Interpreting Three-Dimensional Shape Distributions

Article *in* ARCHIVE Proceedings of the Institution of Mechanical Engineers Part C Journal of Mechanical Engineering Science 1989-1996 (vols 203-210) · June 2005

DOI: 10.1243/095440605X31427

5 authors, including:

Jonathan R. Corney
University of Edinburgh

Nick Taylor
Heriot-Watt University

Interpreting three-dimensional shape distributions

H J Rea[1*], **R Sung**[1], **J R Corney**[1], **D E R Clark**[2], and **N K Taylor**[2]

[1]Department of Mechanical Engineering, School of Engineering and Physical Sciences and [2]Department of Mathematics, School of Mathematical and Computer Sciences, Heriot-Watt University, Edinburgh, UK

The manuscript was received on 19 May 2004 and was accepted after revision for publication on 7 March 2005.

DOI: 10.1243/095440605X31427

Abstract: Effective content-based shape retrieval systems would allow engineers to search databases of three-dimensional computer aided design (CAD) models for objects with specific geometries or features. Much of the academic work in this area has focussed on the development of indexing schemes based on different types of three-dimensional to two-dimensional 'shape functions.' Ideally, the shape function used to generate a distribution should be easy to compute and permit the discrimination of both large and small features. The work reported in this paper describes the properties of three new shape distributions based on computationally simple shape functions. The first shape function calculates the arithmetic difference between distributions derived (using the original D2 distance shape function) from both a three-dimensional model and its convex hull. The second shape function is obtained by sampling the angle between random pairs of facets on the object. The third shape function uses the surface orientation to filter the results of a distance distribution. The results reported in this paper suggest that these novel shape functions improve significantly the ability of shape distributions to discriminate between complex engineering parts.

Keywords: shape distributions, three-dimensional shape retrieval, similarity, three-dimensional search, shape recognition, solid model databases

1 INTRODUCTION

Crucial to shape retrieval systems (ie three-dimensional search engines) is the means to characterize the topology and geometry of three-dimensional models in a way that allows the similarity of shapes to be assessed. The need for such tools is growing as the number of models held in computer aided design (CAD)/CAM (computer aided manufacturing) databases is increasing rapidly. Today even small manufacturers frequently have over 10 000 models in their systems, and the total number of three-dimensional CAD models has been estimated to be ~20 billion [**1**]. Given the shear amount and the implicit content of this data, it is not surprising that technologies for searching it have been identified as the key to enable applications ranging from process planning [**2**] to design reuse [**3**] (see Section 2).

In this paper, several different shape analysis functions are investigated and their effectiveness in extracting characteristic information about the geometry and topology of an object is assessed. After reviewing the literature, a previously published shape function (D2) is used to generate the distributions of some basic shape and to discuss their interpretation. The distributions of more complex shapes are then considered, together with the distributions of their convex hulls, and a new distribution, which emphasizes an object's depressions. However the range of shapes over which the new shape function produces 'good' results is limited. So, two other surface orientation-based shape functions are introduced. The paper ends by presenting the results applying these distributions to the problem of assessing the similarity of components in an experimental database.

2 ENGINEERING APPLICATIONS OF SHAPE RETREIVAL SYSTEMS

Many of the productivity gains associated with e-commerce have arisen from the instantaneous

Corresponding author: Department of Mechanical and Chemical Engineering, School of Engineering and Physical Sciences, Heriot-Watt University, Riccarton Campus, Edinburgh, EH41 4AS, UK.

nature of electronic communications (i.e. email and on-line ordering). Although these types of efficiency gains are valuable, many commentators [**4**] believe that there are potentially far larger productivity gains available if networking and database technologies are used to enable the collaborative reuse of design and manufacturing data. Indeed, academic studies suggest that significant amount of design time is involved in the reuse of previous knowledge (e.g. Ullman [**5**] estimates that this represents as much as 75 per cent of design activity). As much engineering knowledge is embodied in the shapes of existing components, the efficient indexing and retrieval of previously produced models are key to make the design process more efficient. For example, one case study [**6**] reported that the potential cost savings from reuse of plastic clips in a single automotive supply company lies somewhere between one and five million dollars/year. However, obtaining and manually surveying catalogues of existing designs, even within a single enterprise, is a costly and time-consuming task, and, as yet there is no means available for automating such searches [**7**].

Motivated by this need, the work reported in this paper has contributed to the development of an on-line system that allows collections of three-dimensional models to be searched for the components geometrically similar to a user-defined target model [**8**] (i.e. content-based retrieval). The system aimed to enable much wider searches to be made for suppliers and to increase reuse of existing designs within enterprises and to promote collaboration between manufacturers. However, such three-dimensional search engines would also enable many other efficiency gains when applied to large collections of parts. The following are some of the important examples of the potential engineering applications that have been proposed [**9**].

1. Cost estimation for machined components. For some manufacturing domains, such as rapid prototyping, reasonably accurate estimates of cost can be achieved by estimating the volume or weight of the part. However, for other manufacturing domains, such as machining, cost estimation depends on the geometric details of the object, and automated procedures are not available for particular accurate cost estimation. However, as Cardone *et al.* [**2**] propose, the cost of manufacturing a new part can be estimated by finding and costing previously manufactured parts that are similar in shape to the new part. If a sufficiently similar part can be found in the database of previously manufactured objects, then the cost of the new part can be estimated by suitably modifying the actual cost of the currently manufactured similar part.
2. Component family formation. In many manufacturing domains, such as sheet metal bending, machine tools can be set up to produce more than one type of part without requiring a set up or tool change [**10**, **11**]. However, parts need to be shape compatible in order for them to share common tools and set ups. Thus, automatic assessment of this form of geometric similarity would allow parts to be grouped into families. Shared tools and set ups can then be used to manufacture objects in the same family, resulting in significant cost savings.
3. Reduction in component proliferations by reusing previously designed parts. Reusing archived design/manufacturing information would result in a faster and more efficient design process. During the design of a new part, the designer can refer to existing designs and utilize previously used components [**12**].

Another notable application is the three-dimensional design system reported [**3**] that uses a database of three-dimensional parts with a user-defined feature-based retrieval function to enable an impressive cut-and-paste approach to component design.

Like all these reported applications, this paper is concerned with the issues involved in sourcing individual components (rather than assemblies) which have functions characterized largely by their shape (e.g. housings, covers, frames, brackets, and fixtures). Often the role of such components is simply to occupy a space in order to protect, support, or guide, other more critical parts. Although such components, in general, have no unique names, their three-dimensional shapes are independent of particular company part numbers and human language, and they can be used to define the form of engineering components in a universal way. Consequently, prototype three-dimensional search engines let users query them by either sketching [**12**] or uploading a target model [**13**] against which a similarity match is performed.

3 SHAPE INDICES

Currently, three-dimensional models (like engineering drawings) are indexed by alpha-numeric ‘part numbers’ with syntax specific to each company. Although this indexing system works well in the context of ongoing maintenance and development of individual parts, it offers little scope for ‘data mining’ (i.e. exploration) of a company’s inventory of designs.

Various ‘part coding’ schemes have been developed to support the group-technology (GT) approach to manufacturing. However, despite their widespread use, such manual shape classification schemes are subjective and limited to machined parts (i.e. excludes pressings or castings). Because of this, the last 5 years have seen increasing academic research into three-dimensional shape retrieval methods for mechanical components. The goal of much of this research is to identify some form of two-dimensional shape signature that would enable a general purpose geometric indexing scheme. In this context, a number of different indices have been investigated: shape distributions [**13–16**], reflective symmetry [**17**], spherical harmonics [**18**, **19**], weighted point sets [**20**], two-dimensional slices [**21**], and characteristic views [**22**]. An overview of these methods can be found in the recent survey by Tangelder and Veltkamp [**23**] and comparative study by Shilane *et al.* [**24**].

The work reported in this paper has been motivated by the need to refine one of these approaches, namely, shape distributions, for application to mechanical components. The next section reviews the mathematics underlying shape distributions.

3.1 Geometric probability

The work reviewed here has its roots in a branch of mathematics known as geometric probability. Classical geometric probability is concerned with the probability of an event related to the relative location of geometric figures placed at random on a plane or in space. The results of these analyses often take the form of a distance (or shape) function that is a mathematical expression that describes the probability of a system taking a specific value or set of values. A typical result is that two randomly chosen points in an n-dimensional unit cube have an average distance of $\sqrt{n/6}$ [**25**].

Hence, essentially, shape distributions are a means of representing an object as a probability histogram. Fig. 1 plots the frequency of lengths between random points on the surface of a sphere. The graph clearly shows that the distance between any two points is more likely to be large (i.e. close to the diameter) than small. Note that ideally the region under the graph in Fig. 1, and all the probability curves, has unit area, implying all possible outcomes are represented. Beyond unit spheres and cubes, the analytical study of geometric probability of three-dimensional shapes is extremely complex. However, computers allow probability distributions to be generated empirically via explicit calculations and various forms of these have been widely used in image analysis and recognition [**26**].

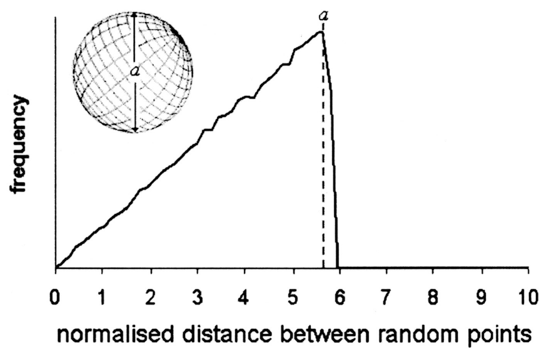


Fig. 1 D2 shape distribution of a sphere

3.2 Shape distributions

Recently several researchers [**13**, **14**, **27**] have studied probability distributions for three-dimensional shapes that are generated by explicit computation. These methods have two distinct steps:

(a) generation of random points over the surface of the object,
(b) application of a shape function.

Points are generated from facetted representations of objects by a procedure described in detail in reference [**15**], but summarized here as:

1. the area of each triangle is calculated, and the triangle is stored in an array along with a cumulative area;
2. a triangle is selected with probability proportional to its area, by generating a random number between 0 and the total surface area, and performing a search on the array of cumulative areas;
3. for each selected triangle, a random point, P, is generated on its surface using the vertices of the triangle (A, B, C), two random numbers, r_1 and r_2, between 0 and 1 and the equation

$$P = (1 - \sqrt{r_1})A + \sqrt{r_1}(1 - r_2)B + \sqrt{r_1}r_2C$$

A number of different shape functions [**13**, **15**] have been proposed and are described in Table 1.

Three general observations can be made about the aforementioned shape functions.

1. The larger the number of random points used, the less sensitive the method is to the presence of small geometric features (e.g. pockets and holes). This is because the chances of four random points all being on a small feature are less than the chances of two points. Also, as each shape function outputs only one number, there are more combinations of, say four, coordinates than two that produce the same value.

Table 1 Shape functions

Shape function	Calculated by	Reflects
A3	Measuring the angle between three random points on the surface of a three-dimensional model	Relative surface orientation
D1	Measuring the distance between a fixed point (generally the centroid) and a random point on the surface	Relative/local distribution of surface area
D2	Measuring the distance between pairs of random points on the surface	Global/dependent distribution of surface area
D3	Measuring the square root of the area of the triangle between three random points on the surface	Reflects both orientation and distribution of the surface area by combining A3 and D2
D4	Measuring the cube root of the volume of the tetrahedron between quadruples of points on the surface	Both the orientation and the relative distribution of the surface, but with reduced sensitivity

2. A desirable shape distribution will be orientation independent and produces distinct graphs for complex shapes.
3. Shape functions in which all the points are randomly selected (e.g. A3, D2, D3, and D4) have the advantage of being orientation independent.

3.3 Behaviour of the D2 shape function

On first encounter, it is not obvious why the probability distributions that arise from the different shape functions are of the form they are. However, familiarity with how form and shape functions interact soon enables one to anticipate the results. Figure 2 shows, for example, how the probability distribution for a cube generated by the D2 function is a combination of the probability distributions for individual faces, pairs of orthogonal faces, and pairs of parallel faces. After noting that the distances/lengths of the probability distributions were scaled by the diagonal length of their bounding box and that the same number of points was used to generate each curve, the following observations can be made.

1. Both the single face [Fig. 2(i)] and the orthogonal face [Fig. 2(ii)] produce distributions that progress smoothly from zero to the maximum distance.
2. The distribution produced by parallel faces in Fig. 2(iii) has a sharp increase at the distance of separation between the faces. This is due to the fact that there is a high probability of the distance between two points closely approximating the distance between the faces.
3. For the entire cube in Fig. 2(iv), the smooth curve from 0 to the point of sharp increase is due to the distribution of distances on each of the faces as in Fig. 2(i).

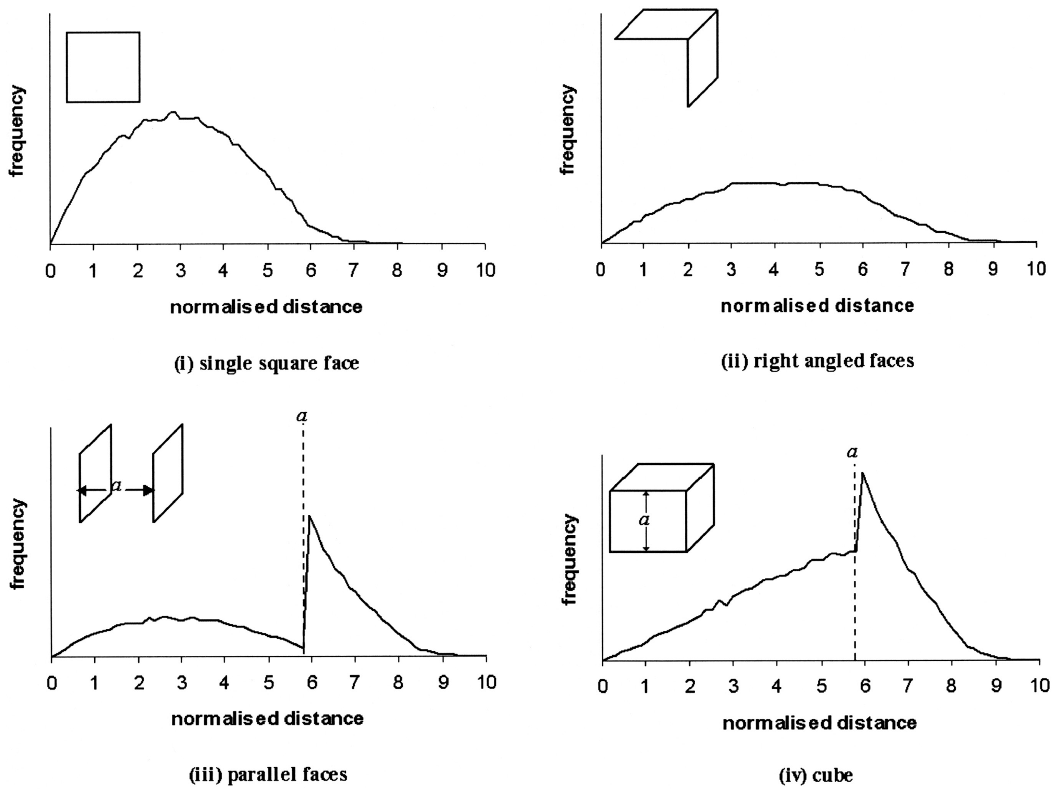


Fig. 2 The build up of D2 distribution of a cube

3.4 Primitive shapes

Examination of a D2 distribution allows one to identify the gross dimensions of simple objects and to postulate regarding the overall shape. For example, consideration of the distributions in Fig. 3 shows that the key dimensions can be identified easily by the sharp peaks/cliffs in the distributions of simpler objects such as the cube and cylinder. This is due to a 'repetition' of the dimension on the object leading to a high probability of it being obtained more frequently. For example, recalling that in all the figures in this paper, the distance values on the x-axis are normalized with respect to the diagonal of the object's bounding box (i.e. scaled so the diagonal length is 10) and that the width, a, of the cube can be computed given the bounding box diagonal d, i.e. $a = \sqrt{d^2/3}$, it is observed that (as $d = 10$, Q1
$a = 5.77$) this is the point in Fig. 3(i) where the sudden rise in frequency begins. A sharp rate of change of frequency often indicates the presence of parallel faces where the discontinuity appears at the shortest distance between the two faces. Two such 'cliffs' can be seen in Fig. 3(ii), where their

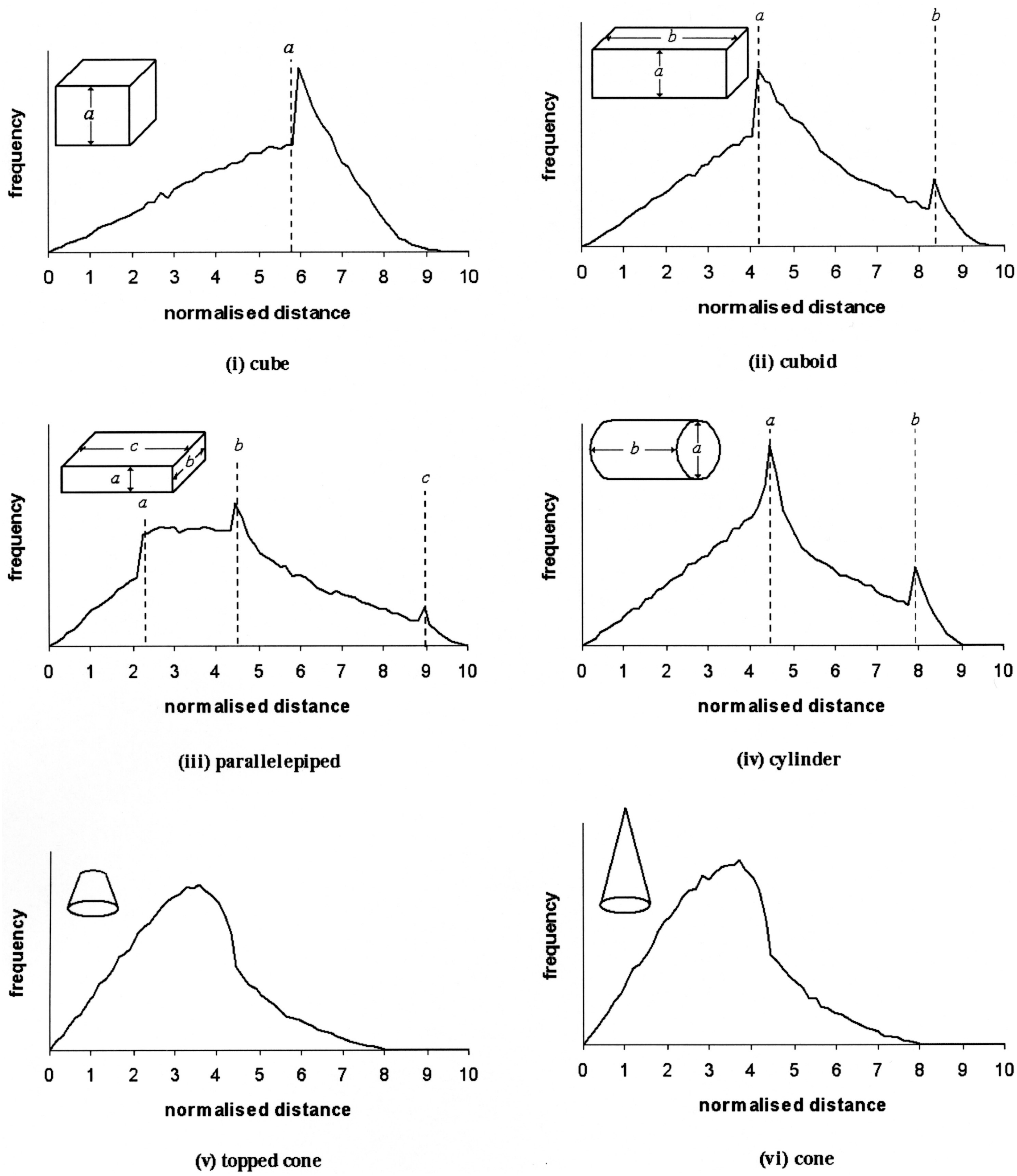


Fig. 3 D2 distributions of common primitives

location reflects the width and the depth of the cuboid. In Fig. 3(iii), three peaks are present one for each of the major dimensions of the parallelepiped; however the peaks are less distinct as the complexity of the shape increases. Figure 3(iv) shows peaks at the diameter and length of a cylinder. In the cone distribution in Fig. 3(vi), no distinguishable features are detected due to the lack of parallel faces. Similarly, no features are seen in Fig. 3(v), as the parallel face distance is similar to, and hence swamped by, the diameter of the cone.

4 DISTRIBUTIONS FOR COMPLEX SHAPES

Osada *et al.* [**27**] have successfully used the D2 shape function to differentiate between grossly dissimilar shaped objects (e.g. aeroplanes and animals). However Ip *et al.* [**14**] have shown that the difference between mechanical parts cannot be distinguished using this simple distribution alone and have accordingly, developed the function further to identify the measured distances as within the solid shape, across a void, or through both solid and void. Talking about the D2 distribution they say:

> These techniques have some limitations when applied directly to matching of solid models such as those found in electro-mechanical design. Specifically, the technique in reference [**15**] is primarily intended for matching gross, or global, model shapes. In our own experiments, as well as those of Osada *et al.* [**15**], pure shape distributions are very efficient at distinguishing models in broad categories: aircraft, boats, people, animals, etc. In this situation, where the models could literally be anything, shape distributions distances generally confirm what one would think of as intuitive similarity between shapes. However, it can often do poorly when discriminating between shapes that have similar gross shape properties, but vastly different detailed shape properties. As models get more complex, the shape histograms then towards a bell-shaped, normal distribution. This can lead to models being classed as similar when their topological properties are vastly different. As a result, the technique often yields false positives and, sometimes, false negatives.

In other words, the D2 shape distributions of objects with even moderate re-entrant features (such as those in Fig. 4) prove difficult to analyse as they have surfaces with very similar separations. The gross shape of the complex object drowns information about individual features, and conversely the effect of internal features on the distribution obscures information about the gross shape.

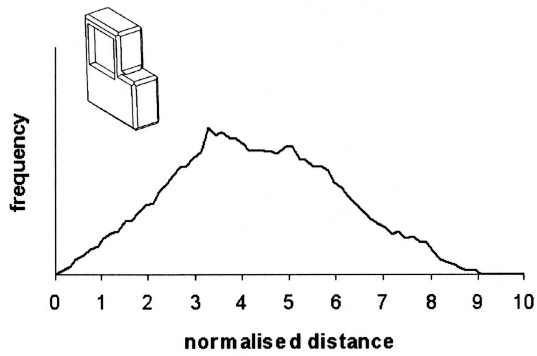
In response to these problems, Ip *et al.* [**14**] described three new distributions that separate the distance measures generated based on geometric properties of the line. They are classified into three non-intersecting groups:

(a) the line segment connecting the two points lies completely inside the model;
(b) the line segment connecting the two points lies completely outside the model;
(c) the line segment connecting the two points passes both inside and outside of the model.

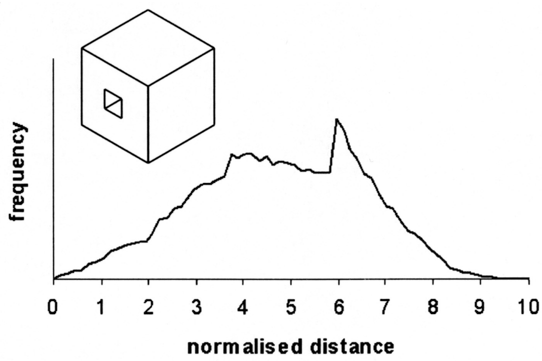
The authors demonstrate that their approach improves the ability of the D2 shape function to distinguish between mechanical parts. However, the generation of these distributions is computationally intensive, requiring repeated intersection calculations and it is reasonable to search for simpler functions that can produce comparable performance.

4.1 Isolating the contribution of internal features

Using the point insertion algorithm introduced by O'Rourke [**28**] and implemented by Pudney [**29**], the convex hull of the object and hence its D2 shape distribution are generated. Typically, this



(i) L-shaped block 1



(ii) Cube with square hole

Fig. 4 D2 distributions of shapes with internal features

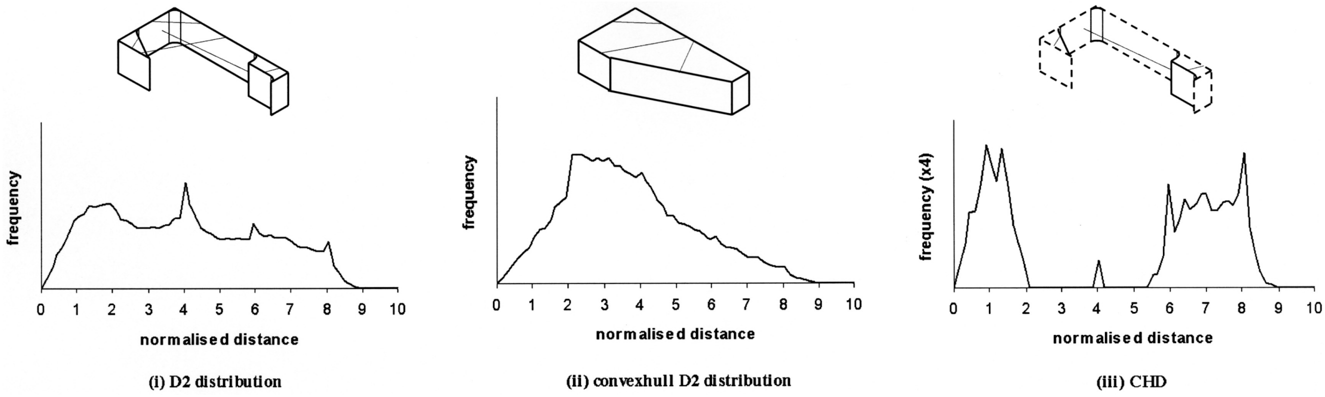


Fig. 5 CHD distribution of tmp-1p4

distribution is a relatively simple one as it is devoid of all concaved features. Indeed, the resulting distributions frequently reflect the 'stock' from which the part is manufactured. It is postulated that subtracting this distribution from the overall shape distribution will provide a distribution reflecting the nature of the concaved features alone (see
Q2 Fig. 5); this is called as the convex hull difference (CHD) curve. In Fig. 5(iii), it is noted that

1. negative values are ignored as this indicates that these are derived from values of length more frequently encountered on the convex hull than the original D2 distribution;
2. the CHD curve has been enlarged for clarity of illustration.

Although the resulting curve is no longer a probability density curve derived from an explicit shape function, it is a reproducible characteristic signature of the object's form. Our premise was that the CHD curve would emphasize the internal features, and this can be seen in the thin-walled* object in Fig. 6. The reasons are as follows:

1. the D2 distribution for the original part contains a higher frequency of small lengths than the distribution of the convex hull due to the thin walls of the part;
2. the convex hull distribution contains a higher frequency of lengths 'around' the depth of the pocket of the part than the D2 distribution of the original part;
3. the original distribution of the part contains a higher frequency than the convex hull D2 of the lengths around the width and breadth of the pockets;
4. distributions of lengths between convex hull faces that are coincident with faces on the original body are approximately the same on both the convex hull and the D2 curves.

When the difference between the average lengths arising from the types of D2 lengths [i.e. Figs 6(i) to (iv)] is significantly distinct (such as with thin-walled objects), the contribution each of the characteristics makes to the CHD curve is easily identified (Figs 5 and 7). The effect is not so evident when the contributions made by the walls, convex hull and so on are similar as in Fig. 8, and the resulting signatures are in this case rather indistinct.

4.2 Surface orientation (SO) distributions

Given the limitation of CHD, another form of distribution considered was based on sampling the orientation between the facets on which the random points were located (i.e. the angles between the surface normals), namely, the SO distribution. It was hypothesized that such a distribution might give a distinctive signal undistorted by variations of scale, orientation, and parameters like wall thickness. Figure 9 shows that for primitive shapes this is indeed the case.

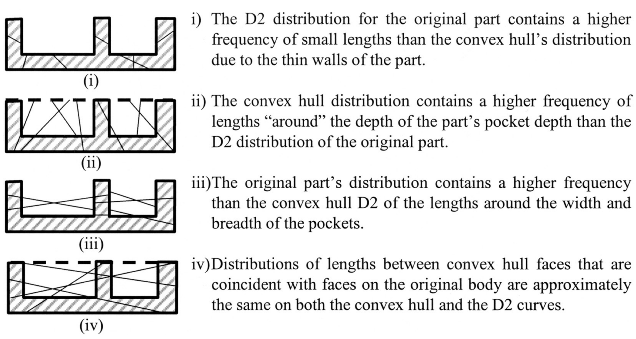


Fig. 6 CHD of a thin-walled object

Although the definition of a thin-walled component is a relative measure, we characterize these as objects constructed from volumes (i.e. walls) whose minimum dimension is <10 per cent of the maximum dimension of the object.

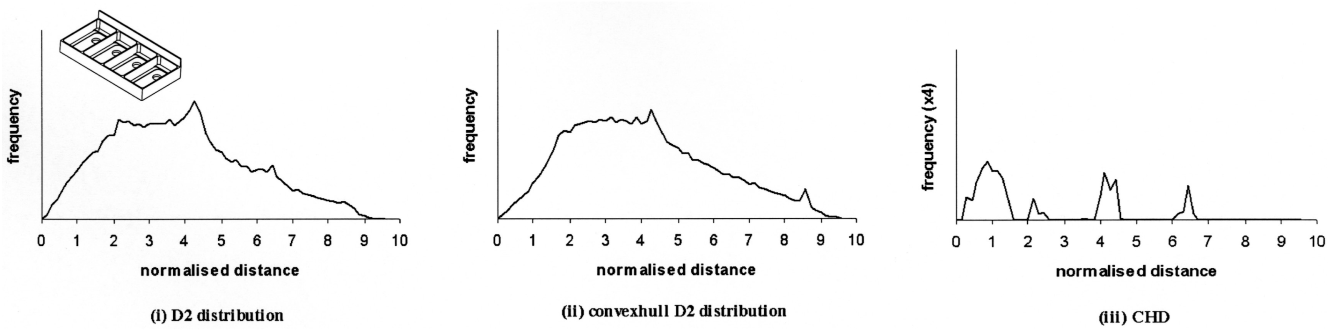


Fig. 7 Difference distributions of Boeing part

However, after further experimentation, it became apparent that the SO is too insensitive. Figure 10 shows the SOs for three quite different components that are nevertheless essentially very similar. The SO produces indistinct signatures in the presence of curved surfaces and the signal rapidly decays into a 'white noise.' After reflecting on the problems of the SO, it was realized that the surface orientation could be used as a filter on the D2 distribution.

4.3 Anti-parallel distances

A new distribution, SO-D2, was investigated which adapted the programme used to generate the D2 curves, so that it only recorded distances between points occurring on facets having a particular orientation. It is apparent from the study of the D2 distribution of a unit cube that the strongest 'signal' arises from points on parallel faces [Fig. 2(iii)]. Consequently, SO-D2 curves were generated by recording the distance between random points only on faces whose normal vectors are anti-parallel. Figures 11 and 12 show that the resulting curves emphasize the signals generated by pairs of planar faces on an object. Indeed, as Table 2 demonstrates, the effects of curved faces (i.e. cylindrical faces) disappear.

5 DISCUSSION

The three shape functions/distributions introduced in this paper, each have their pros and cons:

(a) CHD – produces excellent results for thin-walled objects, but produces indistinct signals for thick-walled objects;
(b) SO – produces strong characteristics for angular objects, but the signal deteriorates in the presence of non-planar faces;
(c) SO-D2 – emphasizes planar/parallel faces, but renders curved faces invisible.

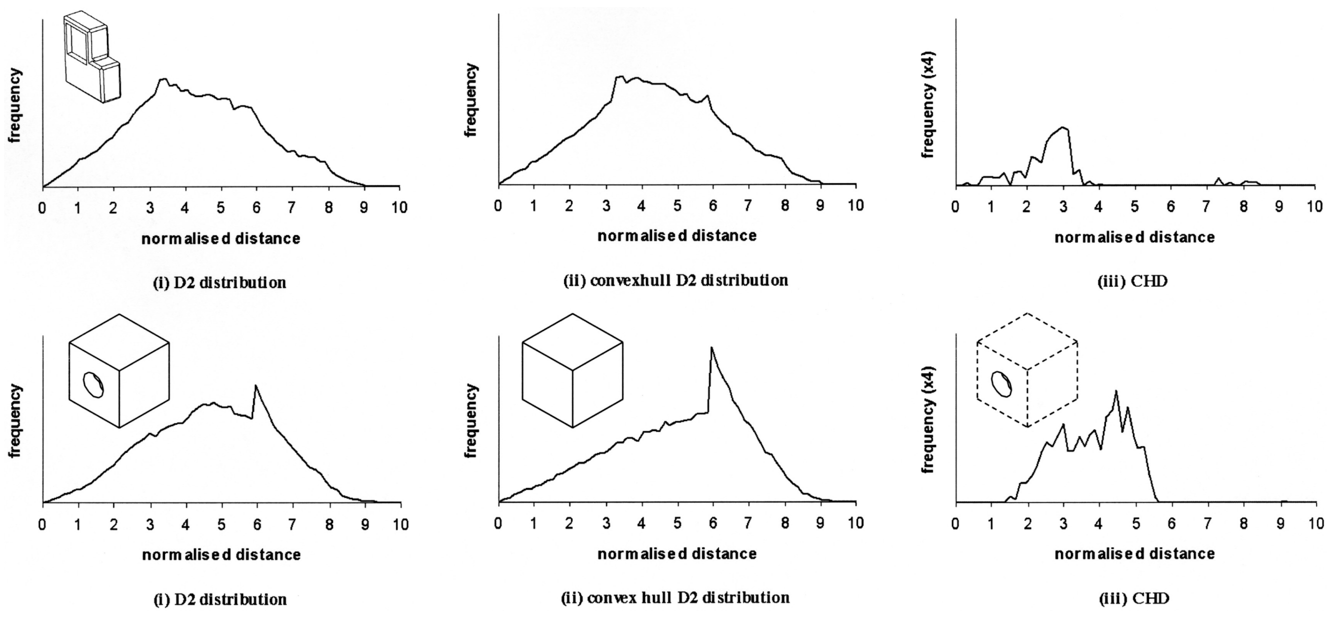


Fig. 8 Difference distributions of thick-walled objects

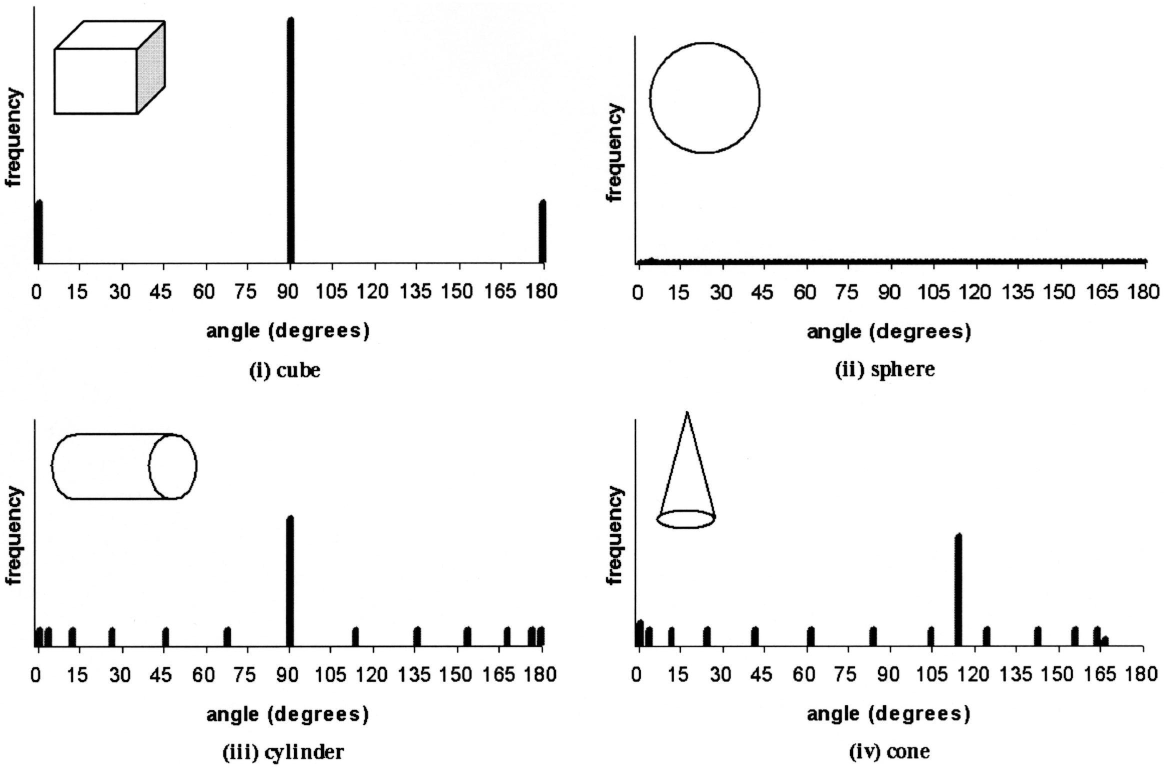


Fig. 9 SO distributions of basic three-dimensional objects

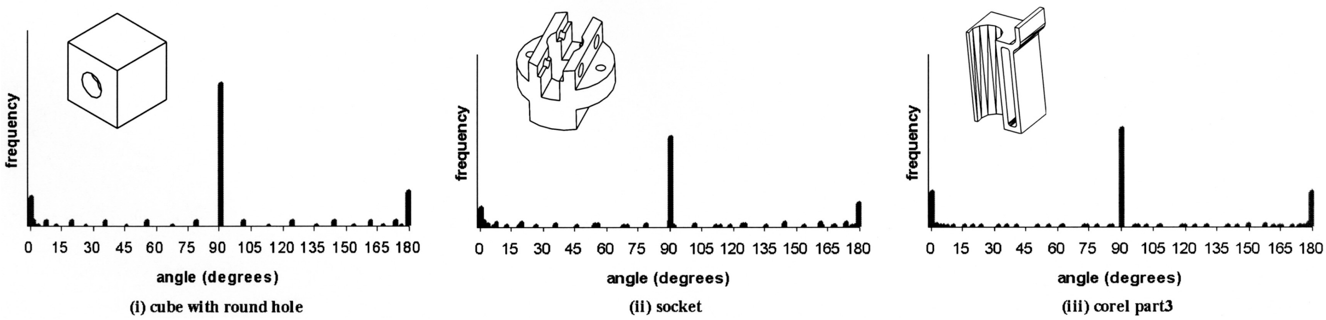


Fig. 10 SO distributions of dissimilar objects

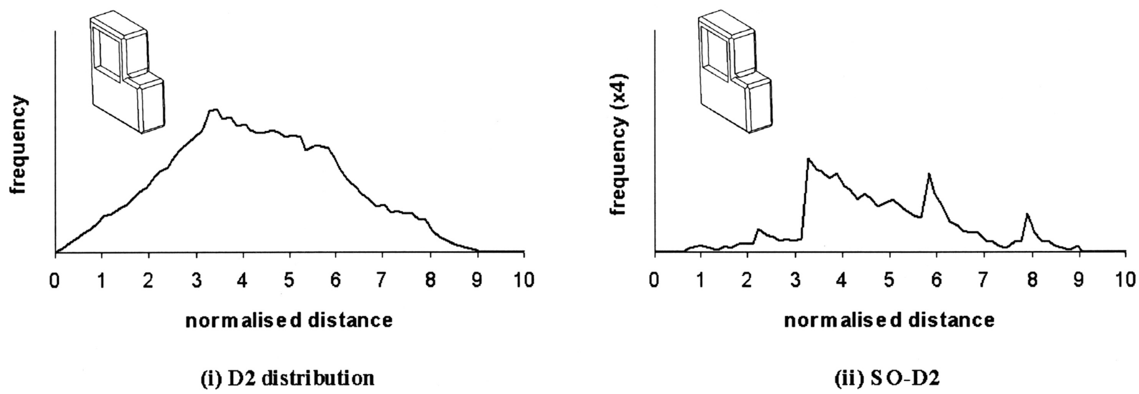
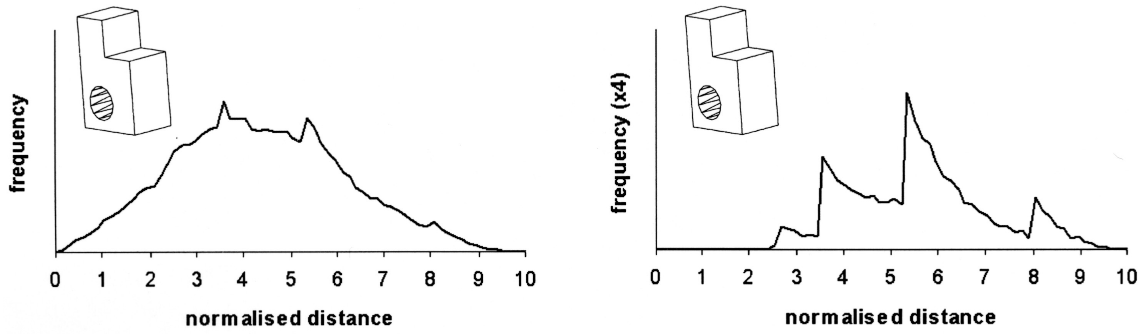


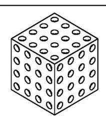
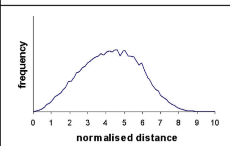
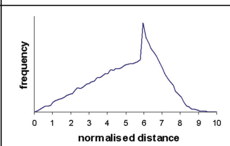
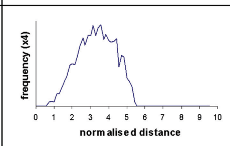
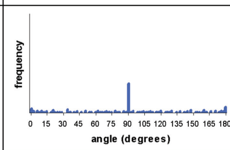
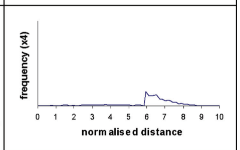
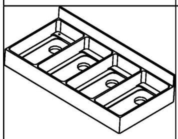
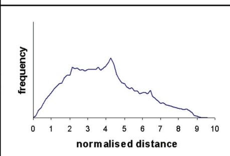
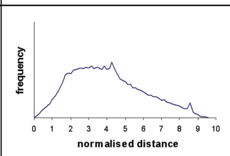
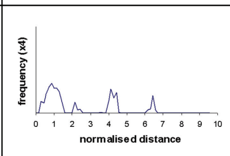
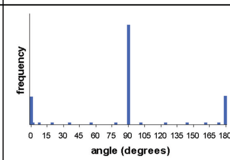
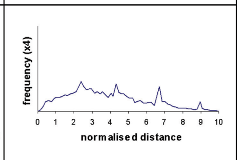
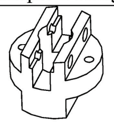
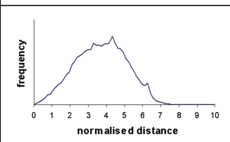
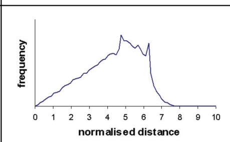
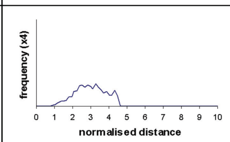
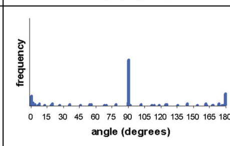
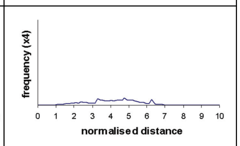
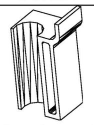
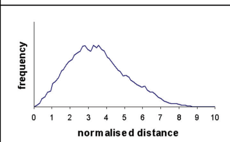
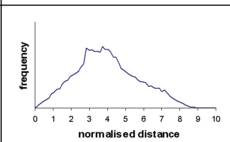
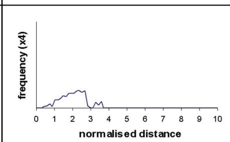
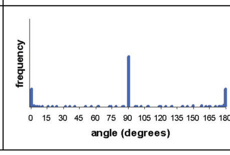
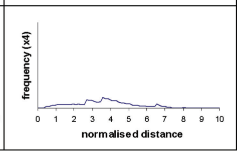
Fig. 11 Anti-parallel distribution of L-shaped block 1



(i) D2 distribution (ii) SO-D2

Fig. 12 Anti-parallel distribution of L-shaped block 2

Table 2 Distributions of complex objects

Models	D2	Connex hull	Connex hull distribution	Surface orientation	SO2
 Cheese					
 Simple Boeing					
 Socket					
 Corel part3					

As a means of comparing the performance of each of the distributions, it is proposed to calculate the Minkowski L_1, value [**30**] when comparing each of the D2, CH, and SO distributions to the same distributions of a cube. The CHD and SO-D2 can be viewed as 'difference distributions' and hence produce unique Minkowski L_1, values for each object. This effectively creates a five-dimensional space where the objects can be plotted around the cube as the origin. A distance measure (or other measure) between the target object and each other object in the database can be used as initial filter to reduce the number of comparisons required, prior to calculating the Minkowski L_1, norm between the target object and each object in the reduced data set.

Examples of these values and their behaviour between similar objects can be seen in Table 3. Here, the values have been calculated for two sets of warped parts, which are included in the benchmark database of 450 warped parts previously introduced in reference [**31**]. Ths data set contains known families of 'similar' components generated by a number of scaling, warping, and editing functions. In this context, a false negative result would be to wrongly classify one member of a family as being dissimilar from its relations.

The false positive/false negative rates were calculated for the benchmark data set for a variety of tolerances for each of the five shape functions and the results are presented in Table 4 and are plotted in Fig. 13. The ideal filter curve is one that has the two axes as asymptotes and a point of inflection near the origin. Of the five measures considered, the CHD curve is closest to this ideal, indicating that it would act as a good initial filter. Choosing a tolerance of ± 0.002 means that it is possible to

Table 3 Cube L_1, values for warped parts

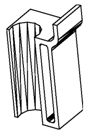
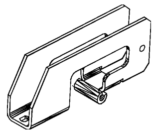
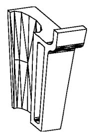
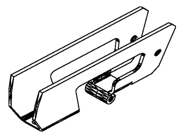
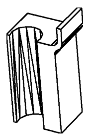
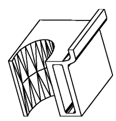
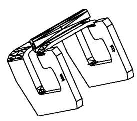
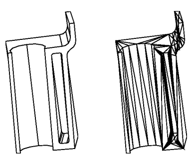
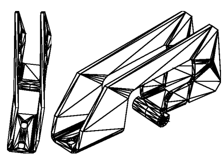
	Corel/part3		Bblox/CAD1	
	Value	Difference	Value	Difference
Original (target)				
D2	0.05	0	0.04	0
Convex hull	0.04	0	0.04	0
Convex hull distribution	0.01	0	0.00	0
Surface orientation	0.27	0	0.47	0
SO2	0.01	0	0.02	0
Taper				
D2	0.06	0.01	0.04	0
Convex hull	0.05	0.01	0.04	0
Convex hull distribution	0.01	0	0.00	0
Surface orientation	1.17	0.90	1.61	1.14
SO-D2	0.00	0	0.01	0.01
Feature removal			N/A (no singly connected features on object)	
D2	0.05	0		
Convex hull	0.04	0		
Convex hull distribution	0.00	0		
Surface orientation	0.27	0		
SO-D2	0.01	0		
Scale to Box				
D2	0.08	0.03	0.04	0
Convex hull	0.07	0.03	0.04	0
Convex hull distribution	0.01	0.01	0.00	0
Surface orientation	0.58	0.31	0.73	0.25
SO-D2	0.01	0	0.01	0.01
Twist				
D2	0.05	0	0.04	0
Convex hull	0.04	0	0.04	0
Convex hull distribution	0.01	0	0.01	0
Surface orientation	1.43	1.16	1.57	1.09
SO-D2	0.00	0	0.00	0.01

Table 4 Filter performance data

	Tolerance	False negative (%)	False positive (%)
D2	0.001	3.44	59.30
	0.005	16.43	33.48
	0.01	32.61	20.51
	0.02	60.33	8.15
	0.05	97.20	0.49
	0.1	100.00	0.00
Convex hull	0.001	6.07	89.44
	0.005	26.44	50.71
	0.01	44.46	25.39
	0.015	58.13	11.37
	0.02	68.71	8.03
	0.05	97.88	0.49
Convex hull distribution	0.0001	3.30	82.89
	0.0002	6.43	69.05
	0.0005	13.51	39.41
	0.001	20.71	24.46
	0.001	27.14	17.05
	0.002	32.96	12.85
	0.003	43.95	9.76
	0.005	64.77	5.56
	0.01	89.80	0.74
Surface Orientation	0.01	1.37	68.44
	0.02	2.51	66.95
	0.05	5.32	64.11
	0.1	10.54	58.93
	0.5	44.71	33.11
	1	71.18	17.05
	2.5	100.00	0.00
SO-D2	0.0001	2.67	69.18
	0.0002	4.89	57.94
	0.0005	9.42	49.17
	0.001	15.98	42.99
	0.005	58.65	14.58
	0.01	88.31	0.37

reduce the data set by >50 per cent, whereas only eliminating 10 to 15 per cent of the possible good matches. Considering the values presented in Table 3, it is likely that the filter excludes grossly differentially scaled objects.

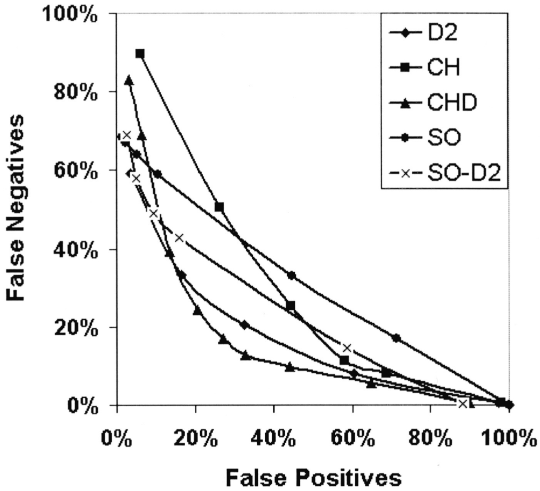


Fig. 13 Filter performance curves

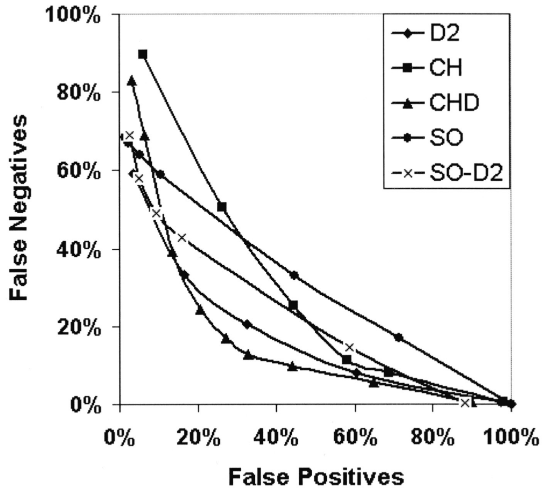


Fig. 14 CHD and shapesearch.net filter performace curves

6 CONCLUSIONS AND FUTURE WORK

The work described here has been implemented on a stand-alone experimental system. In Fig. 14, the CHD performance curve is plotted alongside the performance curve of the filters previously developed by the authors [**32**] and currently available on our publicly accessible search engine at http://www.shapesearch.net. This clearly shows that the CHD acts as a more efficient filter and therefore it should be incorporated into the search engine. Hence, future work will involve:

(a) incorporating these methods into our search engine, http://www.shapesearch.net;
(b) trials on larger and more diverse test data;
(c) analysing the effectiveness of applying Minkowski L_1 norms to rank the results.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the contributions to this research from the following organizations: The UK Engineering and Physical Science Research Council; the Pathtrace PLC; the First Index Ltd; and the Computer Associates and the Scottish Polymer Technology Network. The authors also express their appreciation to Athol A Korabinski for his advice regarding the similarity matrices and to Bill Regli for his assistance with the Design Repository.

REFERENCES

1 **Regli, W. C.** and **Circirello, V. A.** Managing digital libraries for computer-aided design. *Comput. Aided Des.*, 2000, **32**, 119–132.

2 **Cardone, A., Gupta, S. K.,** and **Karnik, M.** Identifying similar parts fur cost estimation of prismatic machined parts. In *ASME 2004 Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DECT 2004*, 2004 (ASME International, Salt Lake, City, Utah).

3 **Funkhouser, T., Kazhdan, M., Shilane, P., Min, P., Kiefer, W., Tal, A., Rusinkiewicz, S.,** and **Dobkin, D.** Modeling by example. In *ACM Transactions on Graphics (SIGGRAPH 2004)*, 2004, (ACM, Los Angeles, CA).

Q3 4 **Dean, A.** In CAD System IP Rights—Entering a New Dimension, 2002, (Thomson Scientific).

Q4 5 **Ullman, D. G.** *The Mechanical Design Process*, 2nd edition 1997 (McGraw-Hill).

Q4 6 **Berchtold, S.** and **Kreigel, H.-P.** S3: similarity search in CAD database systems. SIGMOD 97, 1997, (ACM Press).

7 **Cardone, A., Gupta, S. K.,** and **Karnik, M.** A survey of shape similarity assessement algorithms for product design and manufacturing applications. *J. Comput. Inform. Sci. Eng.*, 2003, **3**(2), 109–118.

8 **Rea, H., Corney, J., Clark, D., Pritchard, J., Breaks, M.,** and **MacLeod, R.** Part sourcing in a global market. *Concurrent Eng. Res. and Appl.*, 2002, **10**(4), 325–334.

9 **Ng, V. T. V.** and **Chan, S. C. F.** A solid modelling library for the world wide web. *Comput. Netw. ISDN Systems*, 1998, **30**(20–21), 1835–1863.

10 **Gupta, S. K.** and **Bourne, D. A.** Sheet metal bending: generating shared setups. *ASME J. Manufac. Sci. and Eng.*, 1999, **121**(November), 689–694.

11 **Alva, U.** and **Gupta, S. K.** Automated design of sheet metal punches for bending multiple parts in a single setup. *Robot. Comput. Integr. Manufac.*, 2001, 33–47. 2. Q5

12 **Hou, S.** and **Ramini, K.** Dynamic query interface for 3D shape search. In *ASME 2004 Design Engineering Technical Conferences and Computers and Information in Engineering Conference, DECT 2004*, 2004 (ASME International, Salt Lake City, Utah).

13 **Ankerst, M., Kastenmuller, G., Kriegal, H.-P.,** and **Seidl, T.** 3D shape histograms for similarity search and classification in spatial databases. In *SSD 99 – Advances in Spatial Databases*, 1999 (Spring-Verlag Berlin Heidelberg, Hong Kong).

14 **Ip, C. Y., Lapadat, D., Sieger, L.,** and **Regli, W. C.** Using shape distributions to compare solid models. In *Solid Modeling*, 2002 (ACM, Saarbrucken, Germany).

15 **Osada, R., Funkhouser, T., Chazelle, B.,** and **Dobkin, D.** Matching 3D models with shape distributions. In *Shape Modelling International*, 2001. Q6

16 **Lui, Y., Pu, J., Zha, H., Liu, W.** and **Uehara, Y.** Thlckness histogram and statistical harmonic representation for 3D model retrieval. In *2nd International Symposium on 3D Data Processing, Visualization, and Transmission – 3DPVT 2004*, 2004 (IEEE Computer Societym Thessaloniki, Greece).

17 **Kazhdan, M., Chazelle, B., Dobkin, D., Funkhouser, T.,** and **Rusinkiewicz, S.** A reflective symmetry descriptor for 3D models. *Algorithmica*, 2003. Q7

18 **Zhang, D.** and **Herbert, M.** Harmonic maps and their applications in surface matching. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR'99)* 1999. Q6

19 **Kazhdan, M., Funkhouser, T.,** and **Rusinkiewicz, S.** Rotatiom invariant spherical harmonic representation of 3D shape descriptors. In *Symposium on Geometry Processing*, 2003 (Eurographics Association, Aachen, Germany).

20 **Tangelder, J. W. H.** and **Veltkamp, R. C.** Polyhedral model retrieval using weighted point sets. Institute of Information and Computing Sciences. Utrecht, The Netherlands. UU-CS-2002-019, 2002.

21 **Pu, J., Lui, Y., Xin, G., Zha, H., Liu, W.,** and **Uehara, Y.** 3D model retrieval based on 2D slice similarity measurements. In *2nd International Symposium on 3D Data Processing, Visualization, and Transmission – 3DPVT 2004*, 2004 (IEEE Computer Society, Thessaloniki, Greece)

22 **Ansary, T. F., Vandeborre, J.-P., Mahmoudi, S.,** and **Daoudi, M.** A bayesian frameork for 3D models retrieval based on characteristic views. In *2nd International Symposium on 3D Data Processing, Visualization, and Transmission – 3DPVT 2004*, 2004 (IEEE Computer Society, Thessaloniki, Greece).

23 **Tangelder, J.** and **Veltkamp, R.** A survey of content based 3D shape retrieval methods. In *International Conference on Shape Modeling and Applications*, 2004 (IEEE Computer Society, Genova, Italy).

24 **Shilane, P., Min, P., Kazhdan, M.,** and **Funkhouser, T.** The Princeton shape benchmark. In *International Conference on Shape Modeling and Applications*, 2004 (IEE Computer Society, Genova, Italy).

25 **Santalo, L.** Integral geometry and geometric probability *Encyclopedia of Mathematics and its Applications*. (Ed. G.-C. Rota) 1976, Vol. I (Addison-Wesley Publishing Company). Q8

26 **Jain, A.K., Duin, R. P. W.,** and **Mao, J.** Statistical pattern recognition: a review. *IEEE Trans. Pattern Anal. Mach. Intell.*, 2000, **22**(1), 4–37.

27 **Osada, R., Funkhouser, T., Chazelle, B.,** and **Dobkin, D.** Shape distributions. *ACM Trans. Graph.*, 2002, **21**(4). Q9

28 **O'Rourke, J.** *Computational Geometry in C*, 1998 (Cambridge University Press). Q8

29 **Pudney, C.** Java 3D convex hull algorithm. The Stony Brook Algorithm Repository, Department of Computer Science, State University of New York, New York, 1998 available from www.cs. sunysb.edu/∼algorith/implement/CONVEX-HULL-JAVA/implement.shtml.

30 **Kullback**, *Information Theory and Statistics*, 1968 (Dover). Q8

31 **Corney, J. C., Rea, H. J., Clark, D., Pritchard, J., Breaks, M.,** and **MacLeod, R.** Coarse filters for shape matching. *IEEE Comput. Graph. Appl.*, 2002, **22**(3), 65–74.

32 **Sung, R., Rea, H. J., Corney, J. C., Clark, D. E., Pritchard, J., Breaks, M. L.,** and **MacLeod, R. A.** Assessing the effectiveness of filters for shape matching. In 2002 ASME International Mechanical Engineering Congress and Exposition, 2002. New Orleans, Louisiana.

APPENDIX

Notation

a, b, c	object dimensions (i.e. width, breadth, and height)
A, B, C	triangle vertices

A3	statistical shape function based on the angles between three randomly chosen points
CH	convex hull D2 distribution
CHD	convex hull distribution
d	diagonal dimension
D1	statistical shape function based on the distance between a fixed point and one randomly chosen point
D2	statistical shape function based on the distance between two randomly chosen points
D3	statistical shape function based on the area between three randomly chosen points
n	dimension
P	random point
r_1, r_2	random numbers
SO	surface orientation distribution
SO-D2	surface orientation distribution of anti-parallel vectors

IMECHE

JOURNAL........MES **ARTID......C09404**

TO: CORRESPONDING AUTHOR

AUTHOR QUERIES - TO BE ANSWERED BY THE AUTHOR

The following queries have arisen during the typesetting of your manuscript. Please answer these queries by marking the required corrections at the appropriate point in the text.

Q1	Please provide units for d and a.	
Q2	CHD is given as “Convex hull distribution” in notation section and as “Convex hull difference” in text. Please check throughout.	
Q3	Author, we have assumed “Thomson scientific” as publisher in ref 4. Please provide publisher location.	
Q4	Please provide publisher location for ref 5,6.	
Q5	Please check the page range of ref 11.	
Q6	Please provide publisher & location for ref 15 & 18.	
Q7	Author please provide volume number & page number for ref 17.	
Q8	Please provide publisher location for ref 25, 28 & 30.	
Q9	Please provide page range for ref 27.	
	PLEASE CHECK, disk did not match hard copy, we have followed hard copy	

Professional Engineering Publishing Limited
1 Birdcage Walk
Westminster
London
SW1H 9JJ
Tel +44 (0)20 7222 7899
Fax +44 (0)20 7222 4557
www.pepublishing.com

Journal of Mechanical Engineering Science

Proceedings of the Institution of Mechanical Engineers – Part C

Offprints/Journal Order

To ensure that you receive the offprints or Journal you require please return this form with your corrections.

MS Number:	C09404
Number of pages:	14
Author	Ms Heather J Rea

If you would prefer to receive a free copy of the Journal issue instead of 25 free offprints, please indicate below:

Quantity	**I copy of the Journal issue**	**25 offprints**
Cost	Free	Free

Please supply .... offprints/1 copy of the Journal issue* and forward to the following address:

*** Delete as appropriate**

Ms Heather J Rea
Department of Mechanical and Chemical Engineering
School of Engineering and Physical Sciences
Heriot-Watt University
Riccarton Campus
Edinburgh
EH14 4AS
UK

Quotations for additional reprints will be provided on request.