3D Model Retrieval Based on Semantic and Shape Indexes

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Abstract

The size of 3D models used on the web or stored in databases is becoming increasingly high. Then, an efficient method that allows users to find similar 3D objects for a given 3D model query has become necessary. Keywords and the geometry of a 3D model cannot meet the needs of users' retrieval because they do not include the semantic information. In this paper, a new method has been proposed to 3D models retrieval using semantic concepts combined with shape indexes. To obtain these concepts, we use the machine learning methods to label 3D models by k-means algorithm in measures and shape indexes space. Moreover, semantic concepts have been organized and represented by ontology language OWL and spatial relationships are used to disambiguate among models of similar appearance. The SPARQL query language has been used to question the information displayed in this language and to compute the similarity between two 3D models.
We interpret our results using the Princeton Shape Benchmark Database and the results show the performance of the proposed new approach to retrieval 3D models.
Keywords: *3D Model, 3D retrieval, measures, shape indexes, semantic, ontology.*

1. Introduction

Recent 3D technologies scanning and 3D modeling lead to creation of 3D models stored in databases, which are used in various domains such as CAD applications, computer graphics, computer vision, games industry and medicine. Content based indexing and retrieval is considered as an important way of managing and navigating in these databases. Therefore, it become necessary to find an efficient method that allows users to find similar 3D objects for a given 3D model query which takes into account not only the shapes geometry, but also their semantics. Indeed, the use of low-level features to generate the objects descriptors can lead to big gap between low-level and high-level features. However, shape descriptors do not solve the problem of shape ambiguity because it does not consider the semantics of the model to be retrieved. 3D Model Retrieval system based on the semantic and ontology allows removing this ambiguity using combined semantic concepts and geometrical information based on 3D shape indexes represented by concepts in ontology.

2. Related work

Several systems and approaches to compute similarity between 3D objects have been proposed in the literature [2] [3] [16] [18]. Most of those are based on either statistical property. Osada and al. [4] proposed the shape distribution based descriptor for extracting global geometric properties and detecting major differences between shapes. This method cannot capture detailed features. To calculate features, Volume-surface ratio, moment invariant and Fourier transform coefficients are used by Zhang and al. [5]. This approach is not efficient, but corrected in [28] using active learning. Vranic and al. [17] proposed the ray based approach, which extracts the extents from the center of mass of the object to its surface. The feature vectors constructed using this method is presented in a frequency domain by applying the spherical harmonics.
For the 3D model-semantic problem, many approaches have been proposed. The work presented in European Network of Excellence AIM@SHAPE [15] has shown the benefits of using semantic indexing based on ontology. The authors introduce knowledge management techniques in modeling the form in order to find 3D objects in terms of knowledge. In the paper [6], author explores an ontology and SWRL-based 3D model retrieval system Onto3D. It can infer 3D models semantic property by rule engine and retrieve the target models by ontology. To add semantics to geometry, Marios in [7] analyzes the 3D shape and can extract and combine knowledge and implicit information coded in the geometry of the digital content object and its sub-parties (volume, surface ...), then it allows the segmentation of 3D shapes based on semantics. The semantic description of an object based on the ontology and matching this description with the low level features such as color, texture, shape and spatial relationships [8] [9] also are used to classify and indexing images. In paper [10], authors incorporate semantics provided by multiple class labels to reduce the size of

feature vector produced by bag-of-features [11] exploiting semantics.
Various studies have also shown interest using shape indexes based indexing. For the shapes characterization and binary digital objects, Thibault [1] [12] presented a study implementing a set of values obtained by calculation of shape indexes. In this study, the author has shown that the use of shape indexes family is a robust and efficient tool in object recognition, and that flexibility and diversity shape indexes allow the creation of shape indexes for each family shapes to be studied. Rectilinearity shape index is proposed by Z.Lian in [13] to describe the extent to which a 3D mesh is rectilinear. This shape index has several desirable properties such as robustness and invariance to similarity transformation. In [14], large shape indexes are described and demonstrated (e.g. Eccentricity, Elongatedness, Circularity, Squareness, Ellipticity, Triangularity, Rectangularity, Rectilinearity, Sigmoidality, Convexity, Symmetry, Chirality). The author notes that selects the most appropriate measures depends on their suitability for particular applications. Corney and al. [27] describe the coarse filter for classifying 3D models. Several shape indexes are computed based on convex hull ratios such bounding-box aspect ratio, hull crumpliness, hull packing, hull compactness, etc.

In this paper, we suggest the implementation of two methods to retrieval a 3D object in database: the geometric method, which uses the measures and 3D shape indexes and Clustering-based Semantic to fill the gap between semantic concepts and low-level features. Motivation for using shape indexes is to extract visual concepts easily, and semantic information can be extracted using unsupervised learning method. These shape indexes, calculated from measures taken from the 3D model, are organized as semantic concepts in an ontology using OWL [19] and questioned by the SPARQL [20] query language to extract similarity between 3D models.

3. System overview

The proposed content-based retrieval system for 3D models consists of two processes: inline that interacts with the user and offline that the system computes descriptors for 3D models (Fig. 1). In both processes, the system extracts the measures of the model, calculating the shape indexes and extract semantic concepts.
The user can navigate in the database and sends a 3D request to the server. The system receives the query model and compares its descriptor with the descriptors of all models of class membership. This phase requires the appropriate distances to signatures, but also strategies to find semantically similar models in visual concepts [22] such as contour-shape, color or texture.

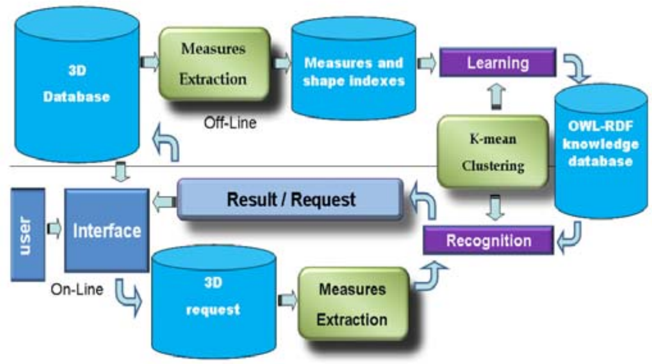

Fig. 1 Overview of the proposed system

Our 3D Database is composed of Princeton Shape Benchmark 3D models [16] that are stored in a format (*.off) which represents the shape of 3D models by polygonal mesh, with the list of vertices V = {v_1, v_2 , ...,v_N } and triangular facets i = { i_1 , i_2 , ..., i_R } defined by points $i_r = (v_{n,1}, v_{n,2}, ..., v_{n,k\,r})$. Where k = 3 for the triangle mesh. Fig. 2 shows some examples of representations.

Fig. 2 various representations of the rabbit

As shown in this figure, there are many ways to represent a model (e.g. Point Set, Polygon Soup, Polygonal Mesh and Solid Model).

4. Measures and shape indexes

Shape is the most important property that allows predicting more facts about an object than color or texture. Shape index is the shape descriptor that is defined as any parameter, coefficient or combination of coefficients for providing quantitative information on the shape. Moreover, shape index must be dimensionless and has invariant to rotation and translation as property. Measure is a numerical value or set of numerical values "measured" on the shape. Shape indexes and measures definitions are detailed in [1]. Shape indexes are computed from the measures of the whole 3D model and have provided global information such as the size and the shape and are chosen for their ratio simplicity/effectiveness. The proposed method approach requires neither initial segmentation step nor the preprocessing.

4.1 Measures

To compute 3D shape indexes, we directly compute 3D measures on the 3D model or transforming 2D measures. The most important 3D measures are surface area and volume. With 3D polygonal model representation, we can compute these measures [5] as follow:

$$area = \frac{1}{2}\sum_{i}^{N}\left|(V_{i,1}-V_{i,0})\times(V_{i,2}-V_{i,0})\right| \quad (1)$$

$$Volume = \frac{1}{6}\sum_{i}^{N}(-V_{i,2}^{x}V_{i,1}^{y}V_{i,0}^{z}+V_{i,1}^{x}V_{i,2}^{y}V_{i,0}^{z}+V_{i,2}^{x}V_{i,0}^{y}V_{i,1}^{z} -V_{i,0}^{x}V_{i,2}^{y}V_{i,1}^{z}-V_{i,1}^{x}V_{i,0}^{y}V_{i,2}^{z}+V_{i,0}^{x}V_{i,1}^{y}V_{i,2}^{z}) \quad (2)$$

V is a vector containing the coordinates of the vertices of the triangle i.

These measures are used directly for calculating 3D shape indexes without transforming 2D measures. For other 3D measures, the 2D measures are used. For example, to calculate the radii, we use the distance between the centroid and a point on the surface area instead of the distance between the centroid and a point on the perimeter. There are other measures, which are dimensionless and shape indexes like a number of holes. In practice, we used the following measures: Volume, Surface area, Ferret diameter, Small and large radii, main axis and plan. In fact, the principal component analysis method is employed and three sets of main axes and planes are obtained. Ferret diameter is the longest distance from two contour points of the 3D object. These measures are used as semantic concepts in ontology and allow to define the spatial relationships. We consider that each measure is the entity.

4.2 Shape indexes

From these basic measures, one can calculate the 3D shape indexes. Surface area (1) and volume (2) may be used as measures for calculating 3D shape indexes like VC (3) and AC (4), which can be considered as the basic descriptors of shape.

$$VC = \frac{V}{V(C_H)} \quad (3)$$

$$AC = \frac{A(C_H)}{A} \quad (4)$$

V and A are respectively the 3D model volume and surface area. C_H is a convex hull that is the minimum enveloping boundary.

AC and VC (called Area convexity index, Crumpliness [27] or Rectangularity and Volume convexity index) are easy to compute and are very robust with respect to noise [1]. Moreover, these shape indexes can distinguish between shapes like angular and rounded objects [23]. Area convexity index and Volume convexity index tell us about the shape of the object, but it is difficult to identify any shape from these 3D shape indexes. Therefore, it is necessary to use a set of 3D shape indexes and combine them to retrieval the 3D model. These 3D shape indexes should be calculated very quickly and interpret the results. Basically, shape index has two types; compactness-based and boundary-based shape indexes.

Various compactness measures are used. For this reason, an early attempt to develop the compactness index is based on the values of perimeter and area. These 2D measures allow calculating the Isoperimetric shape index as follows:

$$\frac{\sqrt{4\pi S}}{P^2} \quad (5)$$

P and S are respectively the perimeter and surface of shape. This 2D shape index, defined between 0 and 1, is based on the surface to the perimeter ratio and reaches the value unity for a disk. We can also calculate the 2D circularity index shape as follows:

$$1-\frac{\sqrt{4\pi S}}{P^2} \quad (6)$$

In 3D models, the perimeter becomes the surface area, and the surface becomes the volume. A ratio between surface area and volume is commonly used in the literature to compute compactness of 3D shapes. With this ratio an IsoSurfacic shape index can be obtained as follows:

$$Is = 6\frac{\sqrt{\pi}V^{1/3}}{A^{1/2}} \quad (7)$$

V and A are respectively the volume and surface area of the 3D model.

IsoSurfacic shape index is a compactness indicator which describes the form based on the surface area-to-volume ratio. Sphericity is another specific shape index for indicating compactness of a shape. It is a measure of how spherical an object is. It can be also calculated from surface area and volume 3D measures (8). The Sphericity (S) is maximum and equal to one for a sphere.

$$S = \frac{\pi^{1/3}(6V)^{2/3}}{A} \quad (8)$$

The Sphericity index shape (S) is very fast in computing. However, it is unsuited as a parameter of elongation. The latter is defined as quality of being elongated. The elongation, in this paper, is the boundary based and can be measured as the ratio of the smallest radius on the greatest radius (9) or ratio major on minor axes called Eccentricity.

$$E = \frac{R_{\min}}{R_{\max}} \quad (9)$$

The ratio of the maximum Ferret diameter and the minimum Ferret diameter is also used as the elongation parameter. We have included two aspect ratios of the bounding box for a 3D model in our system due to the

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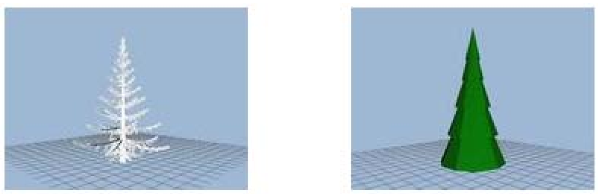
simplicity of computation and its relevance to 3D retrieval: compactness and complexity. Compactness is defined as the non-dimensional ratio of the volume squared over the cube of the surface area [27]. Complexity is defined as the surface area of the convex-hull divided by the volume of the convex-hull. There are several other shape indexes to calculate the elongation or compactness of a shape: (Isosurfacic Deficit, Morton Spread, geodesic Elongation, variance...).
Shape indexes calculated are quick to compute, easy to understand and were chosen mostly for their simplicity and are invariant to rigid motions such as translations and rotations. However, it should be noted that there are some shape indexes that are do not classify objects in the same way.



(a) (b)

Fig. 3 Two models compared with different shape index.

The radius elongation index (9) for example, considers the model (a) in Fig. 3 and (b) similar, since they have almost the same radii, while the Volume convexity shape index (4) considers them different. Therefore, the necessity to combine several shape indexes for computing the most relevance.

5. Clustering-based semantic

Although the shape indexes calculated to provide global information on the 3D model and contain compactness and elongated indicators, the problems connected with 3D model retrieval are not still resolved. The first one regards the 3D shape indexes: they are insufficient to describe the 3D model in a generic 3D database; although these are relevant. Therefore, the necessity to combine several 3D shape indexes to augment our knowledge base with semantic concepts using, in our case, the ontology and spatial relationships. Second problem is caused by the semantic gap between the lower and higher level features. To reduce this 'semantic gap' we use machine learning methods to associate shape indexes with semantic concepts and ontology to define these semantic concepts as shown in fig. 4. In this paper, 3D shape indexes are used to represent visual concepts [22] of a 3D object.

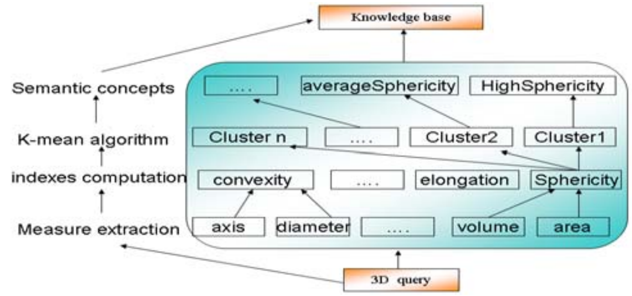


Fig. 4: Definition of semantic concepts and Knowledge base augmented and guided by a 3D Shape index ontology to describe the 3D models.

To be interpreted as visual concepts, a link must be established between computed numerical descriptors and symbolic visual concepts [8]. In our case, measures and shape indexes are clustered by a k-means algorithm into semantic clusters. The notion of similarity is based on each category of 3D shape indexes or measures like in Fig. 4. This approach is divided into the following steps: measure extraction; clustering and definition of semantic concepts. From the 3D Database, the three steps are repeated for each 3D shape index to define semantic concepts. Therefore, 3D model is described by a set of the numerical value associated with semantic concepts. We should create a database describing all models by the semantic concepts guided by a 3D Shape indexes ontology and relations among entities. The ontology defines a database structure as containing of a set of concepts that can describe qualitatively the visual semantic concepts and should allow similarity searches.

6. Ontology

Ontology is a set of concepts and useful relations to describe a domain, and thus makes more explicit the implicit semantics of models. One advantage of shape indexes is its flexibility to create other shape indexes for each model to be indexed in a domain-specific. In this paper, ontology is employed to allow the user to query a generic 3D collection, where no domain-specific knowledge can be employed, using the 3D model as query. The Ontology has been used to organize semantic concepts that are defined by the k-mean algorithm (e.g. Sphericity, elongation, convexity...). It includes other concepts such as semantic entities (e.g. lines, points, surface, and plan), a set of spatial relations and some axioms (transitivity, reflexivity, symmetry). The proposed ontology is represented in Ontology Language OWL [19], is the W3C recommended standard for ontology that precise formal semantics. As shown in Fig. 5, the OWL is structured into two parts: The first part contains shape index concepts and regroups the descriptors into classes according to their characteristic properties: The topological descriptors and geometric descriptors (Fig.6). The second part contains the concepts spatial or entities together in primitive geometric: point, line, surface, Plan…

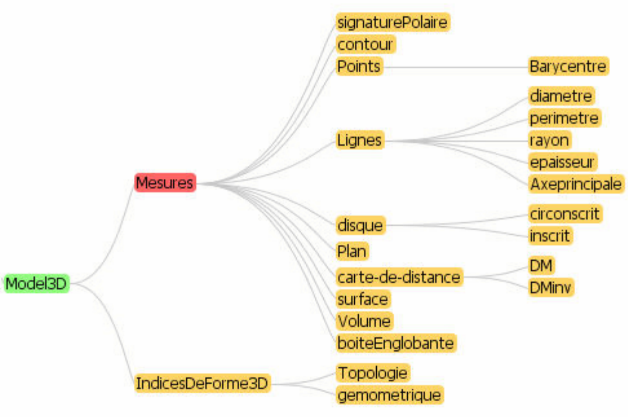


Fig. 5 The structure of our ontology

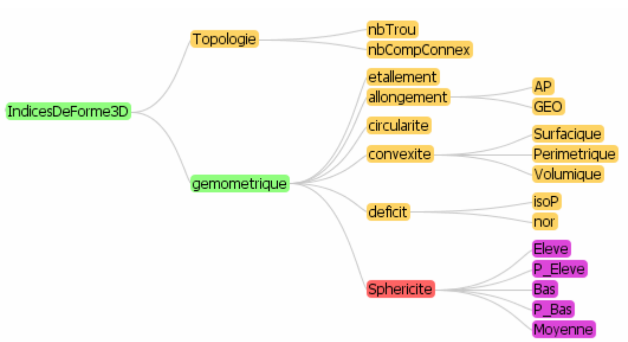


Fig. 6 The partial hierarchy of domain concepts of geometry

The structure of the ontology is represented in OWL as follows:

```
<owl:Class rdf:about="http://www.exemple/ontologie#Mesures">
<rdfs:subClassOf>
<owl:Class
rdf:about="http://www.exemple/ontologie#Modèle3D"/>
</rdfs:subClassOf>
</owl:Class>
<owl:Class
rdf:about="http://www.exemple/ontologie#IndicesDeForme3D">
<rdfs:subClassOf>
<owl:Class
rdf:about="http://www.exemple/ontologie#Modèle3D"/>
</rdfs:subClassOf>
</owl:Class>
<owl:Class rdf:about="http://www.exemple/ontologie#Points">
<rdfs:subClassOf>
<owl:Class rdf:about="http://www.exemple/ontologie#Mesures"/>
</rdfs:subClassOf>
</owl:Class>
<owl:Class rdf:about="http://www.exemple/ontologie#Lignes">
<rdfs:subClassOf>
<owl:Class rdf:about="http://www.exemple/ontologie#Mesures"/>
</rdfs:subClassOf>
</owl:Class>
...
<owl:Restriction>
<owl:maxCardinality
rdf:datatype="http://www.w3.org/2001/XMLSchema#int"
>1</owl:maxCardinality>
<owl:onProperty>
<owl:DatatypeProperty
rdf:about="http://www.exemple/ontologie#haslURL"/>
…
```

Ontology contains the concepts and their relations and facilitates the inference the spatial relation. The implicit rules are defined using OWL properties such as similarity owl: SameAs.

```
<RDF:Description rdf:about="#sphericity">
<owl:sameAs rdf:resource="#circularity "/>
</ Rdf: Description>
```

We can define other explicit rules to infer spatial relationships based on other relationships. For example, the position "leftCenter" has a unique meaning when associated with some information.

7. Spatial relationships

Shape indexes calculated are globally characterized the shape. Without segmenting the model, we calculated the local characteristics using spatial relationships that are usually defined according to the location of the measure in the 3D model. In our method, spatial relationships are defined by measures or entities that can increase the quality of detection and recognition of the model content and can disambiguate among models of similar appearance including for example the meaning of orientation and respect the distances. Therefore, other concepts are added to the 3D shape indexes to describe position, distances and orientation of an entity in the 3D model. There are various entities that need spatial relationships to describe 3D model to represent correctly the 3D models content. In this paper, the following relationships are described (Fig. 7):

- Metric (distance, area...)
- Orientation (near of, left of ...)
- Topology (Inclusion, adjacent ...).

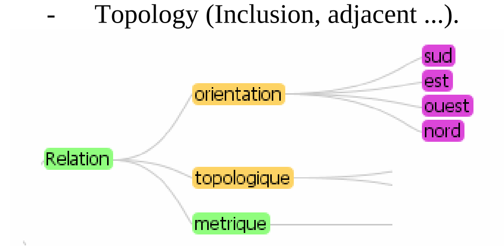


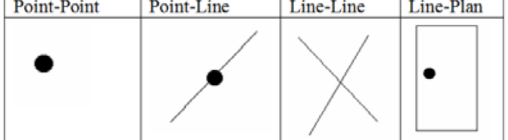
Fig. 7: Partial hierarchy of relationships.

The notion of position, distance and orientation in spatial relations are dependent on the notion of the frame of reference. The object centroid is used as the frame of reference to compute measures and to respect proprieties: Rotation and translation. Then, the method does not require preprocessing for these properties. The bounding box centroid is used as the frame of reference to describe concept of position, distance and orientation. Therefore, to calculate the position "centered", we should calculate the Euclidean distance between the center of the 3D model and bounding box centroid. Entities such as the 3D model centroid, lines (e.g. radii, diameter and axes), plan and its minimum bounding box are used to calculate distances in order to provide spatial information. The distances can be computed from a point to point, line to line, point to line, point to plan and line to plan. In practice, we used the following distances: Distance between radii, Distance between radii and Diameter, Distance between two centers: 3D model centroid and bounding box centroid and A3, D1, D3, D4 introduced in [4].

To describe the distance relationship between two 3D models, the following distances are usually used: very near, near, far, far away. However, such distance relationships single are not sufficient to represent the 3D model content ignoring the topological and directional relationships. To get an idea about the overall direction of the entities in the 3D model, main axes can be used. In fact, the main axes of the 3D model can be calculated, employing the principal component analysis method, and the value of its direction is given by the angle with the axes of the bounding box. The example is the following relationship: RightOf; LeftOf; Above; Below...

We are also interested in topological relationships among entities that are related to how objects interconnect. In this paper, we adopt the topological relationships as shown in table 1. The RCC-8 [24] [25] relations can be used for taking into account spatial relations. RCC (Region Connection Calculus) is a logic-based formalism to symbolically represent and reason with topological properties of objects [14]. Topological reasoning can be implemented based on Pellet engine [21].

Table 1: Topological relations implemented in our system

Point-Point	Point-Line	Line-Line	Line-Plan
			
Overlap	On	Cross	Contained
			
Adjacent	Adjacent	Not Cross	Adjacent

Based on the spatial relationships and their properties, we build the ontology using the web ontology language (OWL).

8. Method for Classification Database

Each model of database, in our content based indexing and retrieval system for 3D models, is represented by two descriptors considered signatures of the 3D model: semantic concept and 3D shape indexes. To increase the identification rate and decrease the time to search for items, we have developed and implemented a classification by applying the k-Means algorithm in the 3D shape index space. K-Means is an efficient classification approach and very easy. Each model of database is clustered by the K-Means algorithm using the Euclidean distance as a similarity measure. Classification based on 3D shape indexes allows a global classification of models and it can detect major differences between shapes. Fig. 8 shows some classes of objects.

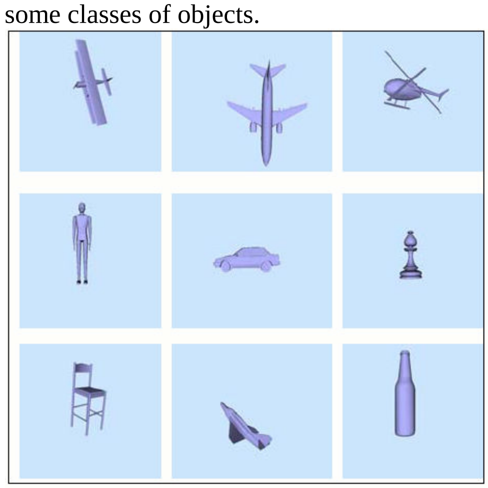


Fig. 8: 3D models of some Clusters

3D models are classified into clusters regardless of their spatial positions and according to the similarity of their 3D shape index.

9. SPARQL engine and similarity

Based on the semantic concepts and the 3D shape indexes introduced, the similar 3D model retrieval will be conducted. To this end, query by concept and numeric value is proposed to evaluate the similarity between two 3D models as has been shown in Fig. 9.

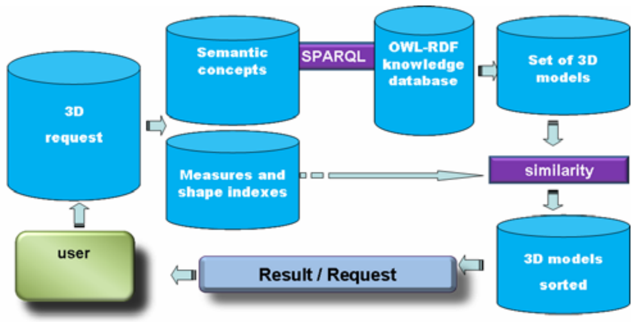


Fig. 9: The evaluation of similarity by semantic and numeric query.

SPARQL, a rich query language for OWL-DL ontology, is used to query the knowledge contained in the OWL ontology for the extraction of implicit and explicit semantics that are included in the model OWL. For example, the query: "Show all 3D Models URLs of a given cluster with a high sphericity and variance" is written in language SPARQL:

```
String jungle=jenaTools.findBasicNameSpace(ONT_MODELE);
String prolog1 = "PREFIX jungle: <"+jungle+">" ;
String qr=prolog1 + NL+"select* where " +
"{" +
"?3Dmodel jungle:hasCluster ?hasCluster FILTER (?hasCluster = "+Cluster+") ." +
"?3Dmodel jungle:hasSpherecity '"+sphericity+"' ." +
"?3Dmodel jungle:hasVarianceSurfacique '"+variance+"' ." +
"?3Dmodel jungle:hasURL ?hasURL " +
" }";
```

SPARQL admits the use of numeric values to compute the similarity on the retrieved models that are semantically similar. The query can be easily adapted to obtain the distance between any pair of 3D models. Therefore, the similarity between two models is measured through the use of distance between their 3D shape indexes. To define the distance between two points, different metrics could be implemented. The most famous and used metric is the Euclidean distance or as it is called "Manhattan" which is just a special case of Minkowski measure:

$$L_p = \left\{ \sum_{i=1}^{n} |Z_i - x_i|^p \right\}^{1/p} \qquad (10)$$

Depending on the parameter p: if p = 1 the distance is "city block" or Manhattan and when p = 2 is Euclidean distance.

In our system, the Euclidean distance is used to measure the similarity between 3D shape indexes. But, the latter does not have the same importance in the recognition process. Therefore, to provide the best results, it is necessary to combine several 3D shape indexes to compute the most relevant ones. A simple approach for the combination of these 3D shape indexes is to calculate the weighted sum of the distances. The following formula which is used to determine the degree of similarity S between two 3D models has been implemented to calculate the distances:

$$S = \sum_{i=1}^{n} W_i L_p(SI)_i , \sum_{i=1}^{n} W_i = 1 \qquad (11)$$

Where Wi >0 (i = 1, 2 … n), are the weights of 3D shape index (SI)i and n number of shape indexes.

Weights are calculated and normalized during learning by k-mean algorithm using precision, recall and F-measure that allow the comparison of the performances of 3D shape indexes. Therefore, for each 3D shape index, we compute the average recall *(aR)* and precision *(aP)* on the entire 3D shape index:

$$aR = \sum_{i=1}^{n} \frac{r(SI)}{n(SI)}, aP \sum_{i=1}^{n} \frac{r(SI)}{r(SI) + w(SI)} \qquad (12)$$

"n(SI)" is the number of models labeled by SI. "r(SI)" is the number of models initially labeled by SI and the system which has returned with the same SI. "w(IF)" number of the unlabeled model by the SI and found by the system with the same SI. F-measure F is the weighted harmonic mean of precision and recall. The formula of F-measure is as follows:

$$F = 2\frac{aRaP}{aR + aP} \qquad (13)$$

When using average recall (*aR*) and precision (*aP*), it is important to specify the number of shape indexes for the finding of at least one model.

10. Experimental Results

Java language has been used to develop our content-based retrieval systems for 3D models. The tests are performed on the Princeton Shape Benchmark Database which contains 1814 objects that are given by triangular meshes and classified by semantic aspect. The concepts of ontology have been created by learning phase whose development has been realized with OWL and the Java programming tool (Jena). The library Jena contains inference engine customizable and offers the possibility of including an external reasoner. The display of the ontology is done with the API (Application Programming Interface) OWL2Prefuse.

Our programs are compiled under the windows platform, using 1.4 GHz, Core 2 Duo machine with 1 GB memory. The average time used to compute all shape indexes is 0.6 seconds for a model, using the Princeton Shape Benchmark Database.

As has been shown in Fig. 1, in the online process, the user submits a query model selected from the 3D collection. During this process, shape indexes are computed, and we can directly retrieve models as will be shown in Fig. 11 (a) and Fig. 12 (c) using our descriptor or Area Volume Ratio Descriptor [5] that is not efficient.

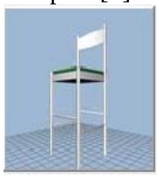
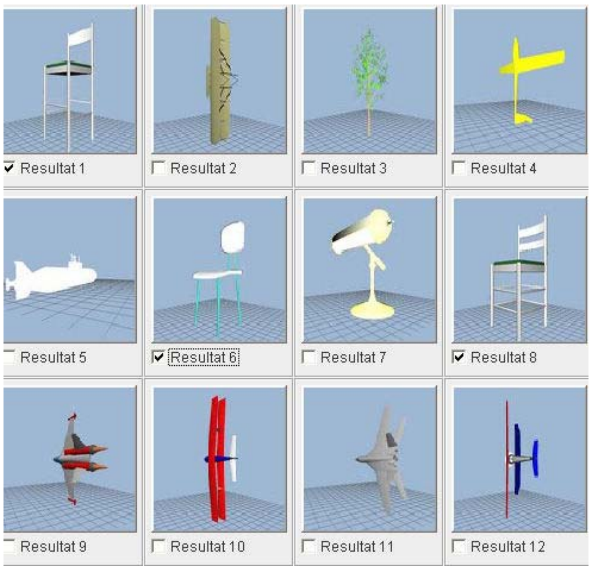
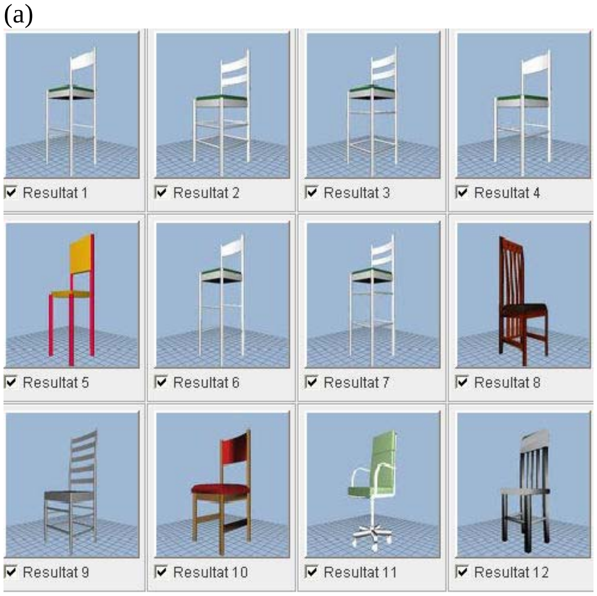


Fig. 10: query model



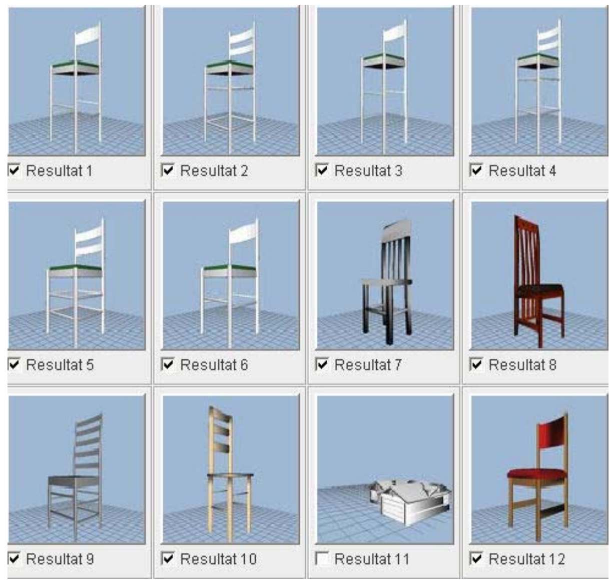
(a)



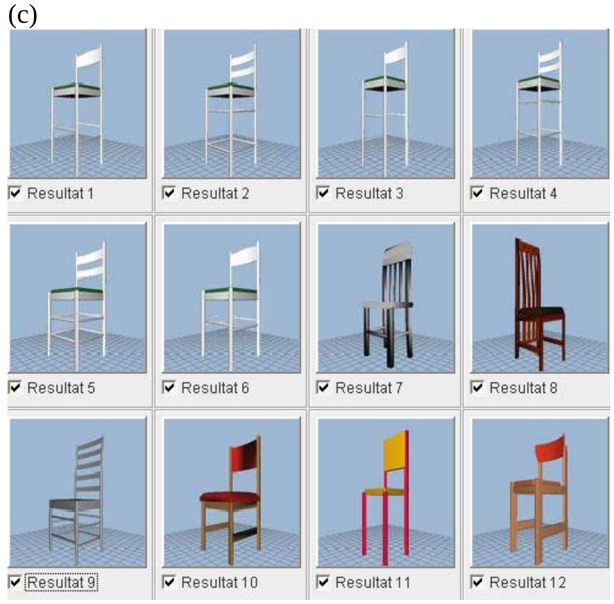
(b)

Fig. 11: (a) Models found by Area Volume Ratio descriptor without introducing the semantic descriptor. (b): Models found with Area Volume Ratio descriptor introducing our semantic descriptor.

In order to retrieve 3D models by introducing the semantic descriptor Fig. 11 (b) and Fig. 12 (d), the query is labeled before the search happens with a semantic concept by associating 3D shape low-level features with high-level semantic of the models.
The 12 most similar models are extracting and returning to user by 2D images. To visualize the 3D models in the 3D space, the user clicks the button or image.



(c)



(d)

Fig. 12: (c) Models found with our descriptor without introducing semantic descriptors. (d) Models found with our descriptor introducing the semantic descriptor.

For the evaluation of the performance of our system based on shape indexes and semantic concepts descriptors, we used also the Recall and Precision. In this sense, we have compared our descriptor to the descriptor based on the volume area ratio proposed by Vranic and al. [5] that is implemented in our system. The volume area ratio is incorporated in our system as a shape index, and according to the evaluation the relevance, it is insufficient alone to characterize a 3D model and is not a performing descriptor, but it is used here to evaluate the performance implemented semantic and ontology.

Two methods are used for each descriptor: content-based and semantic-based retrieval. Fig. 13 shows the Precision-Recall diagram for each one of the two methods.

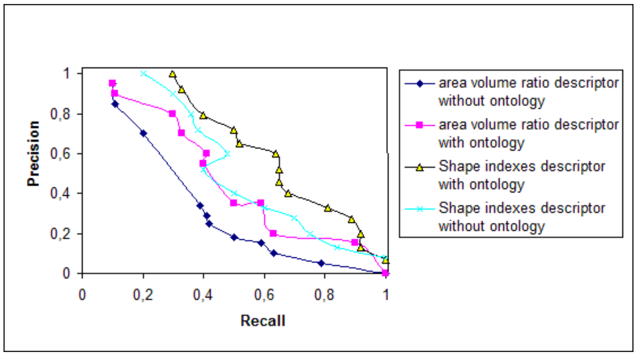


Fig. 13: The precision-recall curves of 3D model retrieval with and without ontology using different descriptors.

Fig. 13 shows that our proposed semantic descriptor performs well, and the descriptor Area Volume Ratio with ontology is compared to our descriptor without ontology justifies the use of ontology and semantic based retrieval as a most efficient method.

The developed classification based on shape indexes reduces the similarity gap, and the retrieval method by introducing the semantic descriptor is considered as more efficient than the one based solely on the shape indexes or Area Volume Ratio. This performance is linked to the combination of shape indexes and semantic concepts structured in ontology.

11. Conclusion

A new method for 3D models retrieval has been introduced in this article. The method combines semantic concepts and 3D shape indexes which are structured in ontology. The new approach is tested with a large 3D database using the developed search engine, which allows us to show the relevance of our method. The results are promising and show the interest of our approach.

To complete our work, it is interesting to improve our system by another method of robust classification based on semantics. For the very soon future, the shape index will be enriched with textures and color indexes.

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