New 3D Shape Descriptor Extraction using CatBoost Classifier for Accurate 3D Model Retrieval

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***Abstract*—Given the wide application of 3D model analysis, covering domains such as medicine, engineering, and virtual reality, the demand for innovative content-based 3D shape retrieval systems capable of handling complex 3D data efficiently have significantly increased. This paper proposes a new 3D shape retrieval method that uses the CatBoost classifier, a machine learning algorithm, to capture a unique descriptor for each 3D mesh. The main idea of our method is to get a specific and a unique signature or descriptor for each 3D model by training the CatBoost classifier with features obtained directly from the 3D models. This idea not only accelerates the training process, but also ensures the consistency and relevance of the data fed to the classifier during the training process. Once fully trained, the classifier generates a descriptor that is used during the indexing and retrieval process. The efficiency of our method is demonstrated by conducting extensive experiments on the Princeton shape benchmark database. The results demonstrate high retrieval accuracy in comparison to various existing methods in the literature. Our method's ability to outperform these methods shows its potential as highly useful tool in the field of content-based 3D shape retrieval.**

Keywords*—3D object retrieval; 3D shape retrieval; 3D shape matching; indexing; descriptor; CatBoost

I. Introduction

The creation and propagation of 3D models in the digital data processing field is one of the great achievements of information processing in the last decades, resembling earlier revolutions in text, image, or audio data. This expansion is largely powered by improvements in scanning and modelling technologies that have made these models more available and flexible in fields such as medicine, engineering, virtual reality, and computer-aided design among others. Consequently, 3D objects are widespread, not only in special professional domains, but also in everyday use since user-friendly modelling tools and the lower cost of 3D scanners or 3D printers are available. However, this proliferation brings forth a complex challenge: the fast and precise retrieval and analysis of 3D information. Unlike text or 2D image search, which are mature enough, 3D object retrieval is still at the development stages, facing the complexities of processing and understanding the rich information stored in 3D models.

An efficient 3D retrieval system can be defined as an active query system that can reliably match user queries with similar models in a database. This similarity is computed based on a descriptor or a signature which is supposed to be a compact representation of the 3D model. Numerous approaches and strategies have been developed in recent years to address this issue, which generally implies the extraction of global or local geometric or topological features, either directly from the 3D object or its two-dimensional representations (projections, depth images, binary images). Once these features are obtained, they are transformed into a more compact form—a descriptor—which then acts as the main means of differentiating 3D models and may be used to determine the most similar models to a specific one.

Although many advances have been made in this area, as can be seen through the work of Lara López et al. [1], Yang et al. [2], and Tangelder et al. [3] , who have extensively surveyed existing methods, offering insights into their performance and comparative analyses. However, the search for more accurate and human perception-oriented retrieval systems remains ongoing. Recently, attention has been directed toward employing various machine learning techniques to enhance the quality and efficiency of such systems. Most of these approaches rely on using features derived from 2D projections for their training process.

For example, studies such as [4], [5], and [6] uses a convolutional neural network (CNN) trained on numerous 2D captures extracted from the 3D model. The CNN's objective is to classify the 3D model into its correct group. Finally, with CNN has been adequately trained, the author extracts a signature from the CNN which, in turn, corresponds to a descriptor of each 3D model. Generally, this kind of technique is highly effective and yield amazing results because machine learning methods are commonly competent enough to tackle classification problems with great accuracy. Meanwhile, the main issue of this method is the necessity for large-scale data for the training step. Each 3D model must be represented by numerous 2D captures, which leads to two main issues: choosing the most representative 2D representations for each 3D model and the requirement for high-level computational resources to accomplish the process. Previous work [7] attempted to address this issue by employing an artificial neural network (ANN) trained on features extracted directly from the 3D model. This neural network was employed next for signatures extraction for 3D models.

In this work, this challenge is addressed by proposing a new method for 3D shape retrieval which is based on extracting a signature or a descriptor for 3D meshes using the CatBoost classifier. The extracted descriptor is then utilized in the search and retrieval process of 3D models. The key contributions of this study can be summarized as follows:

- Novel 3D Model Indexing Method: This study proposes a new method for indexing 3D models using the CatBoost classifier, which offers improved efficiency and performance compared to traditional techniques.
- Optimal Representation of 3D Models: The method represents 3D models using histograms of geometric properties, including dihedral angles, shape diameter functions, and shape index. This approach avoids the need for complex preprocessing steps commonly used in machine learning-based methods.
- Efficient and Rapid Performance: The proposed method demonstrates rapid performance and efficiency, requiring reduced data for training compared to traditional techniques.

This paper is structured as follows: Section II presents a review of various descriptors from existing literature. Section III details the proposed approach. Section IV outlines the results followed by a discussion in Section V. Finally, the conclusion in Section VI summarizes the findings and suggests potential future research directions.

II. Related Work

For last couple of decades, the area of Content-based 3D model retrieval has attracted the attention of many researchers, which has also led to the development of lots of new techniques and approaches, aims to produce a result that closely aligned with human perception. Through these research studies it has been proven that the best solution to the content-based 3D model retrieval would be to have a compart descriptor that will represent the form of a 3D model (unlike traditional techniques such as textual representation). Proposed descriptors can be classifying into two main classes: view-based descriptors and 3D shape descriptors. The following section will present some of the most common methods within each category.

A. 3D Shape Descriptors

This category covers all the methods that use geometry/topological information extracted directly from any 3D representation (points cloud, polygon, voxel). For instance, Osada et al. [8] who suggested five different shape distributions for indexing 3D objects, based on the global geometric. They introduced characteristics such as lengths from the center of gravity to a surface point (D1), the distance between two points (D2), the angles between three points (A3), the square root of the area of the triangle formed by three points (D3) and the cube root of the volume of the tetrahedron formed by four points (D4). After comparing the performance of the different distributions, the authors conclude that the D2 distribution performs best and gives better results. The D2 distribution consists of a histogram representing the shape signature of a 3D model by the distribution of Euclidean distances between pairs of points chosen randomly on the surface of the model.

The 3D shape spectrum descriptor (SSD) was introduced by Zaharia et al. [9] and has been recognized as a standardized descriptor in the MPEG-7 standard. The descriptor is based on the notion of shape index presented by Koenderink, the descriptor is computed as the histogram of shape index over the whole surface of the 3D mesh. Let P be a point on the surface of the 3D model, k_p^1 and k_p^2 are the principal curvatures, with $k_p^1 > k_p^2$, the shape index can be computed using the following formula:

$$IF_P = \frac{1}{2} - \frac{1}{\pi} \arctan \frac{k_p^1 + k_p^2}{k_p^1 - k_p^2} \qquad (1)$$

The use of spherical harmonics as a descriptor for 3D objects was initiated by Funkhouser and Kazhdan [10], [11], [12] this technique consists of decomposing a spherical function into a sum of its harmonic coefficients, this descriptor has been defined for voxelised objects.

Our previous work [13] aimed to develop a novel descriptor capable of integrating multiple 3D features, rather than relying on a single feature. The Data Envelopment Analysis method (DEA) was employed to achieve this goal. This method was used to combine various features, the chosen features are the shape diameter function (SDF) [14] dihedral angle, and the shape index. The output is a new descriptor provided by DEA, which outperforms each of the individual features used separately.

A novel descriptor for 3D models using an artificial neural network (ANN) was proposed in study [7]. The proposed approach employs a neural network trained with many features extracted from the 3D model for a classification task. After training, the ANN is used to generate a descriptor for each 3D model in the database. This is achieved by extracting and combining the values returned by the neuron in the last hidden layer.

B. View-based Descriptors

The second category of descriptors is based on a simple principle: two 3D models are considered similar if they appear identical from all viewing angles. The main idea of this approach is to convert the problem from comparing 3D models to comparing 2D projections, by representing each 3D models by many 2D projections. This approach has the advantage of using powerful descriptors that are already available in the 2D field. The main drawback of these approaches lies in selecting the amount and the representative 2D views, since this choice can significantly impact the final results. Furthermore, it can also affect the performance of the descriptor; more projections mean more comparisons, which in turn impacts the computing time.

Papadakis et al. [15] have proposed a novel indexing method based on panoramic views. These projections are generated by englobing the object in a cylinder and then projecting the 3D object onto the lateral surface of the cylinder parallel to one of its three main axes (generally Z) to generate panoramic views. Once these views have been extracted, the authors propose to use a combination of a Fourier transform and a discrete wavelet transform to describe each view.

LightField Descriptor, proposed by [16], [17] is a descriptor based on the 2D projections of a three-dimensional model. It characterizes a 3D model by a set of 10 orthographic views; the views are taken along the first 10 vertices of a dodecahedron centered on the model. A translational alignment process and scaling are applied as pre-processing to the 3D models before the views are generated. Finally, once the views have been generated, the authors propose the use of a descriptor combining 35 Zernike moments and 10 Fourier coefficients to describe the views.

Su et al. [5] proposed to use the power of machine learning to implement a 3D indexing method. They proposed a new approach based on 2D projections and convolutional neural networks, to classify 3D models into distinctive classes and then generate a signature based on this classification.

A more recent work, Labrada et al. [6] proposed a novel deep learning architecture for processing three-dimensional models that are based on representing 3D models with a set of image views. This architecture makes use of Convolutional Neural Networks (CNNs) and autoencoders to get embeddings for 3D models, instead of the regular view pooling layer approach.

III. Proposed Work

Most indexing work in the literature is based on extracting a feature from a 3D model and using this feature in the form of a descriptor, or by utilizing 2D representations and then using indexing methods already available for the 2D field. In this work, the aim is to propose a novel indexing method based on the CatBoost classifier which uses properties extracted directly from the 3D object, without relying on intermediate representations (2D projection), Fig. 1 summarize this process. Our goal is to make our method as optimal as possible (in terms of response time and quality of results). The proposed method consists of creating a model capable of solving a 3D model classification problem, i.e. after the training phase our model must be capable of providing the appropriate class for each 3D object supplied. Finally, a unique descriptor is extracted by combining the values produced by the decision trees within the model, particularly during the concluding iterations of the classification process. This descriptor will then be used to represent the 3D object in the indexing and content retrieving process. The remainder of this section provides a brief overview of the CatBoost Classifier and presents the used features.

A. CatBoost Classifier

CatBoost, is an innovative gradient boosting decision tree (GBDT) algorithm, was introduced by Yandex in 2017 and further elaborated in following publications by Dorogush et al. [18], and Prokhorenkova et al. [19]. This advanced machine learning model addresses critical limitations of previous algorithms, particularly in handling categorical data and avoiding model overfitting. CatBoost stands out due to its balanced tree construction approach, a feature that enhances its overall efficiency and accuracy in various predictive modeling scenarios.

The theoretical foundation of CatBoost is based on the well-known integrated learning also called ensemble learning, which combines multiple weak classifiers to form a stronger, more accurate classifier through iterative processes, where each iteration is based on the previous one to correct the prediction. This approach was introduced by Kearns et al. in 1989, and was used by various algorithms such as Adaboost, and Light GBM [20]. CatBoost advances these methods by refining the iteration and gradient descent mechanisms, enabling the generation of superior classifiers through the effective fusion of weaker ones.

One of the core features that gives CatBoost a considerable advantage over other supervised algorithms is the way it processes categorical variables, which is generally a problem in many machine learning models. Unlike traditional techniques that involve many preprocessing steps before starting the model training to treat categorical variables, CatBoost was developed especially for quickly converting categorical data to numerical format during training, which speeds and simplifies the modeling process. Such ability does not only save preprocessing time but also it significantly increases model performance through working with categorical data without the need of adding more pre-treatment steps. Furthermore, CatBoost incorporates unique strategies to reduce overfitting, a common pitfall in many gradient boosting models. This is done by using a symmetric tree structure and refined leaf-value calculation method which make the model more robust and generalizable.

When it comes to the computational speed and accuracy, CatBoost shows great efficiency. It uses parallelism which not only enable faster training, but also make it a preferable choice for large-scale and time-sensitive applications [21], [22], [23], [24], [25], [26], [27], [28]. This efficiency stands out particularly when it comes to adopting a model where the fast response time is imperative.

To sum up, CatBoost stands out as one of the most powerful and practical gradient boosting algorithms, presenting advantages like dealing with categorical data, avoiding overfitting, and delivering high computational performance. All these advantages, makes it a preferred choice for various machine learning applications, and this is what influenced our choice for CatBoost in this work.

B. Features

This work aims to develop an indexing method capable of integrating multiple geometric and/or topological properties, regardless of their specific type or order.

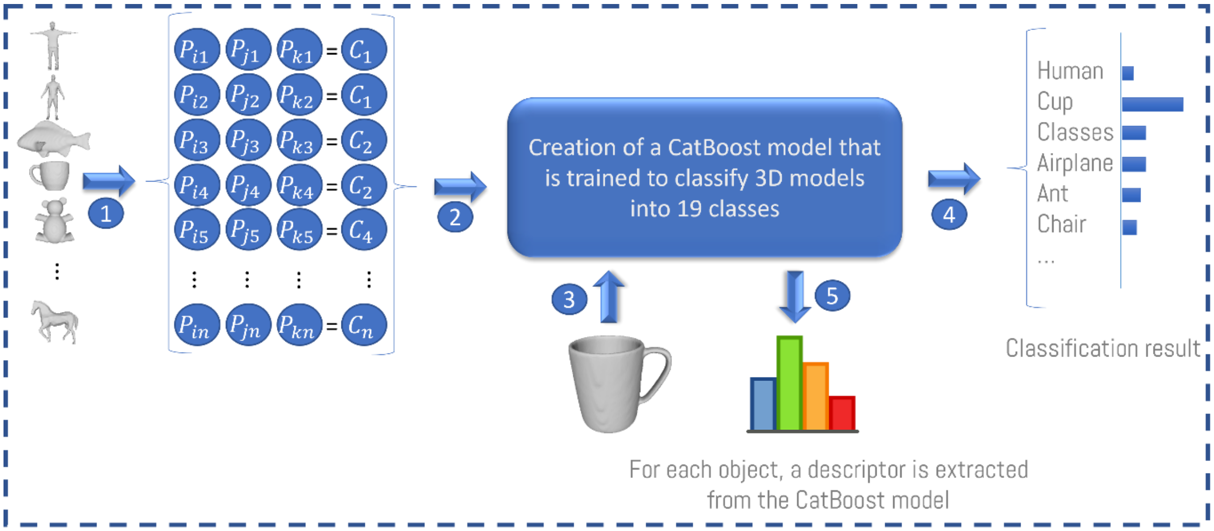

Fig. 1. Process of the proposed method.

The aim is to create a hybrid descriptor that combines these properties and benefits from their advantages. To achieve this goal, three histograms of properties extracted from the 3D object were combined. These properties include:

Dihedral angle: The dihedral angle is one of the best-known features that is widely used in 3D [29], it is defined as the angle between two adjacent faces.

The dihedral angle between two faces f_i and f_j is calculated as follows:

$$\theta(f_i, f_j) = \arccos\left(\frac{dot(\vec{u},\vec{v})}{|\vec{u}| \times |\vec{v}|}\right) \tag{2}$$

$\vec{u}$ and $\vec{v}$ are respectively the normal vector of face f_i and f_j. $|\vec{u}|$ represents the norm of vector $\vec{u}$. Finally, each face is assigned the average angle between the current face and all adjacent faces.

Shape Diameter Function SDF [14] is described as a scalar function defined on the mesh representing its volume or thickness. It computes a measure of the volume of the neighborhood at each vertex of the 3D mesh. The computation of SDF involves directing a cone from each point towards the interior of the 3D mesh and subsequently projecting multiple rays to the opposite side of the mesh. The total length of all rays is then aggregated.

Shape index: First proposed by Koenderink, the shape index is a value which correspond to the topology of the local surface using the main curvatures. It is calculated as follow:

$$s = \frac{2}{\Pi}\arctan\left(\frac{k_2 + k_1}{k_2 - k_1}\right) \tag{3}$$

With k_1 and k_2 representing the main curvatures ($k_2 \geq k_1$). Note that this index is not defined for flat areas ($k_2 = k_1$). This index is widely used in segmentation and has already been used in the indexation of 3D meshes [9].

These properties were chosen for their simplicity (being easy to calculate), their invariance to the various transformations that a 3D model can undergo, and for their discriminating power. All these measures have already been used, (independently) as descriptors for 3D models.

IV. Experimental Results

The fourth section of this paper focuses on experimental studies. These studies include tests to validate and demonstrate the discriminative power of the proposed approach. Results are compared to well-established methods, including Panorama [15], LightField [17], and previous methods proposed by the authors based on DEA [13] and ANN [7]. For these experiments, our choice went to use the Princeton's benchmark database [30]. This database contains 390 3D models divided into 19 classes (Airplane, Table, Human, Cup, Glasses, Ant, Chair, Octopus, Teddy, Hand, Plier, Fish, Bird, Armadillo, Bust, Mech, Bearing, Vase, and Fourleg). Our choice is motivated by the diversity of the models and the fact that many models from different classes share similar geometric aspects even if they are semantically not similar, for instance, birds and airplanes, or humans and armadillos, which will present a challenging task for detection in the retrieval process.

The evaluation begins with a classic test, computing the precision and recall graph. The recall metric quantifies the proportion of relevant results retrieved from the total number of relevant items in the database, while the precision metric assesses the fraction of relevant results within the set of retrieved instances.

$$\text{Recall} = \frac{\text{relevant correctly retrieved}}{\text{all relevant}} \tag{4}$$

$$\text{Precision} = \frac{\text{relevant correctly retrieved}}{\text{all retrieved}} \tag{5}$$

Fig. 2, illustrating recall and precision, demonstrates that the proposed method, based on the CatBoost classifier, outperforms other methods by providing the best results.

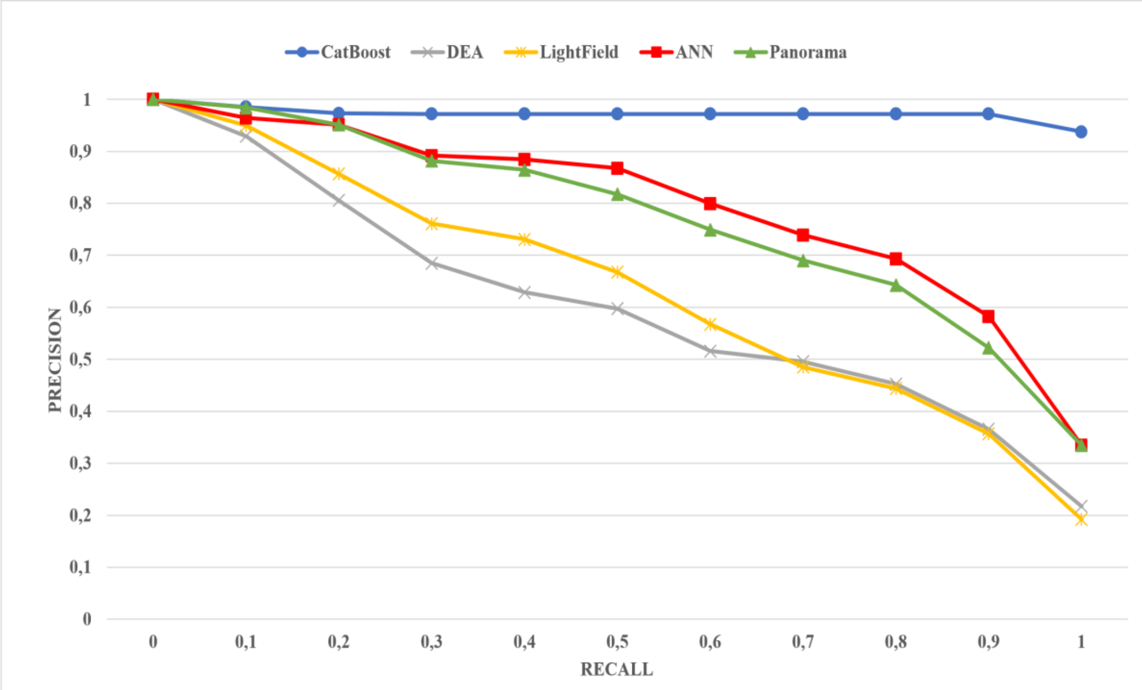

Fig. 2. Precision-Recall graph comparing four different descriptors with the proposed method.

Followed by the ANN, Panorama descriptor, LightField and finally the descriptor based on the DEA.

A second test involves evaluating the method using several metrics, which are:

- Nearest Neighbor (NN): This metric corresponds to the percentage to which the first model found (the most similar to the query) belongs to the query class. This statistic gives an indication of how well a nearest neighbour classifier would perform. Obviously, an ideal score is 100%; high scores are considered good results.
- First Tier (FT) & Second Tier (ST): computes the recall for the top C−1 and 2*(C−1) successfully retrieved objects from the results, where C represents the number of items in each class.
- Discounted Cumulative Gain (DCG): This is a statistical measure which consists of aggregating the contributions of all the models in the database, with weights depending on the rank of the models returned. The contribution of the kth model returned, noted G_k, is equal to 0 if this model does not belong to the query class, and is equal to $\frac{1}{\log_2(k)}$ in the opposite case.
- F-Measure: The F-Measure, also known as the F-Score or F1 Score, is a statistical measure that computes the balance between precision and recall, which are both critical factors in the evaluation of retrieval methods. The F-Measure is the harmonic mean of precision and recall and is defined as follows:

$$\text{F-Measure} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

Table I presents the obtained results alongside those of the following methods: PANORAMA, LightField, ANN and DEA. The results are consistent with those obtained from our first test; Observation shows that the proposed method consistently achieves the highest values across all metrics. ANN and PANORAMA follow, both demonstrating good performance. Conversely, LightField and DEA exhibit comparatively lower scores across all metrics.

The upcoming test will evaluate our method's efficacy across different classes within the used database. Performance evaluation will be conducted by measuring the proposed method's effectiveness based on the top K returned results. The mean for each category will be computed, with K set to both 10 and 20 (given that each category contains 20 items). Fig. 3 and Fig. 4 display the obtained results. From the first figure (K = 10), it is evident that the proposed method exhibits a stable performance across all categories, with scores ranging from 0.8 to 1. The ANN and Panorama method also shows commendable performance across most classes. However, it does experience significant drops in categories such as octopus, vase, bird, and hand. Both LightField and DEA exhibit a greater variability in their results, with LightField generally outperforming DEA. In the second figure (K = 20), the proposed method maintains excellent performance across all classes. This level of consistency is not observed in the other methods, which demonstrate greater variability between classes.

TABLE I. PERFORMANCE COMPARISON USING THE PROPOSED APPROACH, PANORAMA, LIGHTFIELD, ANN AND DEA

DESCRIPTORS / METRICS	NN	NN+1	1st Tier	2nd Tier	DCG	F-Measure
CatBoost	**0.98**	**0.97**	**0.96**	**0.52**	**0.98**	**0.45**
Panorama	0.97	0.92	0.73	0.43	0.92	0.42
LightField	0.91	0.84	0.57	0.36	0.86	0.38
DEA	0.83	0.74	0.53	0.35	0.82	0.36
ANN	0.95	0.93	0.80	0.45	0.86	0.38

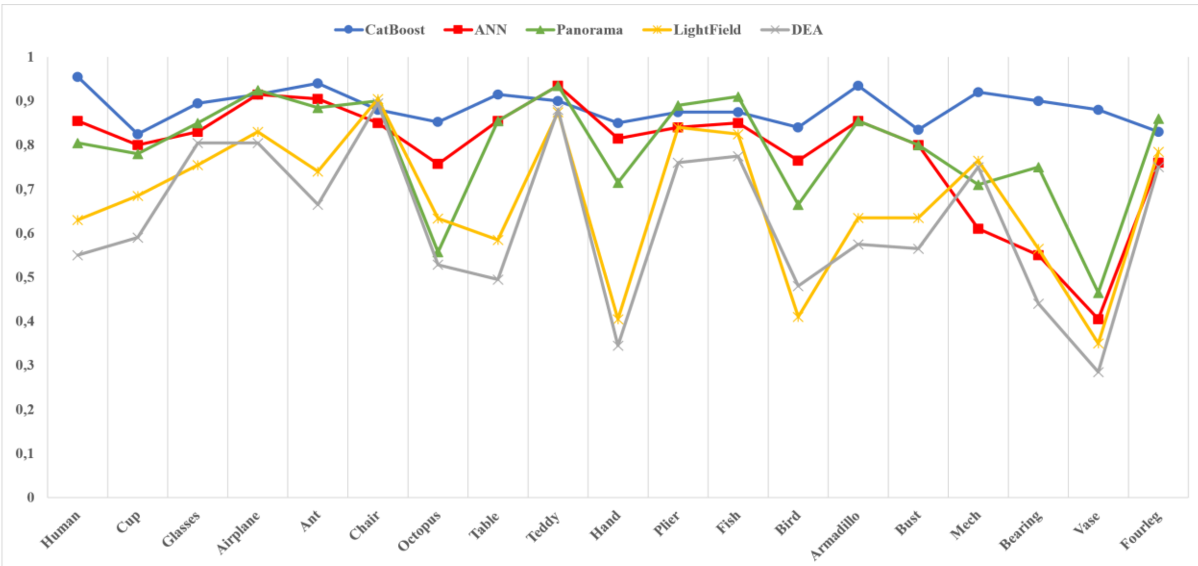

Fig. 3. The results for the top K returned results with K = 10.

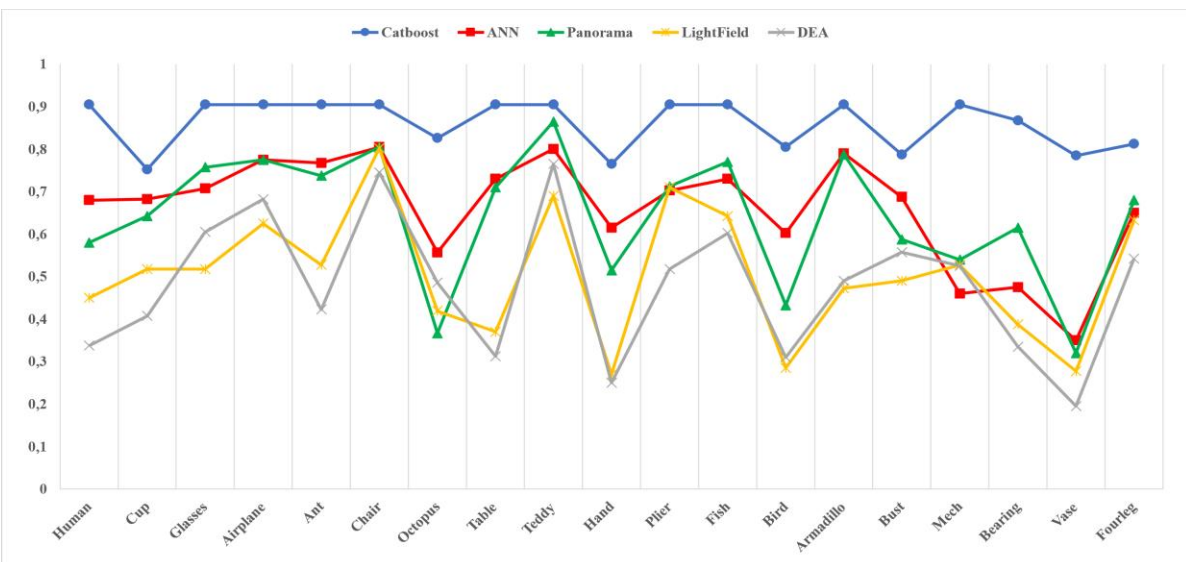

Fig. 4. The results for the top K returned results with K = 20.

The aim of the final test is to provide an overall view of the performance of our methods over the entire database. A dissimilarity matrix is generated by calculating the dissimilarity between all possible pairs of 3D objects within the database. The matrix generated is a square, symmetrical matrix and can be divided into 19x19 blocks (for 19 classes). A robust indexing method should have a low dissimilarity score in the diagonal blocks, which implies high similarity between objects of the same class and high dissimilarity between objects of different classes. Fig. 5 show the results obtained for each method. From these results it can be seen that our proposed method provided the best results with a low dissimilarity score for the diagonal blocks (between 0 and 0.2), and rather high scores elsewhere (between 0.75 and 1). A comparison with other methods reveals that the proposed method uniquely maintains a low dissimilarity between similar objects (within the same class) and a high dissimilarity between dissimilar objects (different classes). This distinction is evident in the dissimilarity matrix, where the proposed method is the only one exhibiting a clearly visible diagonal.

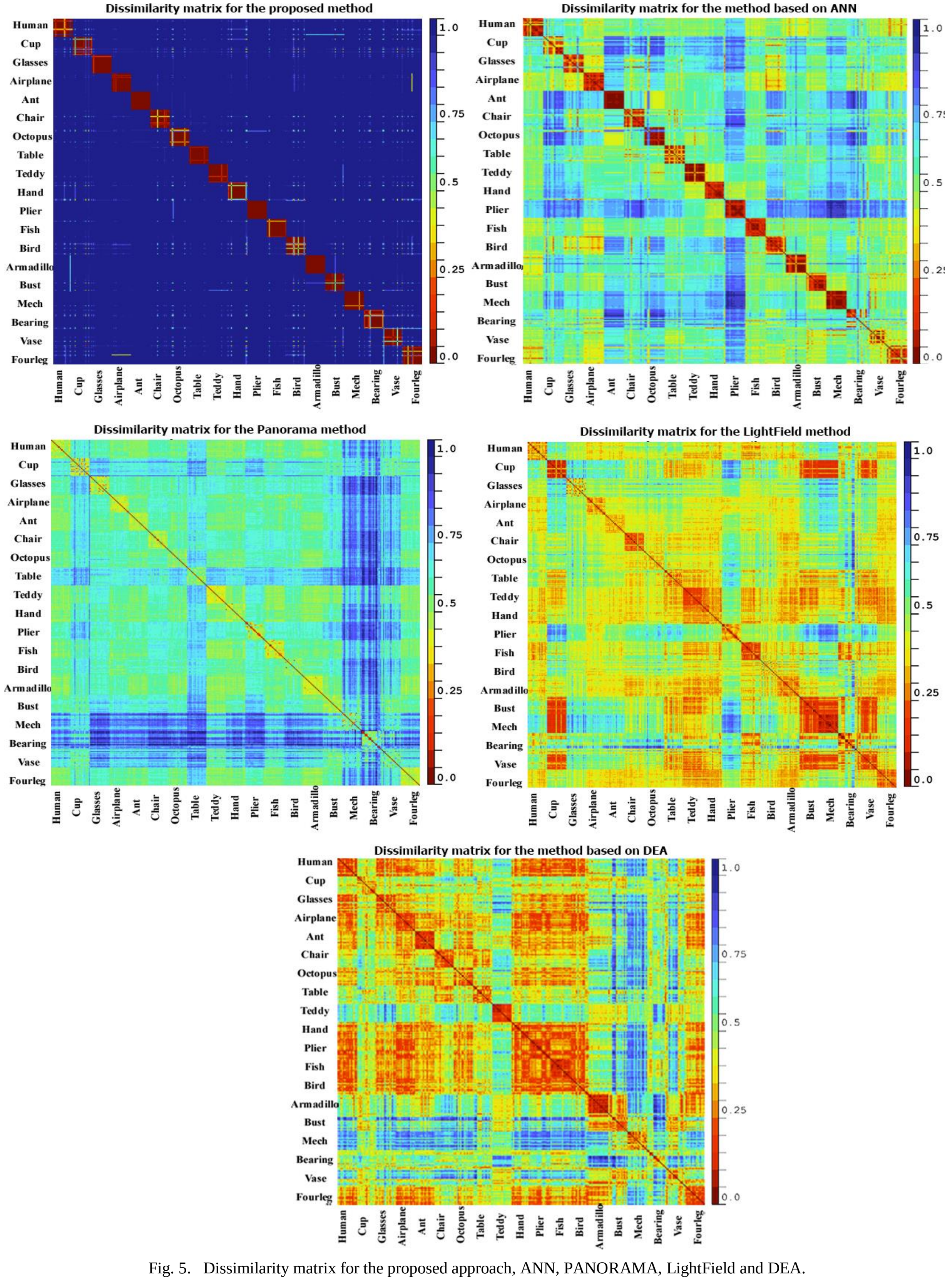

Fig. 5. Dissimilarity matrix for the proposed approach, ANN, PANORAMA, LightField and DEA.

V. Discussion

The experimental analyses illustrated in this paper show that our method, enhances the precision of 3D shape retrieval remarkably. In comparison to other well-established approaches such as Panorama, LightField, ANN, DEA our method consistently outperforms across multiple evaluation metrics.

The obtained results are in line with existing research demonstrating the potential of machine learning algorithms for 3D shape retrieval. While methods like as [4], [5], and [6] employ CNNs trained on 2D projections, our approach uses CatBoost with features extracted directly from 3D models. This avoids the need for extensive 2D representations and associated computational expenses. Analysis of the previous tests reveals the following main strengths of the proposed method:

- High Retrieval Accuracy: The use of the proposed method results in a better performance in various measures such as the NN, FT, ST, DCG, and F-measure which indicates better retrieval performance compared to existing methods.
- Stable Performance across Classes: The method maintains consistent classification accuracy across each of the classes present in the Princeton shape benchmark database, suggesting its application to a variety of other 3D databases.
- Robust Dissimilarity Matrix: The dissimilarity matrix analysis showcases the proposed method's ability to effectively differentiate between similar and dissimilar objects, highlighting its discriminative power in distinguishing between objects belonging to the same/different classes.
- Efficiency and Simplicity: The proposed method avoids complex preprocessing steps and uses features extracted directly from the 3D models, leading to a simplified and efficient approach compared to methods relying on 2D projections.

In conclusion this paper presents a novel and effective approach for 3D shape retrieval using the CatBoost classifier. The proposed method offers high retrieval accuracy, stable performance across different classes, and a robust dissimilarity matrix analysis, highlighting its potential for practical applications.

VI. Conclusion

This paper proposes a novel 3D shape retrieval method, using the CatBoost classifier to construct a unique and efficient descriptor for 3D models. Contrary to traditional methods that require huge data and powerful computational resources, our approach eliminates such needs by extracting features directly from the 3D objects and not using 2D projections. The ability and power of our method have been proven to be much stronger and better than others, based on the experiments conducted on the Princeton shape benchmark dataset.

The proposed method, has shown better results than the other methods in retrieval accuracy, as is clear from the high scores in different scalar metrics. In addition, our approach demonstrated that it can retain stable and high performance in various classes, as shown by results retrieved on top K returned results. Its discriminative power was reflected in its consistent accuracy for all classes. The final test, which was based on the dissimilarity matrix, revealed that the proposed method is robust in identifying similar and dissimilar objects. This validates the efficiency of our method as an efficient means of 3D shape retrieval, meeting the requirements for fast and exact 3D data analysis.

Future work will explore the integration of the CatBoost-based descriptor and machine learning techniques to enhance efficiency and adaptability. Furthermore, the application of our method for bigger and more diverse databases is intended. Such extension can open up the possibility of dealing with a variety of real-world 3D model analysis problems.

Acknowledgment

The authors express their gratitude to George Ioannakis and colleagues [31] for the access to their online platform (http://retrieval.ceti.gr/), which greatly facilitated the evaluation of our method.

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