Benchmarking Search Techniques for CAD

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ABSTRACT

While benchmark datasets have been proposed for testing computer vision and 3D shape retrieval algorithms, no such datasets have yet been put forward to assess the relevance of these techniques for engineering problems. This paper presents several distinctive benchmark datasets for evaluating techniques for automated classification and retrieval of CAD objects. These datasets include (1) a dataset of CAD primitives (such as those common in constructive solid geometry modeling); (2) two datasets consisting of classes generated by minor topological variation; (3) two datasets of industrial CAD models classified based on object function and manufacturing process, respectively; (4) and a dataset of LEGO© models from the Mindstorms© robotics kits. Each model in the datasets is available in three formats – ACIS SAT, ISO STEP, and as a VRML mesh (some models are available under several different fidelity settings). These are all available through the National Design Repository.

Using these datasets, we present comprehensive empirical results for nine (9) different shape and solid model matching and retrieval techniques. These experiments show, as expected, that the quality of precision-recall performance can significantly vary on different datasets. These experiments reveal that for certain object classes and classifications, such as those based on manufacturing processes, all existing techniques perform poorly. This study reveals the strengths and weaknesses of existing research in these areas, introduces open challenge problems, and provides meaningful datasets and metrics against which the success of current and future work can be measured.

Categories and Subject Descriptors

H.3.3 [**Information Storage or Retrieval**]: Information Search or Retrieval; I.3.7 [**Computer Graphics**]: Three-Dimensional Graphics and Realism; J.6 [**Computer Applications**]: Computer-Aided Engineering

General Terms

Experimentation

Keywords

3D Search, Shape Recognition, Shape Matching, Solid Model Databases, Design Repositories..

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1. INTRODUCTION

Research on searching, classifying and comparing CAD models is an active research area, having produced a rich set of computational techniques. Existing research includes algorithms that work with photo images, projected profiles, feature interactions, and shape functions. In most cases, these techniques or systems were often presented and evaluated with their own particular datasets – datasets that contain mostly general shape models and few real CAD artifacts. This makes it very difficult to assess how effective these different techniques would be at managing CAD data.

The objective of this paper is to assist the evaluation of 3D search techniques for CAD data and engineering problems with two contributions. First, we introduce sets of classified CAD objects representing realistic engineering problems. Second, using these datasets we conduct a comprehensive assessment of nine (9) different techniques for matching CAD data.

CAD artifacts and their engineering domains introduce several challenges not adequately addressed by existing research:

- **Engineering artifacts each have a physical realization.** All of the models in the CAD datasets presented in this paper are of actual physical artifacts. Existing shape matching techniques, for the most part, emphasize the comparison of the gross shape of coarse artificial objects. The datasets (e.g. trees, airplanes, and boats) studied in most existing shape retrieval systems do not represent actual, or even acquired models of physical artifacts.

- **Engineering classifications are not subjective.** In existing shape retrieval literature, datasets are pre-classified based mostly on human intuition (i.e., boats get grouped with boats; airplanes with airplanes). In contrast, engineering classifications are usually not so subjective. For example, a part is machinable on a 3-axis machining center; a part has four symmetrically spaced holes for fastening with bolts.

- **Different valid classifications exist for the same objects.** The fact that an object may have several valid classifications is one of the fundamental problems in the field of pattern recognition. However, in engineering domains the differences across classifications can be large and the feature set for discriminating these differences are very hard to isolate.

To address these challenges, the datasets introduced in this paper includes both synthetic models and CAD models of actual artifacts. Synthetic models enable specific tests of topologic and geometric sensitivity of model retrieval techniques. Datasets of actual artifacts present several realistic scenarios where there are multiple valid classifications. For instance, one can classify based on (a) the subjective appearance of the part, (b) the objective manufacturing process for creating the physical artifact, or (c) the function of the part. Hence, the dataset is of actual artifacts under multiple classifications, including manufacturing process classification and functional classification. To enable an objective comparison of CAD models classifications or retrieval systems, all of the datasets introduced in this paper are freely available at
`http://www.designrepository.org/datasets/`.

The remainder of this paper will be organized as follows: we will review related work in CAD model representation and comparison, discuss the relations of CAD model attributes and classification, and then present synthetic and actual artifact datasets. Evaluation with various CAD matching and searching techniques demonstrates the use of the datasets as a common benchmark.

2. RELATED RESEARCH

Before introducing benchmark datasets of classified CAD models, we briefly review the research work on representing and comparing CAD models. Additionally, present a survey of some benchmark datasets from closely related disciplines like computer graphics and vision.

2.1 Representation of CAD Models

Most CAD models are solid models defined parametrically. However, approximated shape models represented by a polygonal mesh are becoming another useful representation thanks to the development of rapid prototyping from approximated models and the acquisition of shape models through 3D scanning.

2.1.1 Solid Model Representations

CAD models are traditionally an exact representations of 3D solids, which are suitable for creating physical models. In commercial CAD systems like Pro/Engineer and I-DEAS, models are dominantly represented by boundary representations (B-Rep). Objects are represented by a data structure that gives information about each of the object's faces, edges, vertices, and how they are joined together. Under B-Rep, two types of information are recorded: (1) a topology record of the connectivity of faces and edges; (2) and a set of parametric equations that describes the geometry and the location of vertices, faces, and edges (e.g. NURBS). Solid models give a complete and compact representation for design, simulation, and manufacturing purposes. Yet these models are usually stored in proprietary data formats across different CAD/CAM systems. Thus, for example, comparing models generated on I-DEAS against Pro/Engineer involves some lossy data exchange process, through conversion from STEP to IGES, or approximated shape models.

2.1.2 Shape Model Representations

3D shape models are approximated models characterized by a mesh of polygons for presentation or rendering purposes in computer graphics. Rather than exact parametric equations, polygons are used to approximately curved surfaces. Only the geometry of triangles are stored without any topological information. In contrast to proprietary solid model formats, open mesh file formats such as VRML and STL, are widely available. Although shape models are not suitable for modeling physical properties or simulations in CAD/CAM systems, polygonal meshes can serve as the lowest common denominator in comparing CAD models, by faceting solid models generated by different modeling systems. Shape models of objects can also be acquired easily by using laser scanners or CT to enable comparison of digital and physical artifacts.

2.2 Comparing 3D CAD Models

This research aims to provide a benchmark for information retrieval in CAD database systems. Enabling them to test the indexing and query mechanisms, in a manner similar to multimedia databases and knowledge management systems. Some of the past work in this area, is reviewed; in addition to the work from computer graphics and computer vision that are related to efforts of this paper.

There are two basic types of approaches for matching and retrieval of 3D CAD data: (1) *feature-based* techniques and (2) *shape-based* techniques.

2.2.1 Comparing Solid Models

Feature-based techniques [5, 19], dating from late 1970s [13], extract engineering features (e.g. machining features, form features) from a solid model of a mechanical part for use in database storage, automated GT coding. Elinson et al. [4] used feature-based reasoning for retrieval of solid models for use in variant process planning. Cicirello and Regli [2] examined how to develop graph-based data structures and create heuristic similarity measures among artifacts; this work was extended in [3] to a manufacturing feature-based similarity measurement. McWherter et al. [14] have integrated these ideas with database techniques to enable indexing and clustering of CAD models based on shape and engineering properties. Recently, Ramani et al. presented a CAD oriented search system [9],[10].

2.2.2 Comparing Shape Models

The shape-based techniques are more recent, owing to research contributions from computational geometry, computer vision, and computer graphics. From the polygon mesh, different transformation invariant attributes can be extracted as the means of similarity among 3D models. Thompson et al. [23] examined the reverse engineering of designs by generating surface and machining feature information off of range data collected from machined parts. Hilaga et al. [6] present a method for matching 3D topological models using multi-resolution reeb graphs. The method of Osada, Funkhouser et al [17] creates an abstraction of the 3D model as a probability distribution of samples from a shape function acting on the model. Novotni and Klein demonstrated the use of 3D Zernike descriptors [16]. Kazhdan et al compares 3D models with spherical harmonics [11]. For further information, Velkamp and Tangelder published a recent survey on shape retrieval methods [22]. While these techniques target to compare general 3D models, Ip et al. [7, 8] and Bespalov et al. [1] are focused on comparing shape models of CAD with shape distributions and scale-space representations.

2.3 Other Benchmark Datasets

There are many benchmark datasets comprised of synthetic and realistic data in the domain of computer vision and computer graphics. The Columbia Object Image Library (COIL-100) [15] aimed to assist object recognition from 2D photos. It contains 7200 photos of 100 objects in different poses. In face recognition research, the Yale face database provides 5760 images from 10 people each seen under 576 viewing conditions for testing. A number of synthetic image sequences are provided to test optical flow and motion analysis applications. Recently, the Princeton Shape Benchmark [20] has provided 1,814 3D polygonal models, collected from the web for evaluating shape-based retrieval and analysis algorithms. The models were chosen from heterogeneous categories ranging from animals, furniture, and airplanes.

3. CLASSIFYING CAD DATA

To outline the important attributes for computers to classify CAD models, we investigate the relationship between information provided by the model representations and various themes in CAD classifications.

A typical classification of CAD models is by their appearance, this is similar to the goal of computer vision and computer graphics, retrieving models that look similar for humans. Moreover, one important distinction in between CAD models and general 3D models is that CAD models are designed to be physically constructed. The manufacturing processes and the use of artifacts are important properties of CAD. CAD models can be objectively classified by their manufacturing processes and functions, in addition to their subjective appearance.

Automatic classification of CAD models consists of two steps. (1) Abstract the models by extracting relevant attributes to support their classification target. (2) Compare the attributes across the dataset and group similar models together. For the purpose of a CAD dataset, the following three criteria illustrate common CAD classification targets.

3.1 Appearance

Classifying parts by their visual appearance is a natural target. Numerous research efforts in computer vision attempted to classify engineering artifacts from their 2D photo images. With respect to 3D models, the computer graphics community used approximated shape models to perform shape matching. Related research focused on comparing meshes of polygons to one another. Attributes related to geometry (locations of vertices and edges of triangles) of the mesh are sampled and have become the focus of representing the model's appearance.

3.2 Manufacturing Processes

One interest in computer aided engineering is computer aided manufacturing, automating the generation of manufacturing process plans from CAD models. Classification of CAD models according to different classes of manufacturing processes has become an important interest. Recently, Yao et al. investigated in milling cutting processes from 3D scan data [25]. Apart from the recent effort, automated process planning is traditional derived from recognized manufacturing features on CAD models. Feature recognition interprets a part in terms of manufacturing features, such as slots, holes, and pockets. Popular approaches to this problem include graph-based, volumetric decomposition, and hint-based feature recognition. All of them utilize exact topology and geometry provided by solids to generate manufacturing features. Graph based approaches extract the topology of the model as a graph (faces as vertices and edges as edges), then recognize subgraphs that compose features. Hint based approach search for features through the set of hints on the models, then employ a completion procedure according to the nearby geometry and topology to generate manufacturing features. Topology and geometry of solid models directly influence the manufacturing process based classifications.

3.3 Functional

Functional classification describes how engineering artifacts are used. This classification ties a part directly to its application. High level semantics of parts becomes the key attributes for comparison and classification. Kopena et al. [12], Szykman et al. [21] and Wood et al. [24] attempted to model the semantics of parts formally with knowledge representation technologies. However, it is unclear if there is a mapping between the low level attributes (e.g. topology, geometry and tolerance) of a CAD model and its function. Current functional classification of CAD models are highly dependent on human labeling. To make a connection in between the semantics and CAD model attributes, it is essential to construct a set of labeled CAD models that permits one to data mine the associations between low level model attributes and functionalities.

4. THE DATASETS

Synthetic models and models of actual artifacts are provided in the proposed CAD dataset. To assist classification, datasets are designed to test the sensitivity with regards to geometry, topology, relevant attributes to appearance, and manufacturing classification. Synthetic models are artificial models tailored for testing behaviors of classification systems to a particular geometry or topology. Actual artifacts are sampled and classified from the National Design Repository. This dataset consists of manufacturing and functional classified models. Furthermore, a LEGO© dataset presents an example of a homogeneous model set. All models are provided in ACIS SAT, STEP, and VRML formats. Each dataset will be presented with a sample view and statistics showing the average size of a model in the dataset under different file formats, average face counts for for solid representations (SAT and STEP), as well as, average polygon counts for shape representations (VRML).

4.1 Synthetic Datasets

Synthetic models are provided to test the behaviors of model retrieval systems towards specific topological attributes in the interest of CAD/CAM. These synthetic models are created by the ACIS solid modeler in both SAT and STEP formats. The corresponding VRML shape models are then faceted by Sat2VRML [1].

4.1.1 Primitive Dataset

Cubes, cylinders, tori, and spheres with various deformations are created to test retrieval systems' behavior on topological and geometrical classifications among the same models. To distort just the geometry, but retaining topology, unit primitives are blended and scaled in x, y, z directions to create 296 models. The set consists of 101 cubes, 141 cylinders ,29 tori, 29 spheres. Two different classifications are produced:

- Group models by their types (Topologically similar groupings, e.g. groups: Cubes, Cylinders, Tori, and Spheres)
- Group models by their deformations (Geometrically similar groupings. e.g. groups: $1\times1\times1$, $2\times1\times2$ and $1\times1\times4$)

[1] `http://gicl.cs.drexel.edu/sat2vrml/`

Table 1: Statistics of the Primitive Dataset

	#Models	Avg. #Faces	Avg. #Polygons
Tori	29	1	2356
Spheres	29	1	1146
Cylinders	141	5	1000
Cubes	101	22	848
Total	300		

	Avg. SAT size	Avg. STEP size	Avg.VRML size
Tori	23KB	37KB	144KB
Spheres	12KB	20KB	72KB
Cylinders	21KB	47KB	48KB
Cubes	27KB	39KB	40KB

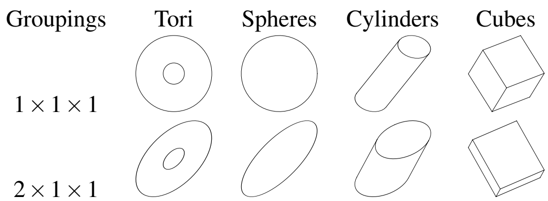


Figure 1: Examples of the models from the primitive models dataset.

Figure 1 gives a sample view of this dataset, and table 1 shows a brief summary of this dataset it is available at:
`http://www.designrepository.org/datasets/primitives.tar.gz`.

4.1.2 *Minor Topological Variation Dataset*

This dataset consists of rectangular boxes with a differing numbers of holes. They are designed to test the behavior of retrieval systems under minor topological variations. It evaluates the effect of varying simple features, such as holes on rectangular boxes.

Figure 2 gives a sample view of the dataset and table 2 shows a brief summary of this dataset it is available at:
`http://www.designrepository.org/datasets/bricks.tar.gz`
and
`http://www.designrepository.org/datasets/cubes.tar.gz`.

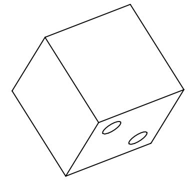
Cubes-Holes. Sixteen (16) cubes were modeled with a different numbers of holes (1, 2, 3, or 4 holes). Holes were made with a different radii, in addition, each model is constructed with holes with the same radii. The models are organized into four groups by the number of holes in each model. Figure 2(a) shows an example of a cube model from the dataset.

Brick-Holes. Eleven (11) rectangular box models with zero to four holes of the same size in different locations were created: one model with no holes, four models with one hole, three models with two holes, two models with three holes, and one model with four holes, as shown in Figure 2(b). Similar to the previous dataset, the models were grouped by their respective number of holes.

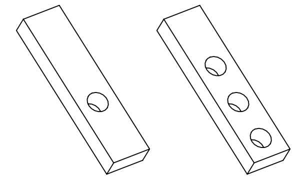
Table 2: Statistics of the Minor Topological Variation Dataset

	#Models	Avg. #Faces	Avg. #Polygons
Bricks	11	8	194
Cubes	16	9	263
Total	27		

	Avg SAT size	Avg STEP size	Avg VRML size
Bricks	6KB	17KB	10KB
Cubes	6KB	19KB	12KB



(a) A two holed cube from the Cubes-Holes dataset.



(b) One and three holed bricks from Brick-Holes dataset.

Figure 2: Examples of the models from the minor topological variation dataset.

4.2 Actual Artifacts Dataset

In addition to synthetic models, models of actual artifacts are also provided, namely, mechanical engineering parts available from the National Design Repository and LEGO© pieces. The National Design Repository models were sampled from industrial CAD data and grouped under multiple classification schemes. LEGO© parts and assemblies are provided as an example of homogeneous part families with repeating features.

4.2.1 *The National Design Repository Dataset*

CAD models in this dataset are collected from industry, and can be obtained through the publicly available National Design Repository. Two sets of models are hand classified under two classification schemes: (1) Manufacturing classification, a binary classification for prismatic machined or cast-then-machined parts. (2) Functional classification, a multi-category classification of brackets, gears, screws, springs, nuts, housing, and linkage arms. A sample view of the National Design Repository CAD models is shown in Figure 3.

Manufacturing Classification Dataset. This dataset was classified by hand into (1) prismatic machined parts and (2) parts that are first cast and then have their finishing features machined. The engineering rationale in this classification is that parts that are exclusively machined are usually high-precision parts, or parts made in small batches (i.e., for custom jobs). Cast-then-machined parts are typically from larger production runs and generally have much looser tolerance considerations for the non-machined surfaces of the object. In this case the investment of the physical plant is larger, as is the manufacturing production plan (i.e., one needs to machine a mold with which to do casting). Figure 4 shows a sample of this dataset, and table 3 shows a brief summary of this dataset it is available at:
`http://www.designrepository.org/datasets/machined.tar.bz2`
and
`http://www.designrepository.org/datasets/cast.tar.bz2`.

Table 3: Statistics of the Manufacturing Classification Dataset

	#Models	Avg. #Faces	Avg. #Polygons
Prismatic Machined	56	106	3600
Casted-then-Machined	54	80	3447
Total	110		

	Avg. SAT size	Avg. STEP size	Avg. VRML size
Prismatic Machined	146KB	233KB	162KB
Casted-then-Machined	277KB	314KB	159KB

Functional Classification Dataset. This dataset consists of seven groups of models. Seventy (70) models are hand classified by

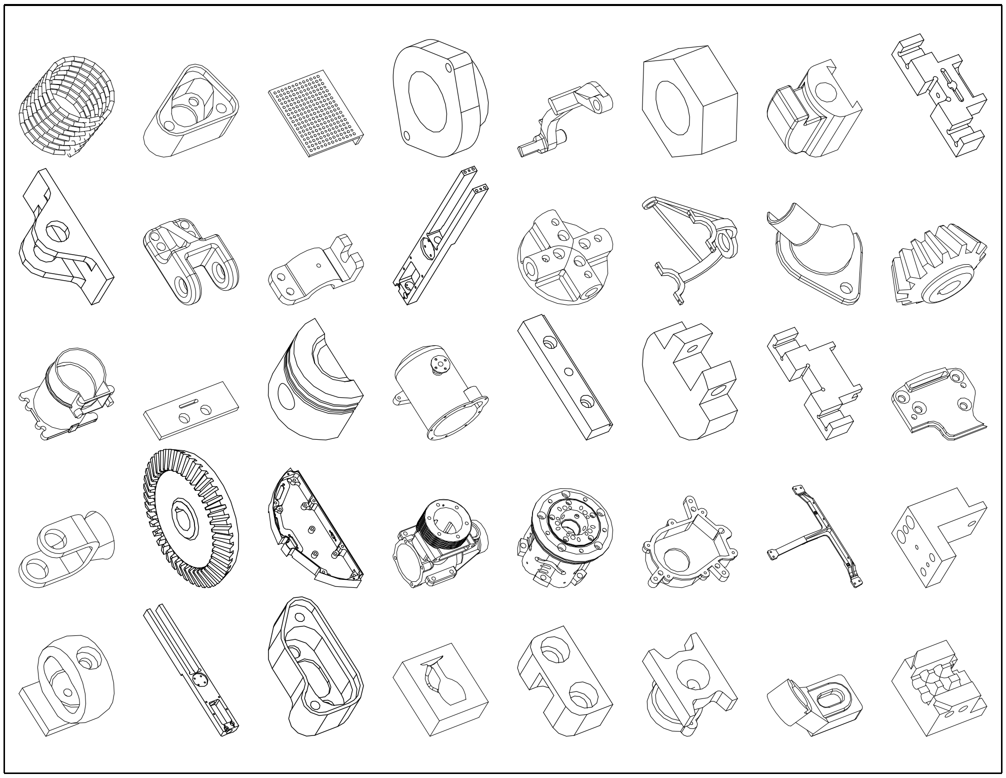


Figure 3: Examples of the models from the National Design Repository.

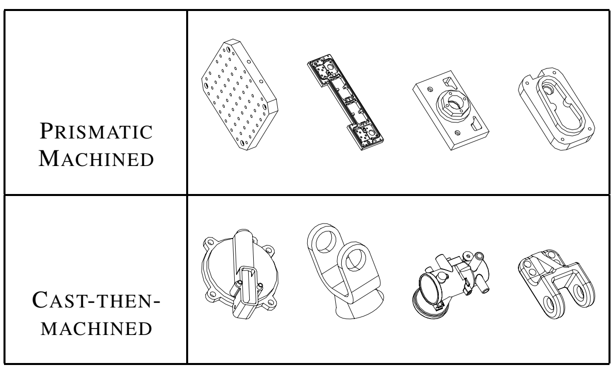


Figure 4: Examples of the models from the manufacturing classification dataset.

Table 4: Statistics of Functional Dataset

	#Models	Avg. #Faces	Avg. #Polygons
Brackets	9	45	911
Gears	12	169	4045
Housings	6	218	5141
Linkage Arms	13	30	1282
Nuts	7	8	518
Screws and Blots	18	15	431
Springs	5	161	7933
Total	70		

	Avg. SAT size	Avg. STEP size	Avg. VRML size
Brackets	56KB	100KB	41KB
Gears	458KB	525KB	191KB
Housings	300KB	450KB	250KB
Linkage Arms	62KB	100KB	57KB
Nuts	13KB	19KB	31KB
Screws and Blots	18KB	30KB	21KB
Springs	620KB	960KB	440KB

their role in mechanical systems. For instance, brackets are overhanging members that project from a structure and are usually designed to support a vertical load or to strengthen an angle. Linkage arms are motion transferring components from the spectrometer assembly. Nuts, Screws, and Blots are commonly used fasteners. Figure 5 shows a sample of this dataset, and table 4 shows a brief summary of this dataset it is available at:
`http://www.designrepository.org/datasets/functional.tar.bz2`.

4.2.2 LEGO© Dataset

The LEGO© dataset aims to provide a benchmark for a part family composed of homogeneous features. This dataset consists of LEGO© pieces from the popular LEGO© Mindstorms© robotics kit. The remarkable characteristic of this dataset is that all LEGO© components are composed with a fixed set of features. In addition, these features exhibit explicit interactions between one another. For instance, a pin on the top of the plate can fit in a hole on another piece. Forty seven (47) LEGO© components were modeled in ACIS and classified into four categories according to their appearance. The groups are named as follows: plates, wheels and gears, cylindrical parts and X-shape axles. Figure 6 gives a sample view of the dataset, and table 5 shows a brief summary of this dataset it is available at:
`http://www.designrepository.org/datasets/legos.tar.gz`.

The performance of retrieval systems on the models with homo-

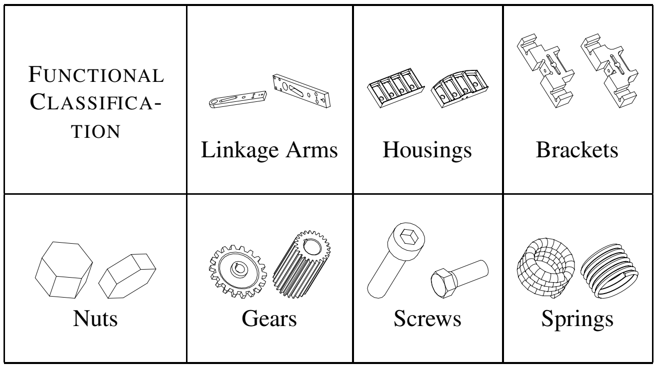
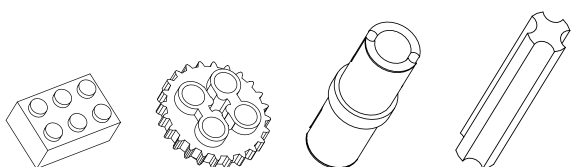


Figure 5: Examples of the models from the functional classification dataset.

Table 5: Statistics of the LEGO© Dataset

	#Models	Avg. #Faces	Avg. #Polygons
Plates	30	69	3328
Wheels-Gears	4	256	2536
Cylindrical Parts	6	30	886
X-Shape Axles	7	10	204
Total	47		

	Avg. SAT size	Avg. STEP size	Avg. VRML size
Plates	40KB	130KB	146KB
Wheels-Gears	40KB	63KB	14KB
Cylindrical Parts	43KB	94KB	57KB
X-Shape Axles	8KB	24KB	10KB



(a) Deep Plate 2X3 (b) Wheels-Gears (c) Cylindrical Parts (d) X-Shape Axles

Figure 6: Examples of the LEGO© dataset.

geneous features can be assessed by the LEGO© dataset. This dataset is designed to be especially useful for systems employing feature extraction in the process of retrieval.

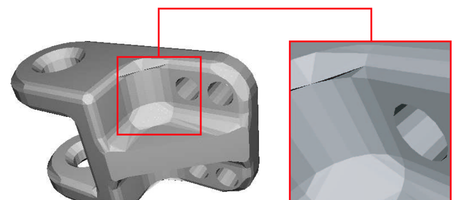
4.2.3 Variable Fidelity Dataset

Lastly, a set of models with various fidelity settings is included to test the robustness of shape based retrieval systems. Polygon mesh representation of the CAD data can serve as a means to compare CAD models across different file formats. This allows shape based model techniques to compare CAD models created by different CAD systems without complex data exchange. Due to the approximated nature of shape models, the fidelity of shape models depends on the granularity of the faceting process.

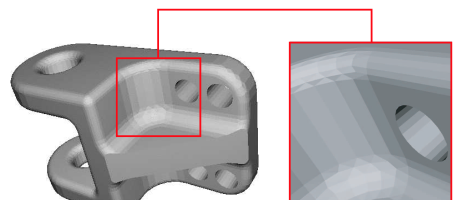
To create this dataset, 40 CAD models classified by part families were used. Each of them was faceted by ACIS for three instances with different normal tolerances (50, 15, 5), resulting in 120 models. Figure 7 shows the mesh of an example model under different fidelity settings. Lowering the normal tolerance will cause the faceting component to approximate a parametric surface with more polygons, hence increasing the fidelity of the resulting shape model. Ideally, a robust retrieval system should be indifferent to fidelity variations of meshes. Models in this dataset are only provided in VRML format, because fidelity only affects the approximated mesh representation of a model. Table 6 shows a brief summary of this dataset it is available at:
`http://www.designrepository.org/datasets/refinement.tar.gz`.

Table 6: Statistics of Variable Fidelity Dataset

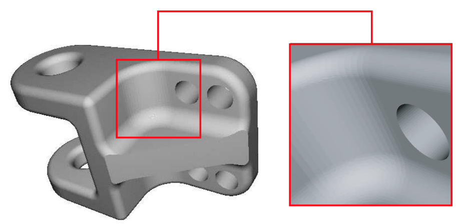
	# Models	Avg. # Polygons	Avg VRML size
High	40	18416	850KB
Normal	40	5908	275KB
Low	40	2699	117KB
Total	120		



(a) Low Fidelity,Normal Tolerance = 50



(b) Normal Fidelity, Normal Tolerance = 15



(c) High Fidelity, Normal Tolerance = 5

Figure 7: Variable Fidelity Dataset. Three copies of the same model under different fidelity settings.

5. EVALUATION PROCEDURE

The datasets is used to show and compare characteristics of different retrieval techniques. The following experiments aim to show how the proposed dataset does test retrieval techniques in the interest of CAD/CAM.

5.1 Experimental Protocol

Nine solid and shape based comparison techniques were evaluated.

- Shape based techniques
  - Shape distributions (SD) [17]
  - Shape distributions with point pair classifications (SD-Class) [7]

- Reeb graph comparison (Reeb) [6]
- Shape distributions with weights learning (SD-Learn) [8]
- Scale-Space comparison (Scale-Space) [1]

• Solid based techniques

- B-Rep based techniques
  * Invariant topological vector (ITV) [14]
  * Eigenspace indexing on B-Rep graphs (Eigen-BRep) [18]
- Feature based techniques
  * Model dependency graph approximate matching (MDG) [3]
  * Eigenspace indexing on machining feature interaction graphs (Eigen-Feat) [18]

Note that feature based techniques are only applicable to models of actual artifacts with explicit machining feature interactions. Feature based experiments were not performed on synthetic datasets nor LEGO© dataset, as they either contain no machining feature (primitive datasets) or the features do not interact (Minor topological variation dataset, LEGO© datasets).

Machining features and feature interactions of actual artifacts were extracted by Honeywell FM&T's FBMach feature recognition system. FBMach decomposes an ACIS part into STEP AP 224 volumetric machining features. These features are typically used for process planning and for programming CNC machine tools. Feature interaction graphs and model dependency graphs used by, respectively, the Eigen-Feat and MDG techniques, are constructed by using these FBMach features. The recognized machining features map to the graph's vertices. Interactions between the features were detected by testing intersections among the feature volumes. These interactions map to the edges and complete the respective graphs.

The performance of various techniques are evaluated by the k-nearest neighbor classification (kNN), and conventional recall and precision measures for evaluating information retrieval systems. The recall and precision values at different thresholds are computed as follows:

$$recall = \frac{Retrieved\ and\ Relevant\ models}{Relevant\ models}$$

$$precision = \frac{Retrieved\ and\ Relevant\ models}{Retrieved\ models}$$

The kNN classification labels a query model with the categories of its k closest neighbors, where k is the threshold for classification. The numbers of labeled categories potentially increase and decrease with respect to k.

Under this experimental setting, the factors of recall and precision computation become:

- *Relevant models*: The number of models that fall in to same category as the query model.
- *Retrieved models*: The number of models returned by a query.
- *Retrieved and Relevant models*: The number of models returned and that fell into the same category as the query model.

Recall and *precision* values were first computed per model at different k values. For each k, the arithmetic mean of the *recall* and *precision* across all models in a dataset was used as a representative value. To illustrate the results, *precision* is plotted against *recall* on different datasets and comparison techniques.

Ideally, a retrieval system should retrieve as many relevant models as possible, both high precision as well as high recall are desirable. A precision-recall graph plots *precision* against *recall*. It shows the trade-off between precision and recall. Trying to increase recall, typically, introduces more irrelevant models into the retrieved set, thereby reducing precision. Rightward and upward precision-recall curves indicates a better performance.

5.2 Experimental Results

Rather than having a competitive evaluation to demonstrate one retrieval technique outperforming the others, experimental results show each retrieval technique possesses different strengths producing satisfactory performance on some but not all synthetic model evaluations. Under the manufacturing classification dataset of actual artifacts, all evaluated techniques produced unsatisfactory performance, indicating there is a need for further research in the interest of CAD/CAM models retrieval.

5.2.1 Synthetic Datasets

Cube-Holes and Brick-Holes Dataset. On this topologically invariant synthetic datasets, graph and solid model based ITV and Eigen-BRep performed the best on the Cube-Holes, Figure 8(a), and Brick-Holes, Figure 8(b). However, reeb graph technique performed better than the other shape based techniques. In these two datasets, models are composed with either holes in different locations or different diameters exclusively. The results demonstrated the difference in topological sensitivity in between solid, graph and shape based techniques. Solid and graph based ITV and Eigen-BRep captured better invariant topology. Among shape based techniques, the reeb graph technique produced a better precision recall than the other shape based techniques.

Primitive Dataset. Under deformation classifications, shape-based techniques, and namely the shape distribution technique was the most effective one, as shown in Figure 8(d), whereas ITV and Eigen-BRep performed the best on type classification of the primitives, Figure 8(c).

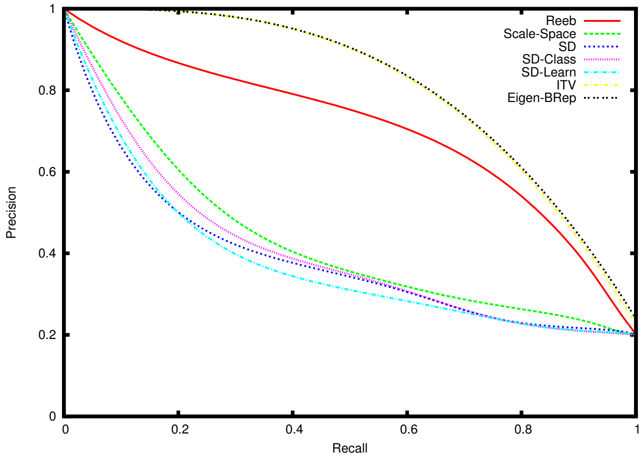
The deformation classification grouped models based on their geometry. For instance, unit primitives were grouped together, long cylinders, and long bricks formed another group. Shape distribution technique performed best on this classification as it was sensitive to gross geometric similarities between models.

Type classification grouped models together according to their topology. For example, bricks, cylinders and ellipsoids formed different categories. ITV, Eigen-BRep capture similar topological structures and are the most effective techniques for this classification.

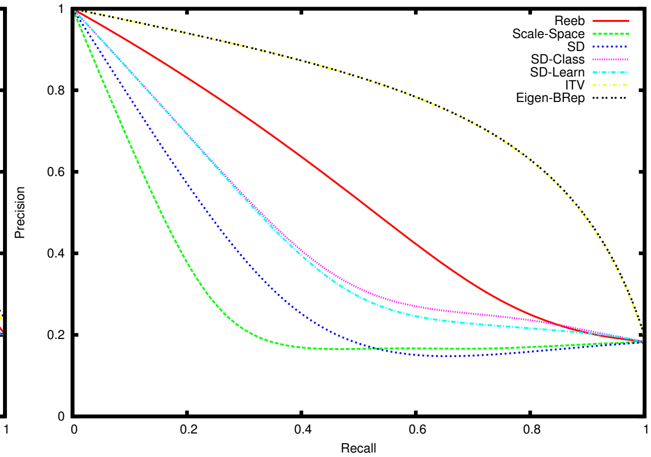
The primitive dataset demonstrated that the performance of retrieval techniques depends on the model classification schema. Moreover, the performance of retrieval techniques can vary drastically.

5.2.2 Actual Artifacts Datasets

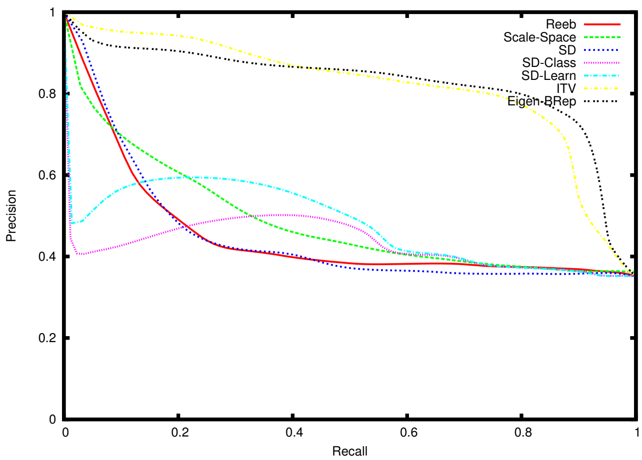
Manufacturing Classification Dataset. All retrieval techniques performed similarly on manufacturing classification dataset, Figure 9(a). However, Eigen-Feat and MDG show slightly better performance than the rest of the techniques. The precision fell to 50%, which is close to random for binary classifications, at a low recall rate, showing the techniques are not able to classify the models properly. The result questions the discrimination power of the



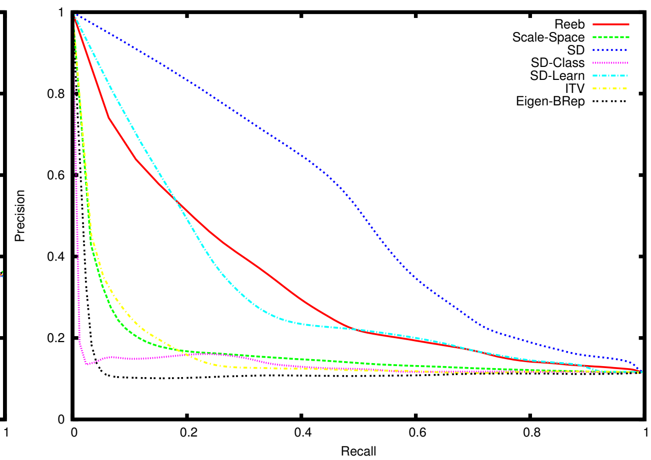
(a) Cubes-Holes



(b) Bricks-Holes



(c) Primitive Models, Type Classification



(d) Primitive Models, Deformation Classification

Figure 8: Precision-Recall graphs on synthetic datasets. (*PLOTS ARE IN COLOR.*)

tested techniques on prismatic machined and cast-then-machined classifications, indicating that there is a need for further work for this classification.

Functional Classification Dataset. In contrast to manufacturing classification dataset, the performance of retrieval techniques remained steady, with the exception of scale-space and MDG retrieval, Figure 9(b). A steep slope of the precision-recall curve shows the technique's precision was low even under low recall settings.

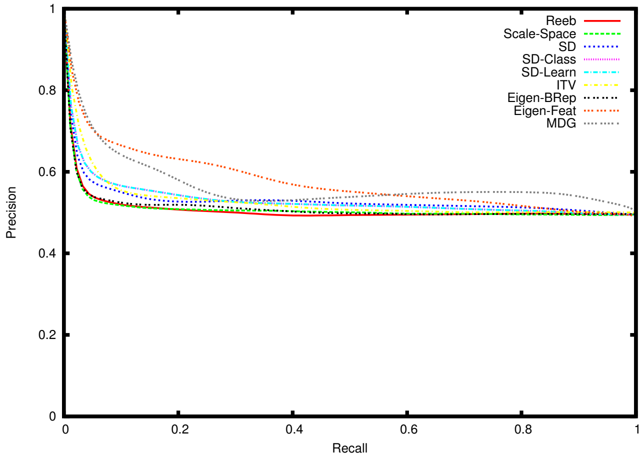
LEGO© Dataset. The Scale-space technique performed slightly better on the LEGO© dataset than the other techniques with a high recall settings, Figure 9(c). The LEGO© dataset provides an example of models comprised of repeating features. This special property allows the scale-space technique to extract the repeating features during its decomposition process.

Variable Fidelity Dataset. The precision-recall performance of shape based techniques remained stable, despite the variable fidelity of mesh models. In the evaluations of this dataset, the performance of each technique was compared against itself across meshes of different fidelity settings, Figure 10. In addition, the performance of the techniques was compared against one another for each fidelity setting, Figure 11. In Figure 10, no significant performance degradation is noticed among reeb graph and shape distribution techniques, where scale-space retrieval improved as the mesh fidelity increased. Figure 11 shows that the techniques maintained relative performance across different fidelity settings. However, there was a slight change in performance for scale-space and reeb graph techniques: scale-space was relatively less accurate on lower fidelity meshes while reeb graph gains in relative accuracy on low fidelity meshes. (Solid based techniques using parametric models as input are irrelevant for this test.)

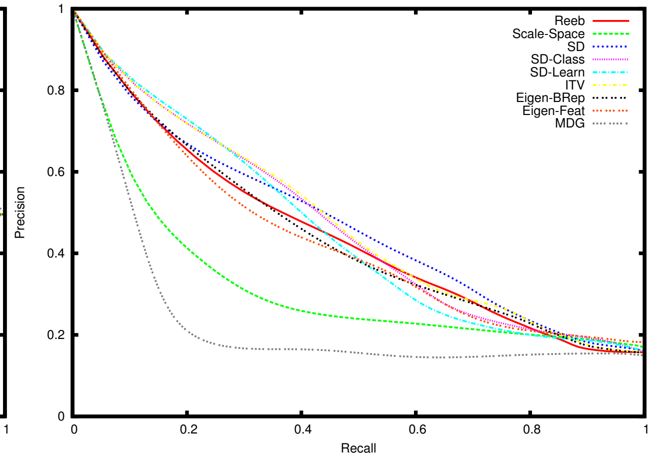
6. DISCUSSION

While the results, as expected, reveal a wide variability in the performance of the different techniques across different datasets, some observations can be made.

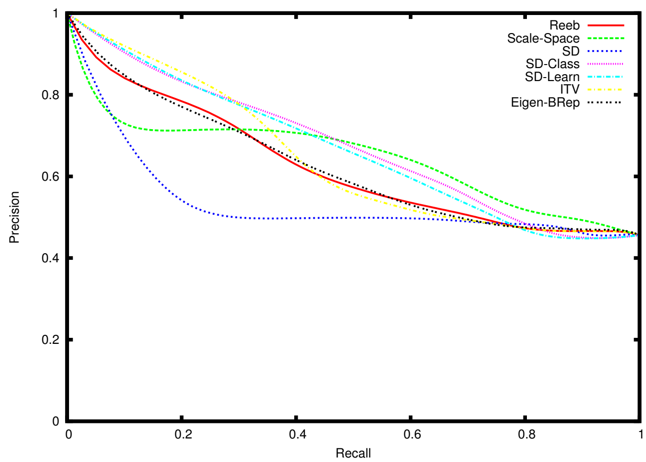
- **Boundary Representations are very useful.** In Figures 8(a-c), techniques based on the boundary representation data structure of the CAD object clearly dominate techniques based on a mesh-based representation. Much of the current literature chooses to ignore the traditional CAD representation and attempt to perform matching and search using only low level voxel or faceted representations. This data would indi-



(a) Manufacturing Classification



(b) Functional Classification



(c) LEGO© Models

Figure 9: Precision-Recall graphs on actual artifacts datasets. (*PLOTS ARE IN COLOR.*)

cate that reverting to a VRML mesh when a boundary representation is available creates uniformly poorer results. All CAD objects have a boundary representation inside the CAD environment, hence this data argues for improving how the boundary representation, whenever it is available, can be better used for matching.

- **Manufacturing classifications are an open challenge problem.** Figure 9(a) clearly shows that all of the techniques perform unacceptably when asked to classify objects as cast or prismatically machined parts. Readers may feel that this distinction is too subtle, in actuality this distinction is readily identifiable in the micro-geometry of the objects themselves. Further, this a binary classification—the simplest possible. Clearly, considerable research needs to be performed before classifiers will be able to distinguish among objects across a wider variety of manufacturing processes.

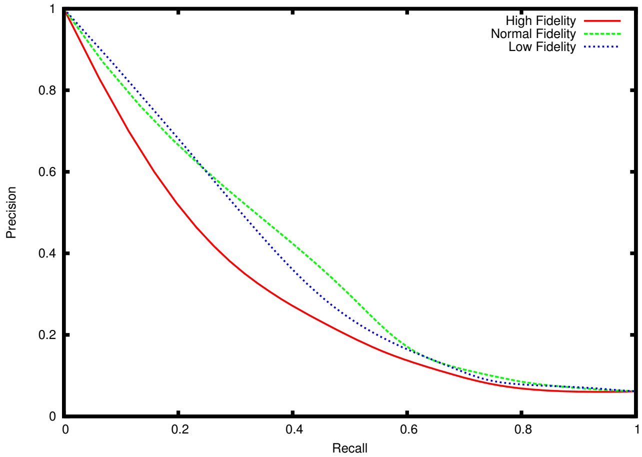
- **Functional classifications are an open challenge problem.** Figure 9(b) shows mediocre results when the techniques are asked to discriminate among objects of different functional classes. It is a common maxim that shape follows function in engineering, not vice versa. Hence, it is not surprising that trying to distinguish functional classes from shape would prove hard. However, it is surprising that these techniques would perform so poorly when given a set of functional classes (Figure 5) that are so distinct in shape.

- **Develop more feature-based techniques.** The bright spot in Figure 9(a) is that the two techniques that compare objects based on machining features performed the best at discriminating across manufacturing processes. We believe this indicates that a more fine-tuned feature set and feature recognition method could produce significantly better discrimination across classes. Further, if we could be given features that related to engineering function, we would expect the feature-based techniques to dominate in example of Figure 9(b) as well.

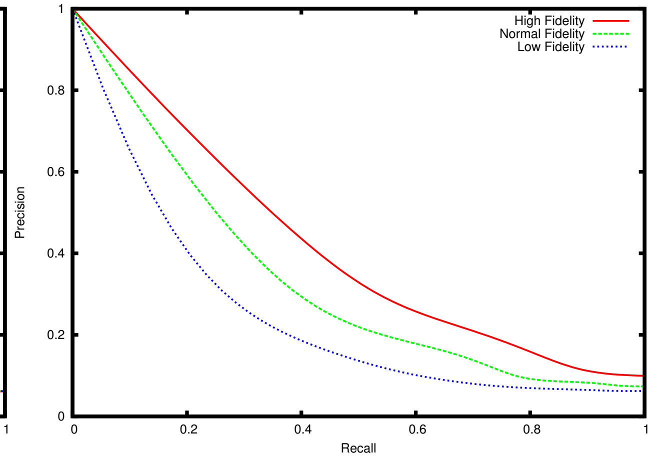
It is important to note that the experiments in this paper look at only those techniques that operate on topology and geometry data. Techniques based on voxelization (Zernikie descriptors, spherical harmonics, etc) are not suitable for these datasets.

7. CONCLUSIONS

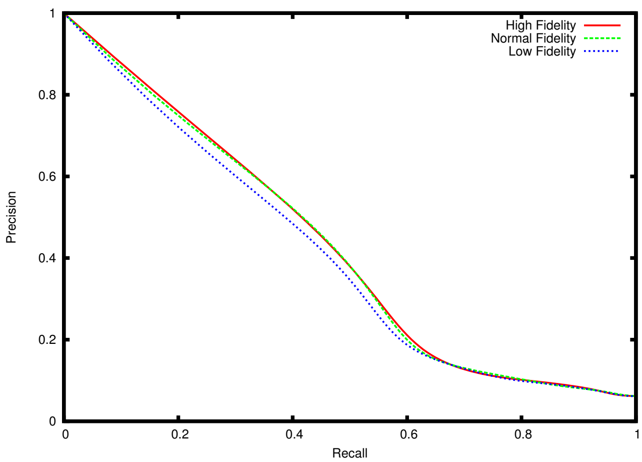
This paper introduced several datasets for use in comparing the performance of 3D search techniques in the domain of CAD models. Based on these datasets, the paper presents a study of nine (9) different 3D shape and solid model matching techniques and their



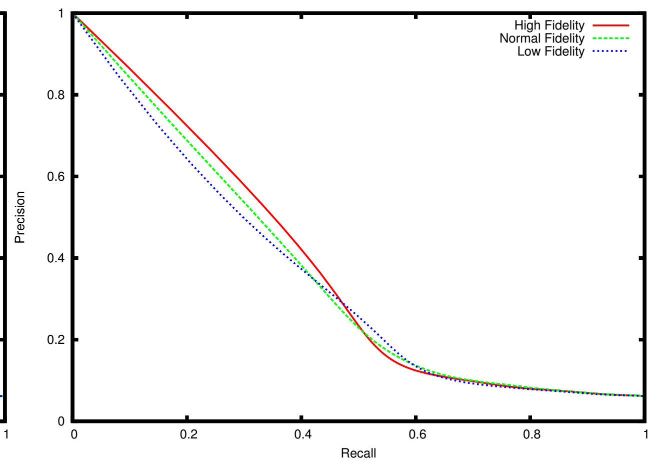
(a) Reeb Graphs



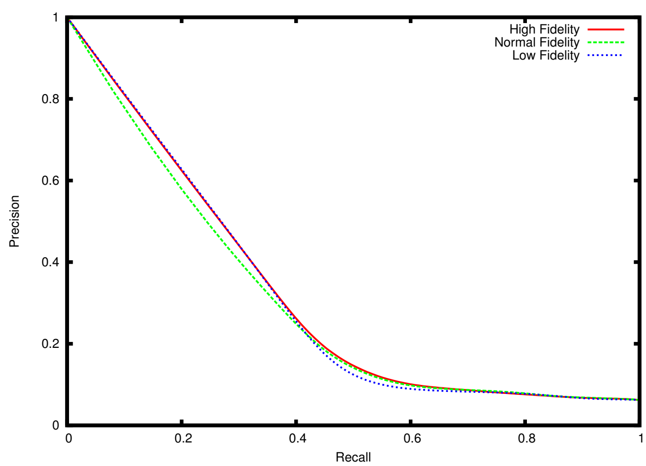
(b) Scale-Space



(c) Shape Distributions



(d) Shape Distributions with points classification

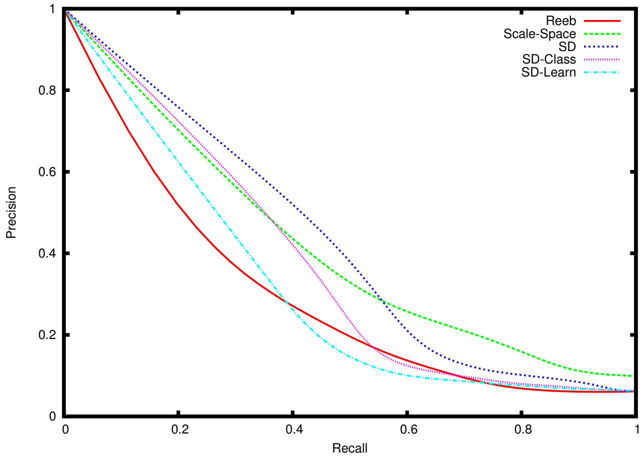


(e) Shape Distributions with weights learning

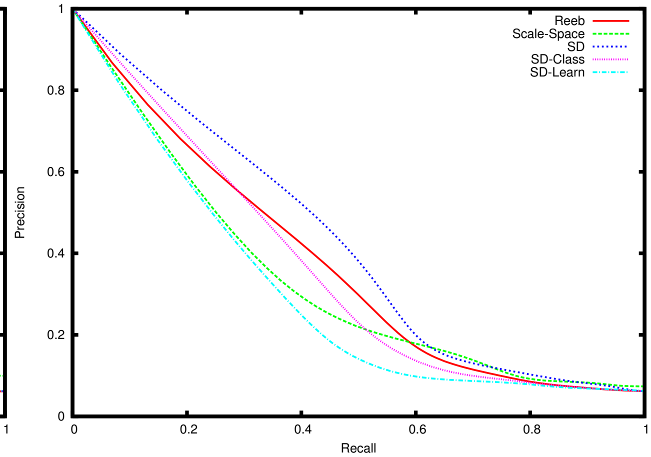
Figure 10: Precision-Recall graphs on Variable Fidelity Datasets. Each technique is compared against itself with different fidelity settings. (*PLOTS ARE IN COLOR.*)

performances on these datasets. In general, most of the technique performed poorly on CAD objects. Based on these results, the authors offer several challenges for future work in Section 6.

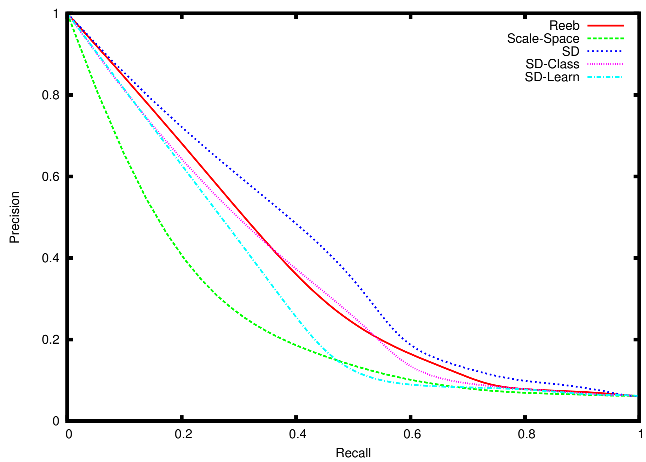
A contribution of this research is the establishment standard datasets for evaluating model retrieval techniques on CAD/CAM artifacts. Additionally, we provided datasets that test the topological and geometrical sensitivity of retrieval techniques, as well as those that illustrate the challenges of multiple classifications. It is our belief that these CAD datasets can provide a standard and accessible testbed to facilitate the development, comparison, and evaluation



(a) High Fidelity



(b) Normal Fidelity



(c) Low Fidelity

Figure 11: Precision-Recall graphs on Variable Fidelity Datasets. The techniques are compared against each other for each fidelity setting.(*PLOTS ARE IN COLOR.*)

of model retrieval techniques of interest in the CAD/CAM domain.

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