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AN ENGINEERING SHAPE BENCHMARK FOR 3D MODELS

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ABSTRACT

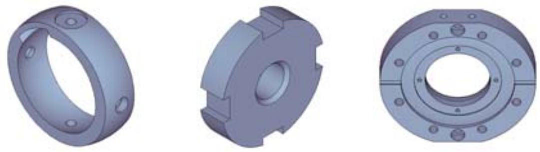
Three dimensional shape searching is a problem of current interest in several different fields, especially in the mechanical engineering domain. There has been a large body of work in developing representations for 3D shapes. However, there has been limited work done in developing domain dependent benchmark databases for 3D shape searching. In this paper, we propose a benchmark database for evaluating shape based search methods relevant to the mechanical engineering domain. Twelve feature vector based representations are compared using the benchmark database. The main contributions of this paper are development of an engineering shape benchmark and an understanding of the effectiveness of different shape representations for classes of engineering parts.

1. INTRODUCTION

Shape-based retrieval of 3D data has applications in various disciplines such as computer vision [1], artifact searching [2], molecular biology [3], and chemistry [4]. The 3D shape searching area has so far been dominated by research in computer vision and computer graphics, where researchers have extensively studied the “shape matching” problem. Extensive reviews of these methods are available in [5-7]. Recently, there has been a lot of interest in shape-based search methods for the mechanical engineering domain [8-16]. In this paper, we will focus mainly on a benchmark for searching overall shape of engineering objects - the 3D Engineering Shape Benchmark (ESB). Based on a classification of 801 engineering components, we have evaluated 12 different shape descriptors that are described in Section 2 of this paper.

One of the few publicly available benchmarks for 3D models includes the Princeton Shape Benchmark (PSB) [15]. However, models in the PSB represent mostly multimedia objects for computer graphics and vision applications. Our focus in this paper is on developing a benchmark specifically tailored towards the mechanical engineering CAD domain. Our hypothesis in the development of a benchmark database for engineering is that shapes in the engineering domain have different characteristics than multimedia shapes such as trees, humans and animals. Two key differentiating characteristics of engineering shapes as compared to multimedia shapes are: (a) engineering shapes have high genus as compared to multimedia shapes, and (b) distances between multimedia shapes are more apparent as compared to engineering shapes. Engineering shapes often have high genus and contain important features of various types, including holes, tunnels, cavities, ribs, and helixes. Their numbers as well as relative positioning are an important factor in the resemblance of two shapes [33], unlike multimedia where the overall shape is more important. As a result, representations developed for multimedia objects may not perform well for engineering objects. For example, structure-preserving representations in multimedia such as shock graphs [34] and Reeb graphs [17] are widely used and work well for multimedia shapes of Genus-0. However, issues related to topological sensitivity of Reeb graphs leads to significant number of false positives in engineering databases [17].

We hypothesize that the performance of various shape representations will be different than the results presented using PSB. The National Design Repository developed by Regli et al. [11] provides a large database of engineering parts in various CAD formats. However, currently the repository contains no classification scheme analogous to the PSB database. An obvious difficulty with creating a benchmark database is that no benchmark can encompass the whole range of naturally occurring or man-made shapes. This is especially true in the engineering domain since the very nature of engineering design, and the increasing complexity of product design have forced engineers to design and manufacture increasingly complex and creative shapes. In addition, it is difficult to categorize engineering shapes into semantic classes. For example, it is easy to see that dinosaurs and humans belong to different categories of shapes, but it is more difficult to characterize the shapes in Figure 1 into different categories.



Gimble Ring Lock Nut Flange

Figure 1: Examples of parts that have similar shape but different functions.

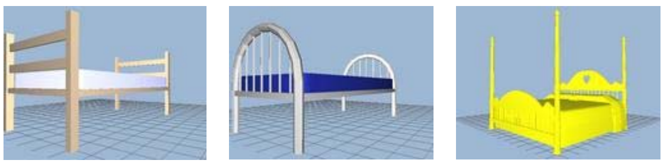


Figure 2: Parts from the "Beds" category from the Princeton Shape Benchmark ([18]).

Another limitation with using PSB for the engineering domain is that PSB classifies models primarily on the basis of function, and secondarily based on shape. Most objects created in the multi-media domain can be classified into a category such as "bed", "tree" or "airplane" purely based on their function; however, in the engineering domain the existence of many varieties of semi-standard and one-of-a-type components makes it impossible to give names to objects or to classify them into different functional categories. For example, in Figure 2 beds with different geometric shapes are in the same category.

However, for the engineering domain a primarily function based classification does not seem logical because parts with different functions may have similar shape as seen in Figure 1. For example, in Figure 1, gimble rings are used in lighting fixtures for fastening; lock nuts are used primarily for locking, while flanges are used for connecting two components. One cannot always explicitly state the function of an engineering component purely based on its shape. As a result, we believe that a function-based classification for the engineering domain is a daunting proposition.

Another major difference between a multimedia database and an engineering database is the motivation behind the search process. In the multimedia domain, the search is performed primarily for reusing the models for different scene creation. On the other hand, in the engineering domain, search may allow designers to not only reuse the 3D CAD model but also associated information (such as manufacturing and analyses) thereby reducing product development time. As a result, the search system must be capable not only of distinguishing between overall shapes, but also consider manufacturing and local shape features in its similarity metric.

The rest of this paper is organized as follows: Section 2 presents a brief overview of shape representations that are compared using our database; Section 3 describes the construction and evaluation of our ESB database along with evaluation methodologies; Section 4 presents a detailed analysis of results along with discussion, and finally Section 5 presents the conclusions.

2. SHAPE REPRESENTATIONS

A comprehensive review of various shape representations and search techniques for 3D shapes is available in [5-7]. Based on these papers existing shape representations can be classified into two classes: feature vector based and topology based. Topology based representations extract information from the topology of a part such as eigenvalues [8, 12], skeletal graphs [9, 12] and Reeb graphs [16] for comparison. In this paper we have only evaluated representations based on feature vectors. Our future work will include benchmarking of topology based methods for 3D shape search. We describe below the twelve feature vectors that we have used for benchmarking against the ESB.

2.1. Moment Invariants (MI)

The three second-order moment invariants for the model are stored as a feature vector. Moment invariants are by nature independent of orientation. For every voxel in the model translation, rotational and scale invariant second order moments are calculated as described below.

κ_{lmn} are calculated as described in Eq.(1) as:

$$\kappa_{lmn} = \frac{\int\int\limits_{-\infty}^{\infty}\int x^l y^m z^n \rho(x,y,z)\; dx\; dy\; dz}{\mu_{000}^{5/3}} \qquad l+m+n=2 \tag{1}$$

where μ_{lmn} are central moments after translation, given by Eq. (2) as:

$$\mu_{lmn} = \int\int\limits_{-\infty}^{\infty}\int (x-\hat{x})^l (y-\hat{y})^m (z-\hat{z})^n \rho(x,y,z)\; dxdydz \qquad l,m,n = 1,2,3,... \tag{2}$$

The integrals above are approximated by summation of the contribution of every voxel to the moment. Since the characteristic function is invariant under rotation, the characteristic function of the matrix M (Eq. (3)) of translation and scale invariant second order moments is RST (Rotation-Scale-Translation) invariant.

$$\mathrm{M} = \begin{bmatrix} \kappa_{200}-\Lambda & \kappa_{110} & \kappa_{101} \\ \kappa_{110} & \kappa_{020}-\Lambda & \kappa_{011} \\ \kappa_{101} & \kappa_{011} & \kappa_{002}-\Lambda \end{bmatrix} \tag{3}$$

After evaluating the characteristic function for this matrix, the three moment invariants that are calculated are described in Eq. (4).

$$\begin{aligned} I_1 &= \kappa_{200} + \kappa_{020} + \kappa_{002} \\ I_2 &= \kappa_{002}\kappa_{200} + \kappa_{002}\kappa_{020} + \kappa_{200}\kappa_{002} - \kappa_{101}^2 \\ &\quad -\kappa_{011}^2 - \kappa_{110}^2 \\ I_3 &= \kappa_{200}\kappa_{020}\kappa_{002} + 2\kappa_{110}\kappa_{011}\kappa_{101} - \kappa_{101}^2\kappa_{020} \\ &\quad -\kappa_{011}^2\kappa_{200} - \kappa_{110}^2\kappa_{002} \end{aligned} \tag{4}$$

2.2. Principal Moments (PM)

The principal moments for a 3D model are the three eigenvalues $\begin{bmatrix}\mu_{xx} & \mu_{yy} & \mu_{zz}\end{bmatrix}$ of the moment matrix M as shown below in Eq. (5).

$$M = \begin{bmatrix} \mu_{200} & \mu_{110} & \mu_{101} \\ \mu_{110} & \mu_{020} & \mu_{011} \\ \mu_{101} & \mu_{011} & \mu_{002} \end{bmatrix} \rightarrow \begin{bmatrix} \mu_{xx} & 0 & 0 \\ 0 & \mu_{yy} & 0 \\ 0 & 0 & \mu_{zz} \end{bmatrix} \tag{5}$$

2.3. Spherical Harmonics (SH)

Spherical Harmonics are a decomposition of a spherical function by finding the Fourier transform on a sphere [16]. The theory of spherical harmonics says that any spherical function $f(\theta,\phi)$ can be decomposed as the sum of its harmonics as seen in Eq. (6):

$$f(\theta,\phi) = \sum_{l\geq 0}\sum_{|m|\leq l} a_{lm} Y_l^m(\theta,\phi) \tag{6}$$
$$0 \leq \theta \leq \pi,\ 0 \leq \phi \leq 2\pi$$

where a_{lm} are the Fourier coefficients and $Y_l^m(\theta,\phi)$ are the solutions to the normalized Laplace's equation in spherical coordinates. The spherical harmonic coefficients can be used to reconstruct an approximation of the underlying object at different levels. Similar to moments, a partial yet accurate description of the part can be obtained by using a limited subset of Fourier coefficients. Intuitively, we expect this method to perform especially well for objects with radial symmetry, because of the spherical decomposition.

2.4. Surface Area and Volume (SAV)

In a general shape-based search system, shape representations are required to be independent of translation, rotation and size. However, in the mechanical engineering domain, the surface area and volume of a component have serious implications on the manufacturability of an object. For the same volume, thin-walled components such as manifolds and tubular parts often have higher surface area for the same volume compared to prismatic components. Due to their relevance to design and manufacturing we include these representations in our tests.

2.5. Surface Area to Volume Ratio (SVR)

In addition to SAV, we tested a separate feature vector-surface area to volume ratio (SVR). Our hypothesis was that this feature will distinguish between thin walled and prismatic components and can be used to prune the database using a multi-step search approach.

2.6. Geometric Ratios (GR)

We also included the two aspect ratios for a 3D model in our tests due to the simplicity of computation and its relevance to classification. Again the assumption here is that the aspect ratios will serve as good search filters.

2.7. Crinkliness and Compactness (CC)

Crinkliness and Compactness are two feature vectors used in [17]. Compactness is defined as the non-dimensional ratio of the volume squared over the cube of the surface area. Crinkliness is defined as the surface area of the model divided by the surface area of a sphere having the same volume as the model.

2.8. 2.5D Harmonics (2.5D)

2.5D Harmonics is a new feature vector proposed in [18] for representing 2D engineering drawings and 3D models. In this work, 3D model is first converted into a set of 2D views through a robust pose estimation algorithm described in [18-19]. The intuition for transforming the problem to 2D space is that many engineering shapes are created using orthographic projections and hence are amenable to orthographic projections.

Each 2D view is represented as a spherical function by transforming it from 2D space into 3D space. Then a fast spherical harmonics transformation is employed to get a rotation invariant descriptor.

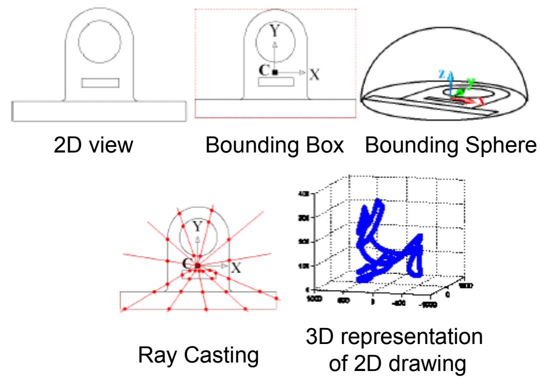


Figure 3: Procedure of converting a 2D view into the 2.5D Harmonics representation.

Thus, the shape searching problem is reduced to several simple steps, such as sampling, normalization, and distance computation between the descriptors.

$$\varphi_i = \arctan\left(\frac{d_i}{r}\right) \tag{7}$$

For example, in our tests we used a bandwidth of 64 for the 2.5D spherical harmonics method, i.e., the descriptor of a drawing contains 64 signatures.

2.9. 3D Shape Distribution (3DS)

Shape distributions represent the shape signature as a probability distribution sampled from a shape function measuring the geometric properties of a 3D model [20]. Selection of the shape function is the primary step in this technique.

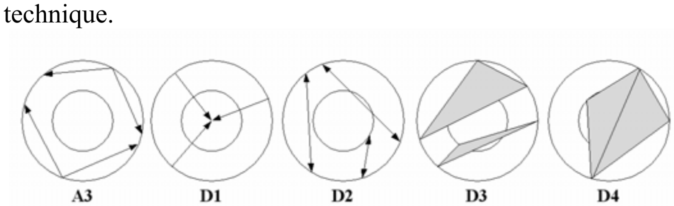


Figure 4: Shape Functions used in the calculation of shape distributions.

Figure 3 illustrates typical geometry based shape functions as explained below:

A3: Measures the angle among three random points on the surface of a 3D model

D1: Measures the distance between a fixed point and one random point on the surface

D2: Measures the distance between two random points on the surface

D3: Measures the square root of the area of the triangle among three random points on the surface
D4: Measures the cube root of the volume of the tetrahedron among four random points on the surface

2.10. Orthogonal Main Views (OMV)

Jiantao and Ramani [18-19] recently proposed a new method to obtain shape signatures of 3D models after automatically obtaining their three orthogonal main views. Subsequently, a statistics based approach represents the shape of the 2D views as a distance distribution between pairs of randomly sampled points. The 2D shape distributions thus obtained are used to compare 3D objects.

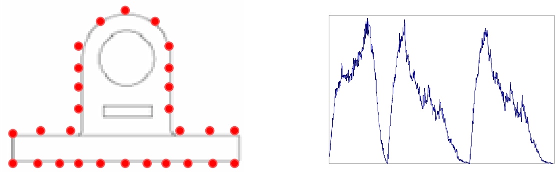


Figure 5: Procedure of converting a 2D view into the Orthogonal Main Views representation.

The methods proposed in sections 2.8 and 2.10 have many valuable properties: transform invariance, efficiency, and robustness. Experiments show that they can not only be applied to vector drawings, but can also be applied to scanned drawings. The insensitivity to noise allows for the user's causal input, thus supporting a freehand sketch-based retrieval user interface.

2.11. Convex Hull Histogram (CHH)

In this new method we compute the 3D convex hull for a given model using the Quickhull [25] algorithm. Then we build a histogram of the pairwise distances based on the points obtained from the convex hull [26].

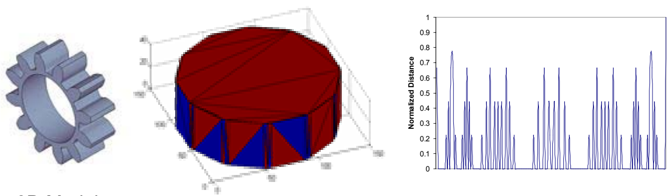


Figure 6: Procedure of converting a 3D model into the Convex Hull Histogram representation.

The number of histogram bins is set based on the accuracy needed for similarity searching. This histogram is also normalized and stored in the database for comparison. Models are retrieved based on the L1 norm for similarity searching [27].

2.12. Solid Angle Histogram (SAH)

The Solid-Angle method measures the concavity and the convexity of geometric surfaces. It is described in more detail in [24]. Histograms are usually based on a complete partitioning of the data space into disjoint cells which correspond to the bins of the histograms. The three dimensional data space is divided into axis parallel, equisized partitions. This kind of space partitioning is especially suitable for voxelized data, as cells and voxels are of the same shape, i.e. cells can be regarded as coarse voxels. Each of these partitions is assigned to one or several bins in a histogram based on different models. We tested a solid angle based similarity model in this paper. Below, we give more details about the solid angle based similarity model.

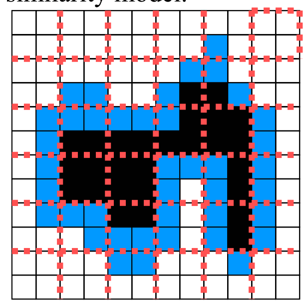


Figure 7: Computing the solid angle histogram for a 3D model.

Let $K_{c,r}$ be a set of voxels that describes a 3D voxelized sphere with central voxel c and radius r. For each surface-voxel $\bar{v}$ of an object o the Solid-Angle value is computed as follows. The voxels of o which are inside $K_{v,r}$ are counted and divided by the size of $K_{v,r}$, i.e. the number of voxels of $K_{v,r}$. The resulting measure is called the Solid-Angle value $SA(\bar{v},r)$ and can be computed as follows:

$$SA(\bar{v},r) = \frac{\left|K_{v,r} \cap V^{o}\right|}{\left|K_{v,r}\right|} \tag{8}$$

The solid angle value of each cell is transferred into three bins - surface voxels, inside voxels and no voxels. Due to its use of the discretization in rectangular coordinates we expect this method to represent prismatic and flat-thin walled shapes well.

3. A 3D ENGINEERING SHAPE BENCHMARK (ESB)

This section describes the processes of acquiring 3D models for the benchmark database, classification of 3D models and evaluation of shape representations described in section 2.

3.1 Model Acquisition

Since we are benchmarking shape-based search systems, we classified 3D models primarily based on shape. It is important to note that we have eliminated duplicates from our database, indicating that no two models in the database are the same. This removes bias from the database, since most shape representations satisfy the condition of self-similarity. The 3D models in the database were acquired from a variety of sources including the National Design Repository [25], websites on the internet [27, 28] and industry. One of the major difficulties in building benchmark databases for engineering arises due to the proprietary nature of many engineering designs. While all standard components have CAD models made freely available to the researchers, most of the semi-standard and non-standard designs are not available for a public benchmark database. As a result, most engineering shape search systems have been tested on freely available CAD models. However, it is difficult to estimate the scalability of shape search algorithms methods to real-world, non-standard components used in industry. In order to overcome this difficulty, we acquired proprietary designs from a heavy machinery manufacturer. Of the 801 models in the ESB, 76 models are proprietary and have a high degree of shape complexity. We have therefore provided the remaining 725 models for public use and encourage other researchers and institutes to use ESB for testing new methods and algorithms for shape based search. We will continue to add models to our ESB to encompass a wider variety of shapes. Our work is the first engineering benchmark for search.

Each 3D model in the ESB has CAD files in two different formats (STL and OBJ) and an associated thumbnail image (JPG). Models from the ESB can be downloaded along with a classification schema from our website http://engineering.purdue.edu/precise/esb.html. Most models in the ESB are of non-trivial complexity in terms of design and manufacturing.

3.2. Model Classification

We believe that users of a shape based search system are likely to search a database of previous parts with some intent in mind. For the purposes of a benchmark database, shapes can be classified into the most granular level (e.g. Gears, Handles etc.). In order to keep our benchmark database as general as possible, we used the classification methodology developed by Swift and Booker for the purposes of cost estimation and process planning [28]. The models for the benchmark database were classified by six individuals unrelated to the research, with varying degrees of training in Mechanical Engineering. Similar to the classification methodology of the Princeton Shape Benchmark, we provided individuals with thumbnail images of 3D models for classification. In case of doubts, the respective 3D models were also provided to users.

A total of 1,391 3D models were partitioned into three super-classes, namely:

- Solids of Revolution: Part envelope is largely a solid of revolution
- Prismatic: Part envelope is largely a rectangular or cubic prism, and
- Flat-Thin Wall: Parts with flat-thin walled sections and shell-like components

Within each super-class, models were classified into clusters of similar shapes. A model was included in a particular category only when the six individuals agreed upon it. This classification process continued iteratively until all the 1,391 models were exhausted. Trivial models, as well as categories with less than 4 models were excluded from the ESB. The final classification consisted of 801 models classified into 42 categories of similar parts such as “Discs”, “T-shaped parts” and “Bracket-like parts.” A list of super-classes along with their respective sub-classes is seen in Table 1.

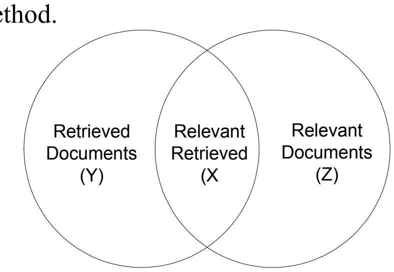
3.3. Evaluation Methodology

We used standard evaluation procedures from information retrieval, namely precision-recall curves and average precision. We also retrieved models randomly to ensure that every shape representation performed better than random retrievals (RDM). Definitions of precision and recall are illustrated in Figure 8. Precision-recall (PR) curves describe the relationship between precision and recall for an information retrieval method. We used standard techniques of constructing PR curves from the NIST TREC standards [29].

Table 1: Classification of Models in ESB.

Flat Thin Wall Components		Prismatic Parts		Solids of Revolution	
Bracketlike parts	18	Bearing Blocks	7	90 degree bends (*)	41
Clips	4	Contoured Surfaces	5	Bearing like parts	20
Contact Switches	8	Handles	18	Bolt like parts	53
Curved Housings	9	L Blocks	7	Container like parts	10
Doors	7	Long Machine Elements	15	Cylindrical Parts	43
Rectangular Housings	14	Machined Blocks	9	Discs	51
Slender Thin Plates	12	Machined Plates	49	Flange like parts	15
Thin Plates	23	Motor Bodies	7	Gearlike parts	36
Total	**95**	Prismatic Stock	36	Long pins	58
		Rocker Arms (*)	10	More than two openings (*)	9
		Slender Links	13	Non 90 bends (*)	8
		Small Machined Blocks	12	Nuts	19
		T shaped parts	15	Oil pans (*)	8
		Thick Plates	12	Posts	11
		Thick Slotted plates	20	Pulley like parts	12
		U shaped parts	25	Round, Change at end	21
		Total	**260**	Shelled Tubes	16
				Spoked Wheels	15
				Total	**446**

A perfect retrieval retrieves all relevant models consistently at each recall level, producing a horizontal line at precision = 1.0. However in practice, precision decreases with increasing recall. The closer a PR curve tends to the horizontal line at precision = 1.0, the better the information retrieval method. If the PR curves for two information retrieval methods cross each other or are very close to each other, it is difficult to make judgements about the relative effectiveness of each method. In this paper, we also attempt to quantify the performance of various representation methods with respect to a base method (in this case, 3D shape distributions) as an Average of Differences (AOD). Although this is not a standard practice in information retrieval, we find that it gives relevant results in the context of this paper. We calculated the average of differences between the precision values of 3D shape distributions and the method under investigation. This average performance is expressed as a percentage of the performance of the base method.



Precision = X/Y Recall = X/Z

Figure 8: Precision and Recall Calculations.

4. RESULTS

We evaluated the precision at various levels of recall for each of the 12 shape representation methods to generate PR curves. We found that all shape representation methods performs better than the random retrieval method as seen in Figure 9.

It was found that on average, the two methods based on 2D views (2.5D Harmonics and Orthogonal Main View) outperform other methods consistently. This is similar to conclusions drawn from [15], where the Lightfield Descriptors based on 2D projections work better than other 3D methods. It is interesting to note that traditional engineering drawings also use 2D projections to represent 3D models. Spherical harmonics and two histogram based methods - Solid Angle

Histogram and Convex Hull Histogram also perform better than 3D shape distributions.

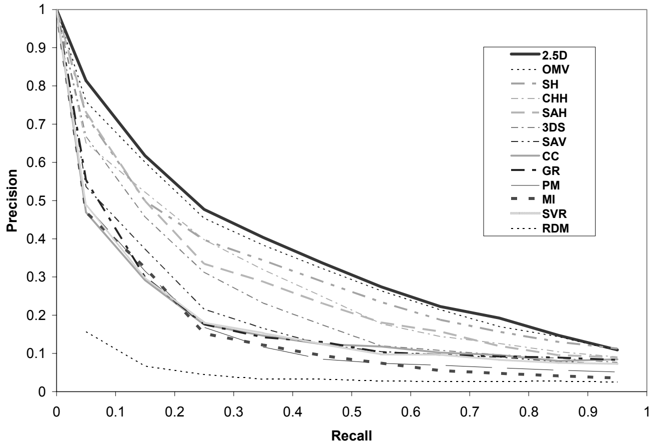


Figure 9: Precision-Recall Calculations for 12 shape representations.

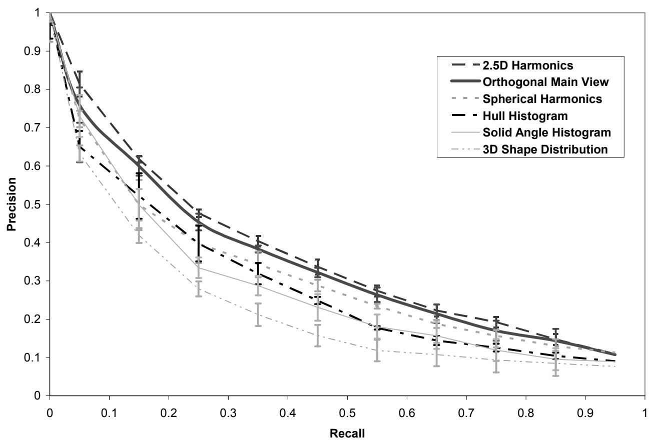


Figure 10: Precision-Recall curves with confidence intervals for the top 6 shape representations.

Table 2: AOD for 12 shape representations with 3D shape distributions as a reference.

Method	AOD
2.5D Harmonics	81.15%
Orthogonal Main View	72.50%
Spherical Harmonics	56.04%
Hull Histogram	33.87%
Solid Angle Histogram	27.00%
3D Shape Distributions	**0.00%**
Surface Area and Volume	-13.17%
Geometric Ratios	-14.10%
Crinkliness and Compactness	-14.38%
Surface Area Volume Ratio	-19.14%
Principal Moments	-35.24%
Moment Invariants	-41.66%

Clearly, histogram based methods outperform feature vector based methods such as Moment Invariants and Principal Moments. This is because histogram based methods capture more of the shape content than feature vectors. The only exception is spherical harmonics, which approximates a shape with 64 harmonic coefficients, thereby capturing more shape content than other feature vectors.

On an average, the base method for AOD, 3D shape distributions, performs 5.57 times better than random retrieval. Table 2 shows the AOD of various methods as a percentage value. From this point forward, we only consider the top six shape representations based on the AOD for comparison of different methods. The results for each super-class are presented below.

4.1. Flat-Thin Walled Components

For the Flat-Thin walled components class, the methods based on 2D drawings outperformed other methods. Surprisingly, 3D shape distributions and Surface Area and Volume performed better than the rest of the three methods based on more complex feature vectors, viz., SH, CHH, and SAH. Although simple, the SAV performs better for this super class because thin walled components have higher surface areas and lower volume, and these features are more explicitly captured in the SAV compared to other point-based methods. The PR curves for these methods for the Flat Thin Walled components super class is shown in Figure 11.

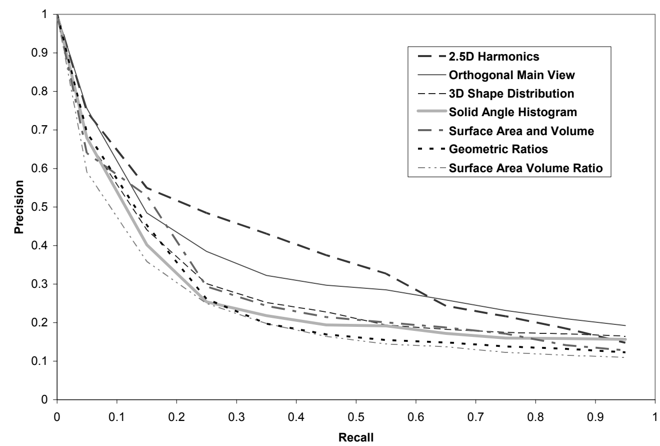


Figure 11: Precision-Recall curves for Flat-Thin Walled Components.

4.2. Prismatic Parts

For this super class, there were four methods that performed consistently better than 3D shape distributions, namely the two 2D view based methods (2.5D and OMV), Spherical Harmonics and Solid Angle Histograms. However, the 2D view based methods did not show a marked improvement in performance compared to other methods for this super class. While the 2D view based methods performed consistently well, two other methods viz. spherical harmonics (SH) and Solid Angle histograms (SAH) performed comparable at higher recall levels (after 0.3 and 0.5 recall respectively) as we had expected. Results can be seen in Figure 12.

4.3. Solids of Revolution

Both methods based on 2D drawings (2.5D and OMV) performed significantly better than other methods on average. Spherical Harmonics and the Convex Hull Histogram performed better than 3D shape distributions. The PR curves for these methods for the Solids of Revolution super class is shown in Figure 13.

As with a text based search engine such as Google, users would like the most relevant 3D models to appear early on in the search results. This is equivalent to saying that we need higher precision at low levels of recall. We ranked methods based on their AODs until a recall value at 0.25. The results are shown in Table 3. Clearly, the shape representations that hold more shape content are better at retrieving more relevant models as compared to the retrieval size. Performing a similar analysis for each of the three super-classes, we found that SAV gives better precision than 3D shape distributions for flat thin walled parts. Not surprisingly, for all three super-classes, both methods based on 2D views outperformed other methods at low recall levels.

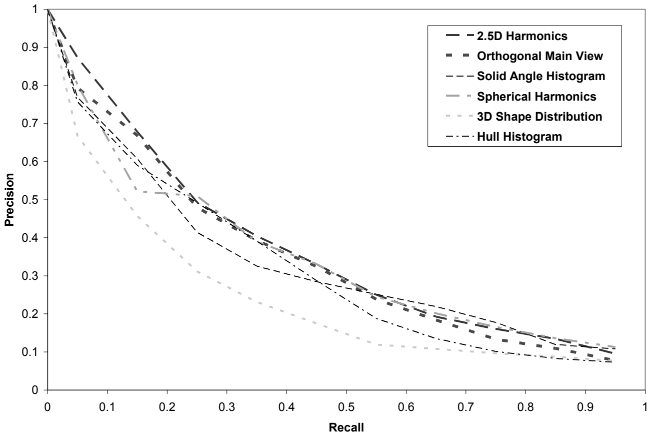


Figure 12: Precision-Recall curves for Prismatic Parts.

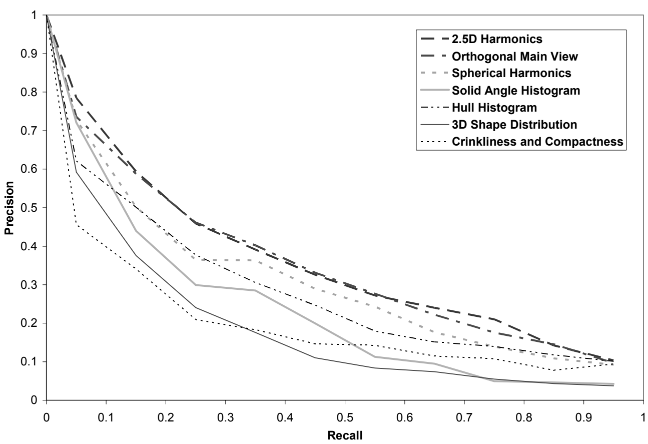


Figure 13: Precision-Recall curves for Solids of Revolution.

Table 3: AOD for 12 shape representations until 25% recall with 3D shape distributions as a reference.

Method	AOD
2.5D Harmonics	49.04%
Orthogonal Main View	41.96%
Spherical Harmonics	25.19%
Hull Histogram	23.29%
Solid Angle Histogram	13.28%
3D Shape Distribution	**0.00%**
Surface Area and Volume	-16.35%
Geometric Ratios	-18.92%
Surface Area Volume Ratio	-29.02%
Principal Moments	-29.09%
Crinkliness and Compactness	-31.12%
Moment Invariants	-31.27%

5. DISCUSSION

We believe that for the engineering domain, it is important to analyze which shape representations perform well for a particular part category, which may seem contrary to the views of researchers in computer vision and graphics. This problem is partly also because engineering shapes have higher levels of shape complexity as compared to other shapes. Part repositories in a single engineering division often hold similar kinds of parts. For example, a division of a car company that designs connecting rods will hold similar connecting rods, while another division that designs steering columns will hold a lot of similar steering columns.

6. CONCLUSIONS

In summary, we have developed a publicly available engineering shape benchmark (ESB) for comparing various shape based search algorithms. ESB includes a set of 725 models in two formats (STL and OBJ) along with associated JPG images and a classification schema. All this data is available publicly from our website http://engineering.purdue.edu/precise/esb.html.

The main contributions of this paper are development of an engineering shape benchmark and an understanding of the effectiveness of twelve different shape representations across three classes of engineering parts. We used 3D shape distributions as a base method to evaluate the performance of other methods on the ESB. It was found that two new shape representations based on 2D views produce consistently better results than methods based purely on 3D models.

We also evaluated the performance of different methods on three classes of engineering shapes. It was found that for Flat-Thin Walled components and Solids of Revolution, the methods based on 2D projections outperformed other methods consistently. However, for Prismatic parts, the best four methods - 2.5D, OMV, SH and SAH perform equally well. The better performance of 2D view based algorithms for all classes of shapes reinforces our intuition that engineering shapes exhibit distinguishing shape features in their 2D views. In addition, spherical harmonics seems to perform reasonably well for the prismatic parts and solids of revolutions compared to other shape representations.

To the best of our knowledge, this is the first attempt at creating a benchmark database for engineering shapes. We will continue to add models to the ESB to encompass a wider variety of shapes so that we can conduct detailed studies regarding the performance of shape representations across the whole spectrum of engineering shapes. We hope that our efforts at building the ESB and conducting studies using ESB for classes of engineering shapes will give rise to more robust shape representations.

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