

# Intelligent Shape Recognition for Complex Industrial Tasks

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**ABSTRACT:** Applications of current machine vision systems in industry demand a highly constrained environment and also limit the number of objects involved. This paper proposes an intelligent shape representation and recognition system that can handle a large class of objects under less constrained situations. The investigation treats intelligent integration of different shape representation schemes and generation of the best shape recognition strategy using global shape properties. The proposed scheme effectively incorporates model-driven top-down and data-driven bottom-up approaches of shape analysis. By analyzing global shape properties, the essential features and their degrees of importance are determined quickly. In the representation phase, objects are described by using these essential features; in the recognition phase, searching for the best candidate is restricted to the models represented by these features and the observed shape is matched to the candidate models in the order of importance of the essential features. Systems are being developed for two- and three-dimensional shapes separately since they are exploiting different visual data—photometric and range, respectively.

## Introduction

Currently, machine vision systems have a pervasive influence in many areas of automated industrial processes [1]–[6]. Particularly, in flexible manufacturing areas involving small- to medium-sized batches, they have been used as the key sensing modality for a robot. With the aid of visual feedback, a robot can deal with imprecisely positioned and/or randomly oriented parts or subassemblies. However, current machine vision systems are not fast enough to provide real-time feedback to a robot, and practical applications of machine vision systems have demanded a highly constrained environment and limited the number of objects involved. As yet, a machine vision system that can

handle a large number of objects in an unconstrained situation has not emerged.

Until now, most machine vision systems in industry have been developed using a two-dimensional binary vision technique [7], [8]. These systems recognize the object shape by matching the boundaries or skeletons extracted from the observed silhouettes with the prototypical ones stored in memory. In addition to the boundary and skeleton, global shape properties such as eccentricity, compactness, Euler number, moments, and principal axes also have been used. Although the binary vision technique often imposes constraints on object pose, scene complexity, and scene illumination, it has been used popularly for many industrial applications, particularly for part identification and inspection, because of its simplicity of design and low processing time. Even in a fairly complex industrial task such as bin picking, this technique has generated some solutions in providing a robot the optimal grasping site [6].

However, because of the aforementioned limitations with the binary vision technique, three-dimensional vision techniques based on range information have been receiving more attention lately, particularly when the objects involved are inherently three-dimensional in nature (or voluminous) and/or when the objects in a scene are not sufficiently well separated. Range information has several advantages over photometric data: (1) it encompasses intrinsic characteristics of the object shape; (2) it is free from artifacts such as contrast reduction and shadow effect; (3) it can be used to generate useful three-dimensional object features such as local surface normals and local surface curvatures. Recently, many schemes based on range information in relation to feature extraction, scene analysis, and object recognition have been proposed [9]–[12].

Although the three-dimensional vision technique exploiting range information is more reliable and flexible than the binary vision technique, it also suffers from drawbacks that might prevent it from being widely adopted in industry. Commercially available range sensors that can acquire sufficiently dense and accurate range data are still very costly. Furthermore, acquisition and interpretation of range data is computationally

much more expensive than that of the photometric data. This is why machine vision systems based on the binary vision technique still remain dominant in most industrial applications.

Of the many problems that must be solved to make machine vision systems practically useful in performing most industrial tasks, the most difficult one might be the inflexibility in representing shapes and the inefficiency in shape recognition. Although a number of shape representation and recognition schemes have been proposed so far, no single method has been successful in handling different classes of objects efficiently.

In general, shape representation and recognition schemes, whether they deal with two- or three-dimensional shapes, are evaluated according to the following criteria: (1) whether a scheme is insensitive to the variances such as scaling, rotation, and translation; (2) how many different classes of shapes it can reliably represent and/or recognize; (3) how flexible and efficient is the control strategy for shape analysis. Most efforts address the first issue, and several schemes that are not very sensitive to the aforementioned variances have emerged. As yet, the second and third issues have not been addressed seriously—particularly from the standpoint of the industrial application of machine vision systems.

Most machine vision systems to date apply to a small number of specific objects; therefore, the best representation scheme for that category of objects can be specified in advance. However, those systems are not flexible; if the objects or their environments change, they become useless. Furthermore, they are inadequate for complex industrial tasks in which a number of different dimensions and shapes of parts and subassemblies are involved. The main reason for this inadequacy is that not all parts can be described equally well by a single feature. As an example of this problem, consider a machine vision system designed for accomplishing an automatic assembly task including such parts as shown in Fig. 1. What would be the best shape representation scheme that can describe all the parts equally well? Is it a scheme based on boundary, skeleton, or hole? The best answer would be that any scheme based on a single feature is

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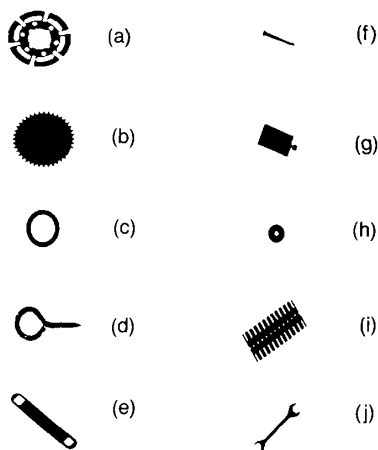


Fig. 1. Silhouettes of different industrial parts.

improper. Obviously, no single feature can describe all the parts sufficiently well. For instance, the most essential feature for the part shown in Fig. 1(b) is the boundary; for the part shown in Fig. 1(d), it is the skeleton. For the parts with complex shape, however, the essential feature may not be a single feature, but multiple ones. For example, for the parts shown in Figs. 1(a) and 1(i), both the boundary and the holes are important in characterizing the shape; although it is hard to tell precisely which feature is more important than the other.

Similar questions arise when the task includes a different class of three-dimensional parts and subassemblies. No three-dimensional shape representation and recognition scheme that uses a single three-dimensional feature could describe different classes of three-dimensional shapes equally well.

The proposed scheme is directed at circumventing the limitations of current shape representation and recognition schemes. In this work, we are developing two- and three-dimensional schemes independently, because, although both are based on similar rationale and structure, they exploit different visual data—photometric and range, respectively. (Although we might differentiate flattish objects from voluminous ones by inspecting and measuring the size of the object, it is difficult to make a judgment objectively. Furthermore, size measurement requires range information.)

This paper is organized as follows. First, we discuss the proposed scheme in general, and describe system units and their functions in detail. We then show the practical application of our scheme to the different classes

of two-dimensional shapes. Here, we overview and discuss two-dimensional shape representation schemes reported so far; detail global shape properties and three major shape representation schemes we currently employ; and provide a set of rules that we are currently adopting to determine the best representation for a given shape.

### System Description

Our method is directed at solving the general representation and recognition problem, and its framework is not constrained to a particular domain of application. However, we believe that this scheme will be particularly useful for situations in which a large class of different shapes are involved, such as in automatic assembly.

#### General Discussion of Proposed Scheme

Our scheme is based on the premise that an object exhibits a wide range of properties. A successful representation and/or recognition requires an integrated synthesis and/or analysis strategy. This philosophy is motivated by the parallel human process—a process that draws from numerous stimuli (such as visual and tactile) and a powerful knowledge that enables humans to describe and recognize object shapes.

In this work, we are developing two- and three-dimensional schemes independently, although both are based on similar rationale and structure. This is because, in practice, they employ different visual data. If one could develop a fast and objective way of differentiating flattish objects from voluminous ones, he or she might integrate two- and three-dimensional schemes into one unified scheme; this is beyond the scope of this paper.

In our shape representation and recognition scheme, we are adopting the intelligent incorporation of model-driven top-down and data-driven bottom-up approaches, which is considered as the ultimate goal of an intelligent shape analysis. The overall strategies of our scheme can be described as follows:

- (1) The global shape property of the object is measured, and the features that are most important in representing and/or recognizing the given object are determined. Eccentricity (or elongatedness), compactness (or complexity), and Euler number are used to determine the essential feature of two-dimensional objects, while the local surface curvature is used for three-dimensional objects. For two-dimensional objects, candidate features are boundary, skeleton, and hole. Whereas, for three-dimensional objects,

they are wireframe (or edge-vertex), surface orientation, and surface curvature.

- (2) If the essential feature is dominant, the object is then represented by a scheme based on that feature and stored in the corresponding subspace in memory. If the essential feature is not dominant but ambiguous—if there exists more than one feature that is important—we represent the object by using all those features and record the order of their importance.
- (3) During recognition, searching for the best candidate is done in the order of importance of the essential features in such a way that, if the matching certainty with the model of higher priority is less than threshold, the next one is tried, and so forth. Certainly, if the global shape property measurement yields one essential feature that is dominant, searching is limited to the corresponding subspace in memory.
- (4) If the overall matching certainty is less than threshold, the object is declared as unclassifiable.

#### System Configuration

At the core of this system (Fig. 2) is the Supervisor (SV). It interacts with other units with the aid of a Knowledge Base (KB). The Knowledge Base contains a set of rules that help the Supervisor determine the shape representation scheme best suited to produce the description of an input object shape. Once the Supervisor decides on a plan of action, it activates schemes that produce representations that are added to the Shape Model (SM) or used to recognize the object by comparing it with stored representations. The Knowledge Base contains a set of rules adopting a context-limiting strategy whereby rules are separated into groups, and only some rules are activated at any time. Forward and backward chaining are incorporated for flexible reasoning. Further, a meta-rule based on specificity ordering is used to resolve the conflict when more than one rule are triggered simultaneously.

Whether the visual data is photometric or range, real-world images require some noise cleaning; this is done by the Preprocessor (PP). For the case of a two-dimensional shape, we use morphological erosion and/or dilation; for a three-dimensional shape, we exploit the averaging-of-nearest-neighbor technique proposed by Hoffman and Jain [13]. This technique is known to suppress noise effectively while preserving useful features such as edges.

Generally, it is the global properties of an object that determine the validity of a rep-

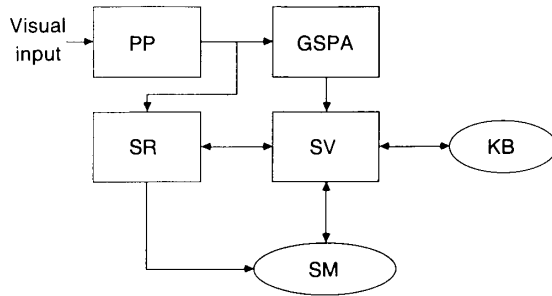


Fig. 2. Block diagram of the proposed shape representation and recognition system consisting of PP (Preprocessor), GSPA (Global Shape Property Analyzer), SV (Supervisor), KB (Knowledge Base), SR (Shape Representer), and SM (Shape Model).

resentation. This introduces a new functional unit—the Global Shape Property Analyzer (GSPA). As the global shape properties for a two-dimensional shape, we use eccentricity (or elongatedness), compactness (or complexity), and the Euler number. The reason we include the Euler number in the global shape property is because many industrial parts often contain holes in the interior (Fig. 1), which are crucial in characterizing a shape. (Note that the Euler number is computed by subtracting the number of holes from the number of connected components in the image.) The essential feature or features of the given shape are then determined by global shape property measurement coupled with knowledge as to the fuzzy relationships between these measurements and human judgments on the essential features. The Knowledge Base uses the values of these global properties to fire rules on the basis of which the Supervisor generates strategies.

For a three-dimensional shape, we exploit surface curvature signs and histograms as global shape properties to determine the essential feature. By analyzing these properties, we characterize the shape into one of the following types: nonconvex polyhedral, convex, nonconvex curved with simple solids, or complex. We prefer the surface curvature as a global shape property since it is a viewing-direction-invariant characteristic. Furthermore, combining surface curvature signs with curvature histograms makes the global classification of the observed three-dimensional shape fairly reliable and easy.

Currently, the Shape Representer (SR) for a two-dimensional shape consists of a normalized distance-versus-angle measurer, a morphological shape recognizer, and a relational modeler based on skeletal structure. For objects whose shapes are best described

by their boundaries, the Knowledge Base might suggest the use of a boundary representation produced by the normalized distance-versus-angle measurer. In the representation phase, this is added to the SM; in the recognition phase, it is used to restrict the search space in the model based on boundary representations, and then to look for a match in this reduced space. Objects that are thin and have a well-defined principal axis may be represented by their morphological skeleton. If there are holes in the interior that decrease the reliability in using the principal axis for detecting scale and/or orientation variance, a relational model based on skeleton features may be the better representation. A large Euler number is a distinctive characteristic, and Euler numbers are also stored in the Shape Model.

For three-dimensional objects, the Shape

Representer consists of a wireframe representation based on edges and vertices, an extended Gaussian image, a three-dimensional relational modeler based on surface curvature, and a surface representation based on surface curvature. For a nonconvex polyhedral type, we use a wireframe representation. For a convex type, we use an extended Gaussian image. For a nonconvex curved with simple solids, we use a three-dimensional relational modeler based on surface curvature. For a complex type, we use a surface representation based on surface curvature. In the representation phase, we generate the model from different viewing directions and classify the object type by the view from that direction. (Note that for the object-centered representation scheme, such as an extended Gaussian image, model generation from different viewing directions is unnecessary.)

Table 1 depicts the comparison of the Preprocessor, Global Shape Property Analyzer, Shape Representer, and Shape Model used for two- and three-dimensional systems.

Since the GSPA employs different global shape properties to determine the distinguished feature, and the SR and SM consist of different shape representation schemes, this system is highly amenable to parallel implementation.

During the model generation phase, the system works as follows: First, the GSPA computes a number of global shape properties; next, the SV determines the suitability of a particular representation from the values of the global shape properties using rules in the KB. Based on its decisions, the SV activates modules in the SR to generate representations. Although each of these three

**Table 1**  
Comparison of the Preprocessor (PP), Global Shape Property Analyzer (GSPA), Shape Representer (SR), and Shape Model Used for Two- and Three-Dimensional Systems

Unit	Shape	
	Two-Dimensional	Three-Dimensional
PP	Morphological Erosion/Dilation	Nearest Neighborhood Smoothing
GSPA	Eccentricity, Compactness, Euler Number	Surface Curvature Signs, Surface Curvature Histogram
SR, SP	Normalized Distance-versus-Angle Measure, Morphological Skeleton Function, Relational Model Based on Skeletal Structure	Wireframe Representation, Extended Gaussian Image, Three-Dimensional Relational Model, Surface Representation Based on Surface Curvature

tasks have to be executed in sequence, each of them can be implemented in parallel. The task of computing the global shape properties can be distributed among several processors, with a particular processor assigned to a particular shape property. The SV can start determining the suitability of the representations as soon as the shape properties begin to become available. Again, several processors can be used in parallel to do this task, each computing the appropriateness of a particular representation. Finally, the model generation task can be executed in parallel with each parallel process computing a different representation.

The recognition phase is quite similar; its first two tasks are the same as those of the representation phase. The global shape properties are first computed and then the suitability of a particular kind of representation or representations is determined. This latter task is that of hypothesis generation. These two tasks can be implemented in parallel as discussed earlier for the representation phase. The final task, that of recognition or hypothesis verification, can be implemented as a highly parallel process depending on the hypotheses generated and the number of processors available. If several hypotheses of comparable strength are generated, different processors can be assigned to different subspaces of the model base, with each processor trying to match the object in the scene to the representations in its model subspace. If more processors are available than there are hypotheses, or if one hypothesis is much stronger than the others, search can proceed on a best-hypothesis-first basis. In this case, all the processors can be set up to match the object with the different representations in the model subspace corresponding to the strongest hypothesis.

In either the representation or the recognition phase, the Knowledge Base only gives suggestions to the Supervisor. These suggestions may sometimes compete in priority. Resolution of such ambiguities is crucial to the success of the system.

## Practical Application to Two-Dimensional Shapes

### Overview and Discussion

Two-dimensional shape representation schemes can be categorized broadly as follows [7], [8]: external shape representation based on boundary, structural representation based on skeleton, representation based on spatial occupancy, representation based on global shape properties.

External shape representation exploits one-dimensional entities that are used to describe

the boundary of the object and, hence, of the region enclosed. Boundary approximation by piecewise analytic functions, Fourier descriptors, chain codes, and angle-versus-length signatures belong to this category. On the other hand, structural representation directly uses a two-dimensional internal structure of an object shape constructed from a skeleton. The medial axis transformation (MAT), morphological skeleton function, and relational model based on skeleton features (i.e., junctions, branches, loops) are structural representations. Spatial occupancy-based representation employs a quadtree to describe an object. The root of the quadtree corresponds to the entire image. Each node corresponds to a subdivision, and each node has four descendants, if the region represented by that node is inhomogeneous. Global shape properties such as moments, projections, compactness, shape number, and Euler number are useful measures of specific aspects of shape and can be used to describe two-dimensional shape.

Of the above-mentioned two-dimensional shape representation schemes, boundary-based and skeleton-based have been used more widely because they are less sensitive to the variances and encompass rich information as to the shape of the object. Quadtree has been applied mostly to the shape representation and reconstruction, and used as a tool for the split-and-merge technique for region-based image segmentation. Global shape properties also have been used successfully for shape recognition when a small number of objects that are precisely distinguishable by their global shape properties are involved.

### Global Shape Property Measurement

In our system for two-dimensional shapes, eccentricity, compactness, and Euler number are used as global shape properties. Eccentricity determines whether the shape is long and thin or short and thick. We use the definition described in [7] for measuring eccentricity ( $e$ ). ( $M_{ij}$  is the  $ij$ th moment and  $A$  is the area.)

$$e = [(M_{20} - M_{02})^{1/2} + 4M_{11}]/A$$

Compactness measures whether the shape is elongated, irregular, or has a wiggly boundary. In most cases, compactness ( $c$ ) is defined as shown, where  $p$  is the perimeter and  $A$  is the area.

$$c = p^2/A$$

Euler number ( $E$ ) is defined as follows, where  $C$  is the number of connected components and  $H$  the number of holes.

$$E = C - H$$

The most direct method of computing the Euler number is via connected-component labeling, but this takes more time than we can allocate to the computation of global shape properties. An alternative and faster scheme exploits the additive set property of the Euler number. If the image is swept in one direction by a scanning line, it can be shown that the Euler number equals the difference of convexities and concavities that are incident on the scanning line. The scanning process can be implemented locally as Boolean window operations. The two windows that detect convexities and concavities in an eight-connected image, when the scan direction is from the northwest to the southeast, are shown in Fig. 3.

Table 2 lists the properties measured for different objects in Figs. 1(a)–1(j).

### Shape Representation and Model

**Normalized Distance-Versus-Angle Signature** A signature is a one-dimensional representation of a boundary. One of the simplest ways of generating a signature is to plot the distance from the center of the object region to the boundary as a function of angle. Scale variance can be normalized by setting the maximum value of this signature to unity, while orientation variance can be normalized by shifting this signature in such a way that the angle that gives the maximum distance is set to zero. Figure 4 illustrates a normalized distance-versus-angle signature of the object in Fig. 1(g).

**Morphological Shape Representation and Recognition** Mathematical morphology exploits the concept of structuring elements, which interact with the image to extract a more expressive version of the shape in the image [14]. Since two fundamental morphological operations such as erosion and dilation can be implemented via the use of Minkowski subtraction and addition, respectively, it is possible to implement all the morphological set operations using shift and Boolean primitives in parallel.

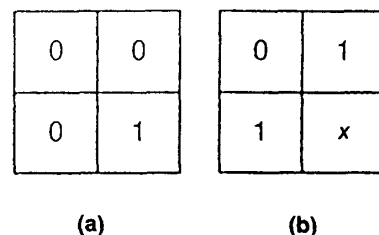


Fig. 3. Two windows that detect convexities and concavities in an eight-connected image.

**Table 2**  
Eccentricity, Euler Number, and Compactness of the Objects Shown in Fig. 1

Object	Eccentricity	Euler No.	Compactness
a	0.0047	-12	232.21
b	0.0009	1	26.92
c	0.0024	0	59.52
d	0.0093	0	79.52
e	0.9658	-1	40.18
f	-1.0185	1	34.63
g	-0.1097	1	16.57
h	0.0124	0	16.04
i	-0.2072	-10	260.7
j	2.0963	1	54.72

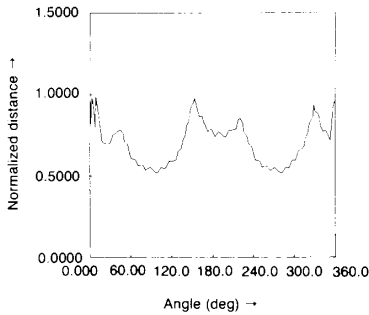


Fig. 4. Normalized distance-versus-angle signature of the shape in Fig. 1(g).

As described in [15], two-dimensional shape can be represented uniquely via a morphological skeleton function. Using the morphological skeleton as a prototype, we can implement a very fast and robust shape recognition scheme. This scheme measures the goodness-of-fit of the prototypical skeletons to the silhouette of the observed object. Similarity is measured by taking morphological erosion using a skeleton as a structuring element. An erosion of the observed silhouette by the prototype skeleton will leave a residue of a single or at most a few points where the object is located. Since erosion is a translation invariant operation, the object will be recognized regardless of its position. Inasmuch as the skeleton contains size and orientation as well as shape information, a general recognition scheme should incorporate mechanisms for rotation and scaling variance. One way to do this is using the principal axis defined as the eigenvector associated with the larger eigenvalue of the covariance matrix of the object. The principal axes of both the skeleton and the object to be recognized are determined, and the skeleton is rotated and scaled so that the di-

rection and length of their principal axes become equal. For details concerning this recognition scheme, see [16].

Figure 5(b) depicts a morphological skeleton of the object (wrench) in Fig. 5(a). Figure 5(d) shows the residue remaining after the silhouette of the observed object [Fig. 5(c)], which is a scaled and rotated version of the silhouette in Fig. 5(a), is eroded by its prototype morphological skeleton [Fig. 5(b)].

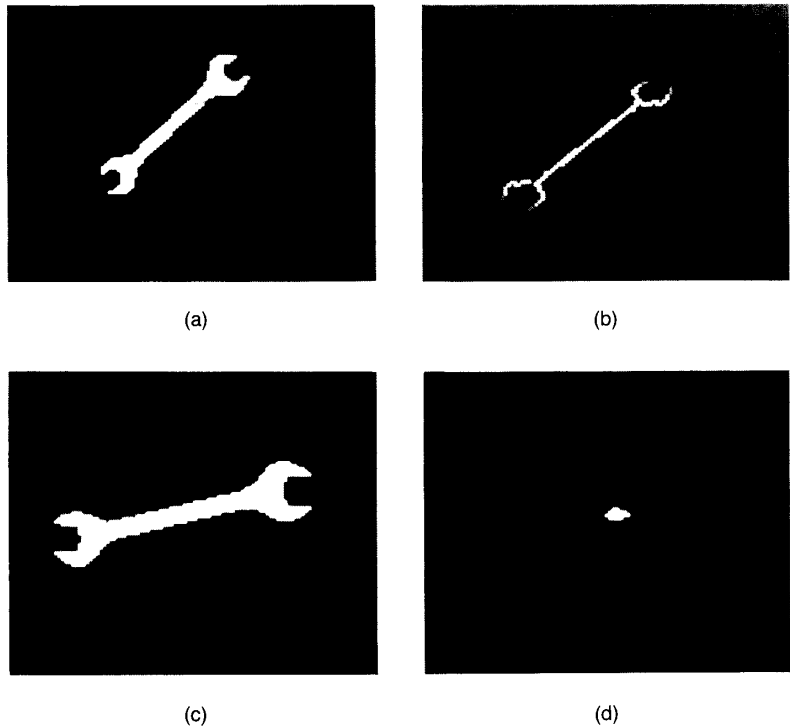


Fig. 5. (a) Silhouette of a wrench used for generating a prototype morphological skeleton, (b) morphological skeleton of Fig. 5(a), (c) silhouette of the wrench that has been scaled and rotated, (d) residue after Fig. 5(c) is eroded by a morphological skeleton [Fig. 5(b)].

### Relational Model Based on Skeletal Structure

In order to describe a two-dimensional shape using its skeleton features and their relationships, a connected and single-pixel-width skeleton must be generated. Although there exist some methods that can generate a connected and single-pixel-width skeleton [17], [18], they are not adequate for constructing a relational skeletal model since they do not generate a consistently four-connected or eight-connected skeleton. (Inconsistency in the connectedness makes decomposition of the skeleton into its subsets impossible.) We use Boolean window operations to generate an eight-connected skeleton consistently. Since we use window operations instead of component labeling to determine simple points, the time required for skeletonization could be as competitive as Zhang and Suen's [18].

Points are deleted from the four cardinal directions successively until the skeleton remains. A point is deleted from the north if its neighborhood matches with any of the windows of Fig. 6. The number of four neighbors of the point is determined, and the matching is done on the basis of this number. If the number of four neighbors is 3, the

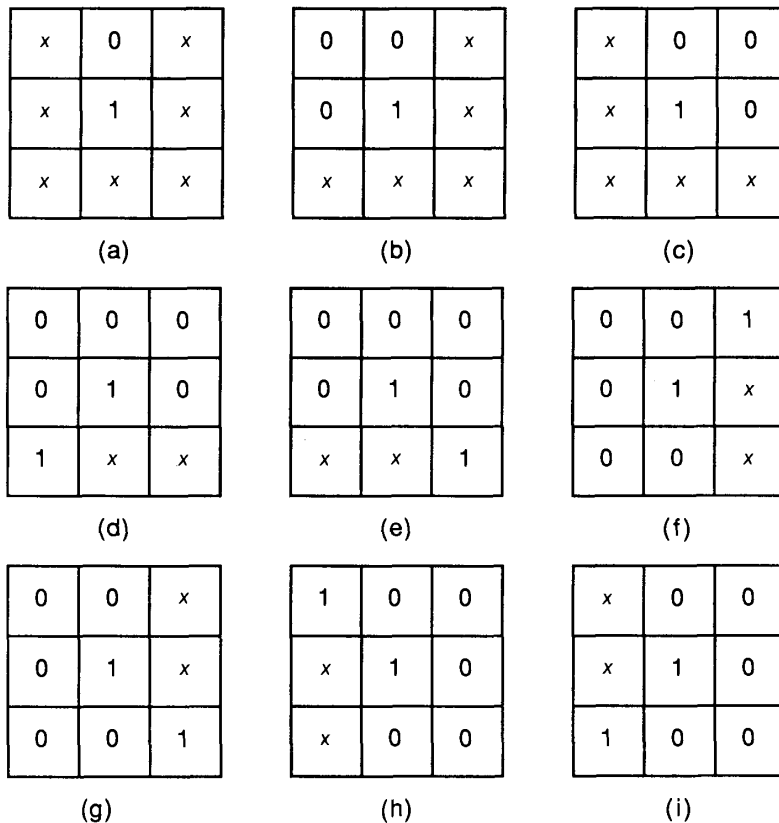


Fig. 6. Boolean windows used for generating a consistently eight-connected and single-pixel-width skeleton.

window of Fig. 6(a) is used; if it is 2, then we try to match with the windows in Figs. 6(b) or 6(c); and if the number of four neighbors of the point is 1, we try to match its neighborhood with the windows of Figs. 6(d)–6(i). If a match is found, the point belongs to the skeleton; otherwise it is deleted. Since points with only 1 four neighbors are rare, usually only one or two windows need to be tried out. The same windows are used for the other directions, with the row and column indexes manipulated.

An eight-connected and single-pixel-width skeleton is then decomposed into its primitives using graph traversing algorithms and represented by their structural relationships. Figure 7 shows a skeleton of the object in Fig. 1(e).

#### Knowledge Base and Supervisor

The KB contains heuristic rules formulated from an intuitive perception of the relationship between the global shape characteristics and candidate representations. Some

heuristics for our two-dimensional problems are derived as follows:

- An object may have a reliable skeletal representation if it satisfies two global shape constraints. First, it should not be too

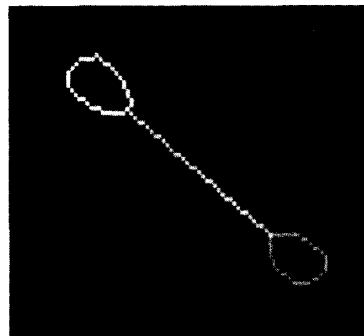


Fig. 7. Labeled skeleton of the object in Fig. 1(e).

rounded (disklike), because then the skeleton would be a small structure consisting of a few points near the center. Second, it should not have a rough boundary with many protrusions and intrusions, because such a boundary induces unreliable branches in the skeleton. The first requirement is met if the object is not very compact (a disk is the most compact shape). On the other hand, if the object has very poor compactness, it may have a tortuous boundary and many holes in its interior. Such an object violates the second requirement and is probably not a good shape for skeletal representation.

- Faithful representation of an object's shape by its morphological skeleton requires that it have a smooth boundary and that the length and direction of its principal axis be determined reliably. Such an object is generally elongated, with few holes in its interior. Thus, in addition to the compactness criterion, it should have a high eccentricity and a low Euler number.
- Shapes with very low compactness are unsuitable for skeletal representation. Such shapes can be represented adequately by their outer boundary, together with their Euler numbers.
- Of the two skeletal representations, the morphological one is extracted faster. Thus, it is to be preferred if both skeletons are equally valid candidates for representation. This is an example of a metarule that helps the SV choose between competing representations.
- There may be situations where the object shape is rather compact and has a low eccentricity. These values of the global shape properties indicate a lack of feature in the external boundary and in the internal structure of the shape. In such cases, it may be useful to store multiple models of the shape, which represent both its internal structure and its boundary.

These heuristics form the basis of rules for the KB. Experiments conducted with a large variety of shapes suggest instantiations of these rules listed in Table 3. (Note that if a shape has no hole, then its Euler number is equal to 1, and a low value of  $c$  corresponds to a compact shape.) A relational skeletal representation is to be chosen, for example, when the value of compactness lies between 30 and 100, regardless of the value of eccentricity and of the Euler number. The values in Table 3 were obtained empirically and do not represent hard limits. Instead, they are typical values that could be used for creating fuzzy decision functions.

**Table 3**  
**Knowledge-Base Rules Based on Heuristics for Selecting Suitable Representations**  
**Using Global Shape Property Values**

Representation	Global Shape Property		
	Compactness ( <i>c</i> )	Eccentricity ( <i>e</i> )	Euler No. ( <i>E</i> )
(1) Relational Skeleton	$30 < c < 100$	— <sup>a</sup>	—
(2) Morphological Skeleton	$30 < c < 100$	$ e  > 1$	1
(3) Boundary and Euler No.	$c < 30$ or $c > 100$	$ e  < 0.01$	—
(4) 2 and 3	$c < 30$	$0.01 <  e  < 0.1$	1
(5) 1 and 3	$c < 30$	$0.01 <  e  < 0.1$	—

<sup>a</sup>— = "don't care."

The SV module uses global shape property values provided by the GSPA and rules and metarules stored in the KB to decide on the appropriate representation or representations. For example, the shapes in Figs. 1(f) and 1(j) are found suitable for representation with the morphological skeleton. Figures 1(c)–1(e) satisfy the compactness criterion but have internal holes and are not elongated. In their case, the relational skeleton is the better model. The shapes in Figs. 1(a), 1(b), 1(h), and 1(i) do not have good compactness values for skeletal representation but can be represented adequately with their outer boundary together with their Euler number. Figure 1(g) has a relatively large eccentricity and no internal holes, but it is rather compact for skeletal representation. We represent this object by both its boundary and its morphological skeleton.

### Concluding Remarks

We have discussed the problems and limitations of current shape representation and recognition schemes and the necessity of an intelligent and flexible shape representation and recognition system for complex industrial tasks. We confirmed that intelligent integration of different shape representation schemes is essential in dealing with a number of different classes of objects effectively.

Using global shape properties, we could determine distinguished features of the object together with their degrees of importance fast and reliably. In the representation phase, we exploited this information to describe objects; in the recognition phase, using this information, we could restrict the search space and perform matching in the order of importance. This strategy yields a fairly efficient shape recognition. Currently, we are

implementing an intelligent shape representation and recognition system for three-dimensional shapes following the strategy proposed in this paper.

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