distributed in the server. It will handle with the request from users, and send response to users by internet or local network. Request sent by users reflects the 3D shape users want to search. In this system, search engine can handle with shapes with triangles. After server recieves the request, it will start up the process of feature computation. Here search engine adopts the MWA method because MWA is adaptable to real time retrieval. And this server stores the feature of input shape in the memory, and it is natural the storage size of feature descriptor of 3D shape will determine the storage performance in the server. The next stage is to compare this feature with all the features in the database. Feature database is formed by computing all the shapes in shape database and storing the computed features to a physical disk. Feature in the feature database has one-to-one relation with shape in the shape database. This job will be finished in the off-line, and only excuted once. After similarity comparison, the similarity will be sorted by sorting algorithm. The features corresponding to near similarity values

**Table 4** Storage size and average computation time of other methods.

| Method | Storage Size (bytes) | Average Computation Time (seconds) |
|---|---|---|
| SHX | 3072 | 1.23 |
| SHD | 2184 | 1.69 |
| SWD | 2048 | Unknown |
| SD | 136 | 1.12 |
| SSS | 136 | 0.66 |

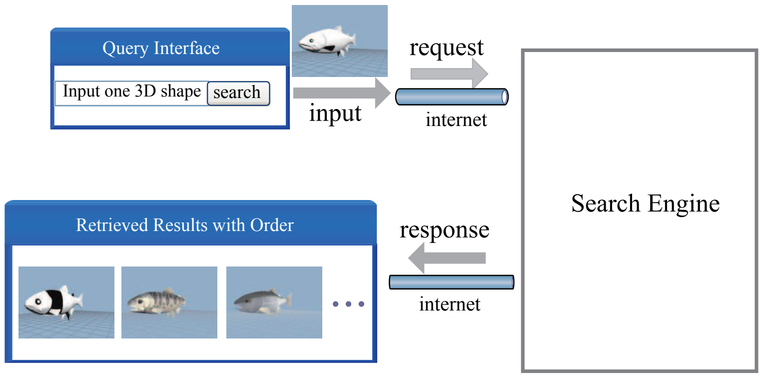


**Fig. 4** Structure of Client

will be sorted to the front. The shapes keeping up with features will also be sorted and formed to one sorted list. This list as the final response, will be sent to users waiting for retrieval result. Users will see the sorted shapes with similar order. See the figure 5 for detailed structure of search engine.

### 5.3 Implementation

In the client side, we adopted html and javascript to help users input their own shapes and see the retrieved results conveniently. We also created one Java Applet to draw 3D shape, and users can see 3D shape in the retrieved result when users click the thumbnail of one 3D shape. And users can utilize mouse to change the pose of 3D shape, and see the back or front, up or down parts of 3D shape, and understand this 3D shape overall. Users can also click any thumbnail to search this thumbnail relative to one 3D shape. In the server side, the most important one is to compute the feature of 3D shape. One library has capsuled all the classes about feature computation by MWA method, and this library can be extended by adding another feature computation method. Server classes based on servlet supplied by Java will call this library, and compute the feature of input shape. And then server classes compute the comparison between feature database and the feature of input shape. Finally sort all the relative shapes for the users. See the screen shot Figure 6 for this implementation.

(1) Input one 3D shape. In this interface, users can pick up one 3D shape from any position in own disks or networks and this shape must be right in topology, that is, this shape can not have any vertex which does not belong to any triangle, or have any triangle which can not be found its any vertex. This shape can be one watertight shape or not, and can be two manifold shape or not, and can even own some intersection triangles. These shapes could be handled with in this shape retrieval system.

(2) Retrieval results with similarity order. The similar shapes sorted by measuring the distance to input shape will be sent to users in this part. Here the features in the feature database have been precomputed in the offline process. The search engine will only compute the feature of input 3D shape. And then this engine will compare the distances between the input shape with all the shapes. Finally it will sort these shapes for users.

(3) Retrieval time. The retrieval time is the search engine which costs the time of feature computation and comparison. It is the sum of two sort of times. Therefore, as for one shape descriptor which only costs little time, this search engine will finish one task in a high speed. The comparison between the input shape and all

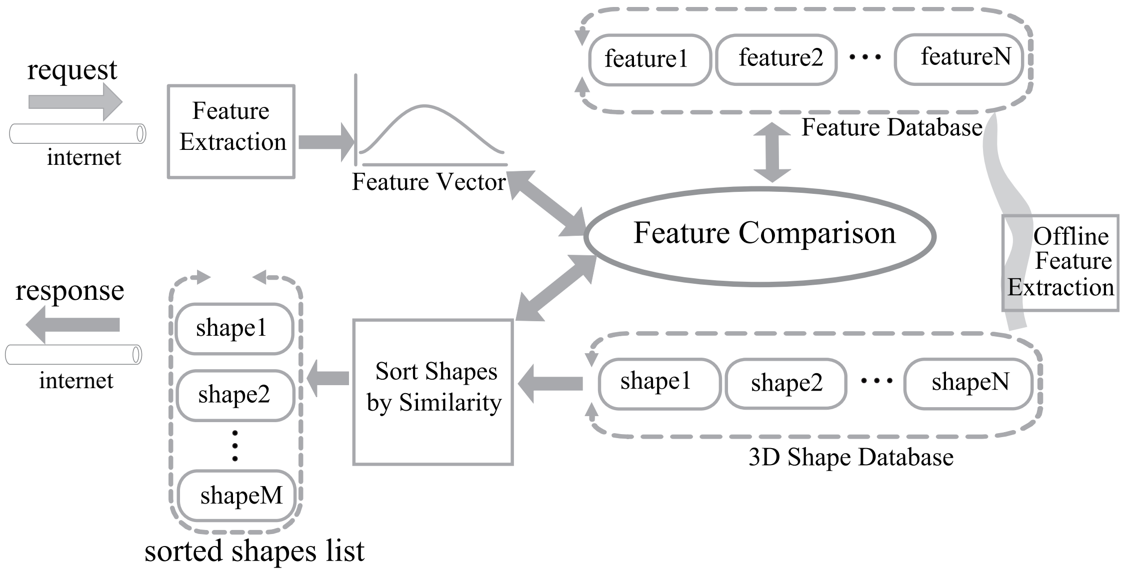


**Fig. 5** Structure of Search Engine

the features in the feature database, will be implemented by the distances, then one way of measuring distance in a high speed will save some time for users. From the view of real time search engine, one simple, speedy, and powerful 3D shape retrieval algorithm will be welcomed by users.

(4) Thumbnail of 3D shape in focus. The thumbnail of shape is one image describing one 3D shape only by one 2D view, and users can simply distinguish these shapes by one shot. Users can see which shape is in focus now. By this function supplied for users, users could search this shape in focus freely.

(5) 3D view of 3D shape in focus. This is one 3D view of selected shape, different from the above mentioned thumbnail. Users can scroll their mouses to see the each view of 3D shape including up and down, left and right, front and back views, or other perspective views. This function is developed by the Java Applet, and this applet must be downloaded when users open this web page. In this site, it can be downloaded automatically, the only thing users should do is the permission to this applet in the Mozilla Firefox, Microsoft Internet Explorer, and other web browsers. The size of this applet is small, but the 3D data has so larger size that users must wait for the download of 3D data for seeing this shape in the applet. This time has no relation with retrieval performance, even if users can not wait for this time. It is difficult for us to improve this function and it is not also the content of this research to display 3D data in the internet efficiently. Some methods has researched the display from coarse content to detailed content of one 3D data. Here this system has not integrated this function.

(6) Examples this system supplies. There are some examples supplied to users. By these examples, users can understand this system immediately. These examples are chosen without any rule, only as one convenient function.

## 6. Conclusion

In this project, we realized a 3D shape retrieval web system based on multiresolution wavelet analysis of shape orientation. And we considered the spatial orientation of the polygon surfaces of a shape as important information and characterize this information by setting view planes. This way using only orientation improved the robustness and efficiency of characterizing distances, for example, distances of surface to mass center, distances of surface to view planes, and so on. We then analyzed these view planes by multiresolution wavelet analysis (MWA), a powerful tool used in signal processing, and lowered the high resolution

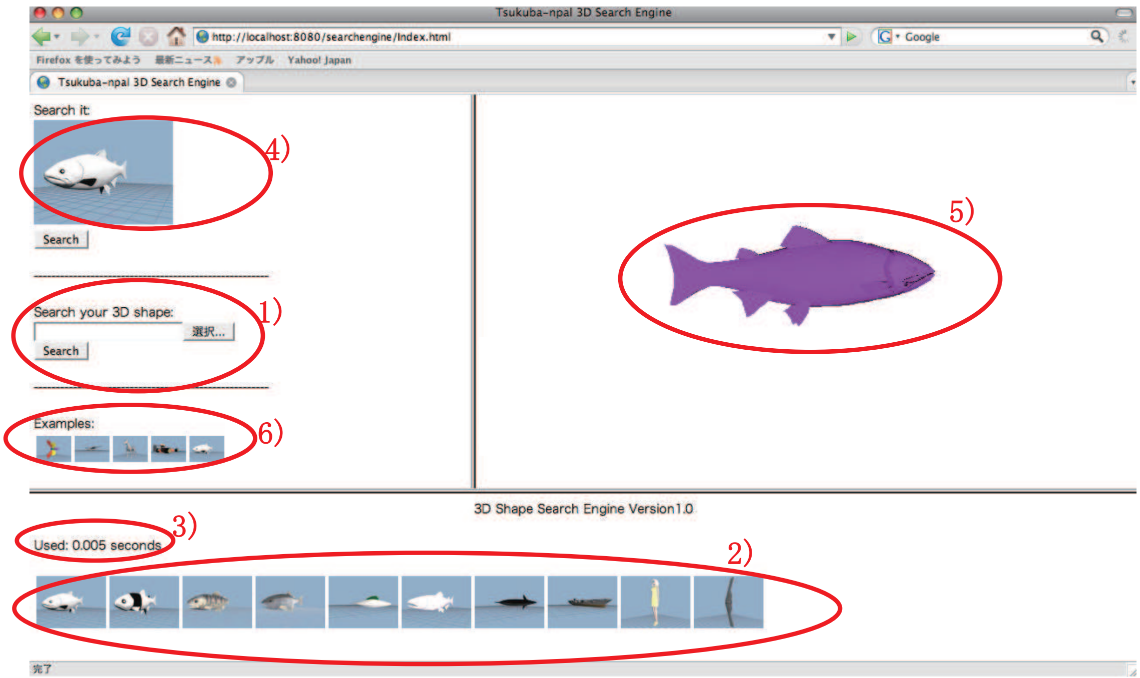


**Fig. 6** Screen shot of 3D shape retrieval system
1)Input one 3D shape;2)Retrieval results with similarity order;3)Retrieval time; 4)Thumbnail of 3D shape in focus; 5)3D view of 3D shape in focus; 6)Examples this system supplies.

to low frequency domains because the high resolution contains too much information, which must be reduced in order to capture the main components. This method utilized shape orientation attribute, characterized this signal and extracted one shape descriptor. We conducted some experiments on Princeton Shape Benchmark, and found that this method achived higher retrieval performance.

### 6.1 Applications

There are wide applications in 3D shape retrieval, especially 3D shape domain, for example, CAD, computer game, biology, object recognition, robot, and so on. The target of these applications is retrieving the interesting shape in one database, one big scene, and so on.

(1) CAD domain. As for mechanical factories such as car factories, airplane factories, electronics factories, electrical factories, even toy factories, there is need to search one mechanical part, for example, gears, brackets, linkage arms, springs, and so on when designers want to find some similar shapes with the own shape. Because one 3D shape must be cost a long time from several days to several months to design, it is meanful to reuse some existent similar shapes and revise these shapes simply to get one new shape. This can save the time of designers. As one example, Geometric and Intelligent Computing laboratory in Drexel University has built the National Design Repository[43] for designers and researchers to test and reuse these 3D CAD shapes.

(2) Biology. Scientists want to find some important relations between some similar 3D Molecular structures and one special structure. By the way of searching these similar structure, scientists could discover important featured molecules, for example, virus molecule, growable molecule, and so on. Some scientists created one Protein Data Bank[44] for reusing these structures for biologists in the world. Other research including visualizing organs from MRI data of mouse, or other animals has been positively making process. Organs in these animals are digitally sampled using this method without destroy to be supplied for biologists for research. Biologists can find

some useful information from these 3D organs, then, there is one need to build one huge database of 3D organs. However, searching some organs from the database is not one simple thing, and it need algorithm of 3D shape retrieval to confirm the retrieval concision. Riken in Japan has begun to build this database for biology research[45)].

(3) Internet Service. Google, Yahoo!, Baidu, MSN and so on have built valuable retrieval sites for people to search their interesting news, blog, websites, and so on. They also added some new functions such as image retrieval by keywords. These internet services have changed the internet life style of humans, and become indispensable for people. But as for people liking to search their 3D shapes, models, characters, and so on, it is difficult to realize by some keywords, because keywords can not represent the meaning of 3D models or shapes fully. There is one need for us to develop one 3D shape retrieval system to help them. In another aspect, some E-commerce companies have been discussing to build 3D database for the shopping items. These shopping items will be showed in 3D space. This will be convenient for users. It is natural for users to search one 3D shopping item from one huge 3D shopping database, and websites will recommend other similar items as the item one buyer selected.

(4) Object recognition. In one certification system, there is one need to certify one 3D body, head or face by searching this body, head or face from one 3D shape database. NIST (National Institute of Standards and Technology, USA) also introduced this face database such as Face Recognition Grand Challenge (FRGC)[46)] to construct one available face database for researchers. Because 3D shape contains plentiful information for one human, recognizing the body, head, and face will be more efficient.

(5) Modeling interface support. Developing one modeling interface easy to use is one big challenge. Because special skills are required in some commercial softwares such as Maya, common users are limited to simple operation. If one interface assembles one 3D shape retrieval system, when users sketch one simple shape, interface will demonstrate some cues including similar shapes as the sketch, and users can choose these shapes and composite other shapes to one own shape. This operation will speed up the modeling and let the design interface easy to use.

### 6.2 Future Work

In this present research, there are also some difficulties to realize one shape descriptor and put it to practical use. 3D shape has many formats and varieteis, one retrieval method can not deal with all the shapes, and also, each shape descriptor can not achieve satisfied enough retrieval effects to be a commercial search engine. There are many challedges to let algorithms realize the recognition and retrieval of 3D shape as human completely. I think there is a long road to implement a real application. In the future, I consider three main aspects.

(1) The precision of 3D shape retrieval should be advanced, the precision of all the existent methods are not enough high for complex 3D objects. This precision is decided by the method of feature extracton, or shape descriptor, that is, a better shape descriptor is needed.

(2) Retrieval of parts of 3D shape (Figure 7), for example, tire of a car, arm of robot, and so on, is also needed in the actual situation. It is a difficulty how to find a car which has the same tire as another car has.

(3) Simple interactive 3D shape modelling interface (Figure 8)is liked by searchers. A input 3D shape can be drawed up in a short time. It will speed up the application of 3D shape retrieval.

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**Fig. 7** Retrieval of parts of 3D shape


**Fig. 8** Simple interactive 3D shape modeling interface

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