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A Real-Time Part-Presentation Algorithm Using Retroreflective Vision Sensing

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abstract

This paper presents a real-time algorithm for identifying and locating parts for robot pick-up. The algorithm is based on the search for "best feature points" and has been developed for identifying and locating industrial parts. Both the feature points in the database and the object in the scene can be characterized using the same algorithm. By effectively excluding noisy feature points from the computation of the part's location and orientation, the algorithm can deal with parts with partial overlapping, missing or unwanted features, and scale changes. The computation load can be minimized in an off-line process for real-time implementation using a low-cost machine such as a personal computer.

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1. INTRODUCTION

The term "part-presentation" addressed here refers to the determination of the location and orientation of the part for a robot to pick up for subsequent processes such as machining and assembly. A real-time part-presentation system must be computationally efficient such that the computation cycle-time is less than the process cycle-time. In addition, it must be able to handle complex industrial parts. This includes the ability to verify incoming parts, robustness to uncontrolled ambient lighting, and the determination of the position and orientation of the parts within the dimensional tolerance specified.

In typical industrial applications, parts to be handled are often known a priori. They may be represented as CAD models or defined by using a series of feature points to represent the parts. The vision-guided part-presentation may often be addressed as a model-based vision problem. Chin and Dyer [1] presented a survey of existing techniques. Three basic problems can be identified; namely, image generation, feature or model representation, and object recognition and locating. Most images are generated by using a structured illumination system which often requires a prior knowledge of the object geometry and surface reflectance. Object-dependent structured illumination systems may have proven useful for automating product inspection, but have often been found in practice to be too expensive, less flexible, and less reliable than required for on-line real-time part-presentation [2].

Several authors have developed a number of pattern matching algorithms to discriminate the targeted objects from its environment. Persoon and Fu [3] used a Fourier descriptor to discriminate shapes. Perkins [4] developed a matching technique based on cross-correlating the curvature functions between the scene descriptions and the model. The techniques, however, are computationally expensive for real-time part-presentation. The availability of sophisticated edge detection techniques allows several authors to reduce the complexity of the gray-scale image prior to the template matching process such as Ayache and Faugeras [5]. Liu and Srinath [6] used a distance transformation and measurement scheme to discriminate between shapes. Ciuti el at. [7] suggested a relatively simple technique which uses a set of feature points rather than the shape or contour of the parts for comparing parts. Although these techniques, in general, may have been successful in identifying the object in a noisy environment, the success in efficently and accurately locating the part for robot pick-up for subsequent processes often depends on the quality of the contour or the feature points.

The three basic problems (image generation, feature represenation, and objection locating) have traditionally been addressed separately in the vision research community. We present here an integrated approach in solving the part presentation problem, in particular, to highlight the inter-relation between these problems. The machine vision technique which we have developed for part-presentation has been built on the basis of structured surface reflectance rather than object-dependent structured lighting. We introduce an algorithm to search for a minimum but accurate set of feature points to locate parts. The main advantages of this approach are as follows: (1) The algorithm effectively excludes noisy feature points from the computation of the part's location and orientation. (2) The computation load can be minimized in an off-line process for real-time implementation using a low-cost machine such as a personal computer. (3) The model in the data base and the object in the scene can be characterized using the same algorithm. (4) It can deal with parts with partial overlapping, missing or unwanted features, and scale changes. Although the approach of structured surface reflectance is not a strictly necessary prerequisite to the use of the algorithm, as it will be demonstrated later, this ability allows us to generate reliable silhouettes using a low-cost collocated illumination despite the ambient lighting conditions, thereby, using some simple procedures to reliably detect feature points.

In the next section, we describe the basis of the algorithm and the method of feature presentation for characterizing parts. We then examine the influence of a quantitative design parameter on the effectiveness of the real-time implementation. An experimetal analysis using two different types of parts is then presented. Finally, we conclude the results of our investigation and propose possible future work.

2. MODEL-BASED VISION-GUIDED PART PRESENTATION

The goal of the model-based part-presentation is to use a precompiled description of the part to verify or recognize an object in the field of view, and to specify its position and orientation. The model-based part-presentation discussed here has been developed on the basis of the following assumptions:

a. Parts are placed on a flat surface, but unoriented. This assumption does not pose a serious restriction as it is most often done today.

b. The orientation of the part can be determined from the object silhouette and/or well-defined fiducial marks.

c. If the location and the orientation are to be determined from the silhouette, the thickness or the depth of the parts must be relatively small as compared to the illumination distance such that the effects of the shadow and perspective do not significantly alter the shape of the silhouette. As it will be demonstrated later, provided that the undistorted portion of the silhouette contains three or more feature points, the location and orientation of the part can be uniquely determined.

The pre-compiled description of the part is referred here as a template. In this work, only certain feature points along the boundary are extracted to describe the template. The part modeling technique discussed here searches for only feature points such as corners and locations of high curvature which can be obtained relatively quickly. The curve partitioning task as described by Fischler and Bolles [8], can be computationally expensive. The main advantage of the technique described here is that the information required for further computation can be significantly minimized.

Knowing the coordinates of the template feature points, the matching problem can be solved by using the following procedure: 1) to search for a similar triangle in the image, 2) to determine the transformation parameters which allow the template to be mapped onto the silhouette, 3) to verify the remaining points in the image by using the templates' description, and finally, 4) to determine the location/orientation from the best match. Fig. 1 outlines the sequence of the solution procedure of the model-based technique.

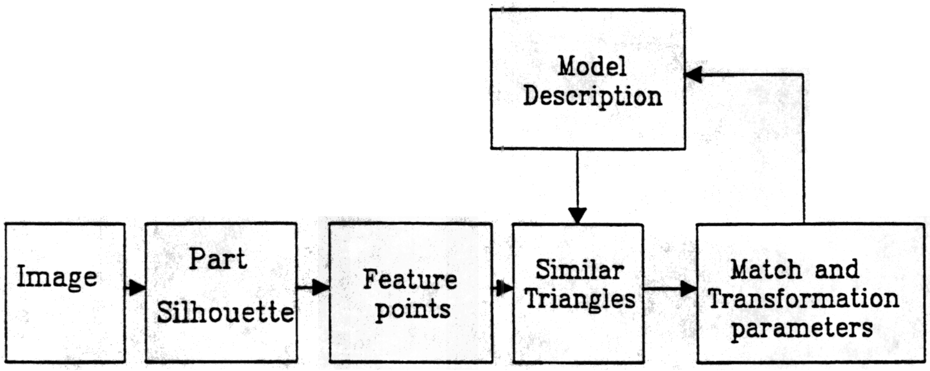


Fig. 1 Sequence of the Solution Procedure

2.1 Feature representation

In order that the part-presentation be implemented in a real-time environment, the feature representation should be easy to build and yet, should be robust and provide sufficient information for fast recognition and accurate computation of the location/orientation of the parts. Reliable images for part-presentation can be generated using retroreflective materials as structured surface reflectance [9] as follows: (1) Well-defined retroreflective landmarks are designed on parts so that the landmarks are brightly illuminated against a virtually dark background. These landmarks can be processed to identify the part and to define the orientation. (2) The surface of the generic part-feeder is coated with retroreflective material so that the image of the part which is placed on the retroreflective surface appears as a dark object (silhouette) against a brightly illuminated background. The choice depends on the part design and manufacturing process. For the purposes of the following discussions, we consider the following two examples:

<u>Structured Fiducial Marks</u>

Often, parts have a series of common features such as circular holes or fastening devices. Templates can be created inexpensively by using the patterns of these common features to distinguish them from one another. Fig. 2(a) shows an instrument cluster of an automobile to be located for assembly. Standard screws with their screwhead coated with retroreflective paint can be used as typical low-cost generic "engineered landmarks." Since the fiducial marks are retroreflective, these marks appear as well-defined brightly illuminated blobs in the image as shown in Fig. 2(b). The features representing the part can be obtained both for the template and the part to be handled by using the retroreflective fiducial marks. Since structured fiducial marks are well-defined, the location of these features (or the centroid of the fiducial marks) can be accurately determined by a relatively simple technique.

<u>Silhouette</u>

When the location and the orientation of the parts can be distinctively determined from its boundary, retroreflective materials can be effectively used as a background to generate reliable silhouette. Since silhouettes obtained are well-defined, the boundary of both the template and the silhouette can be readily derived using some edge-finding procedures. Fig. 3 shows an example of machine components which are often fabricated from raw materials pre-processed to meet a certain specification.

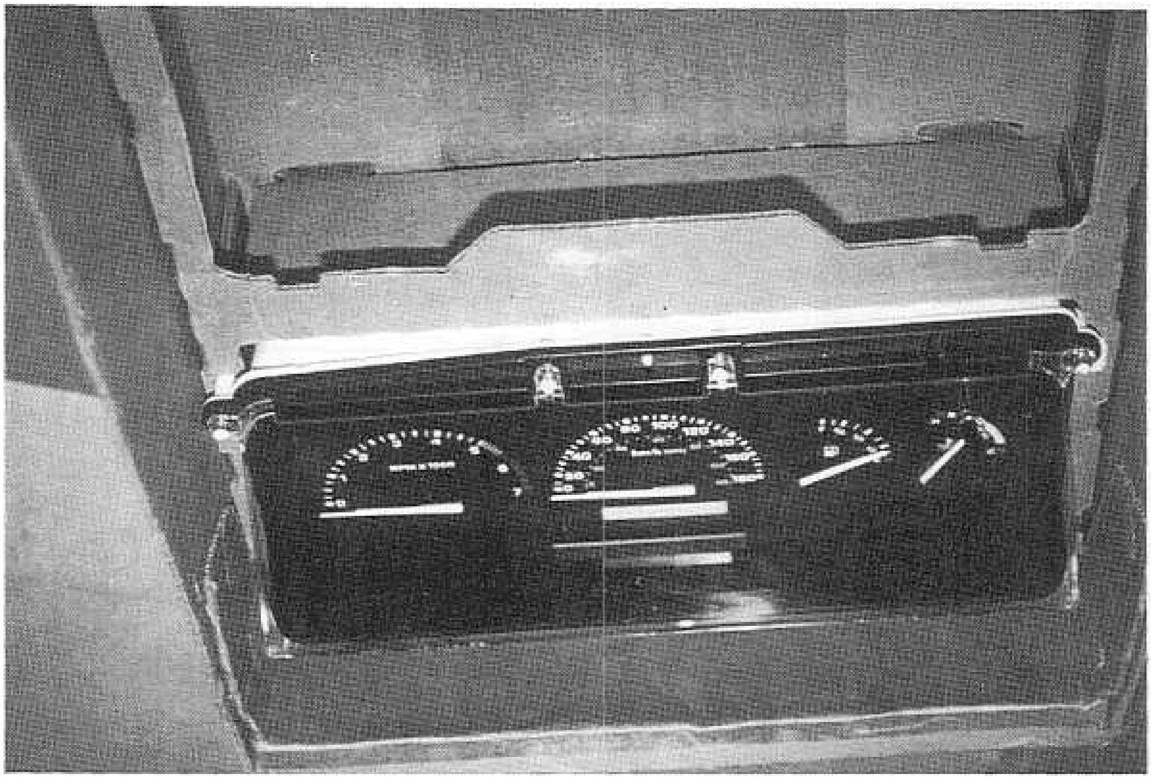


Fig. 2(a) Instrument Cluster with "Generic Engineering Landmarks"

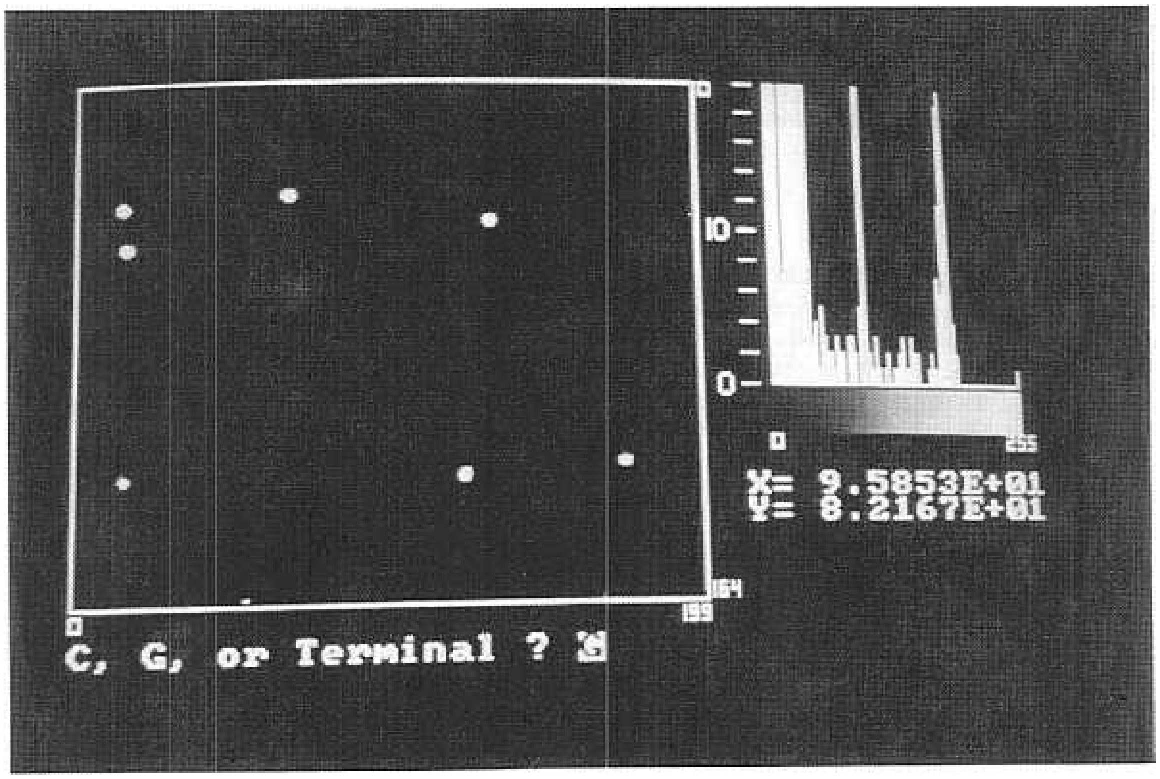


Fig. 2(b) Image of the Illuminated Retroreflective Landmarks

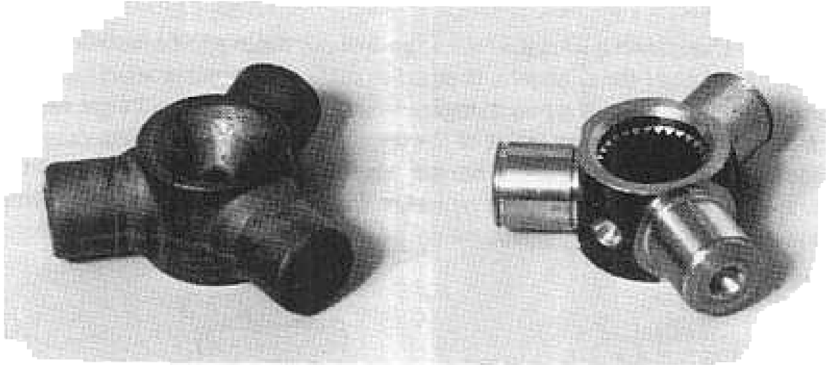
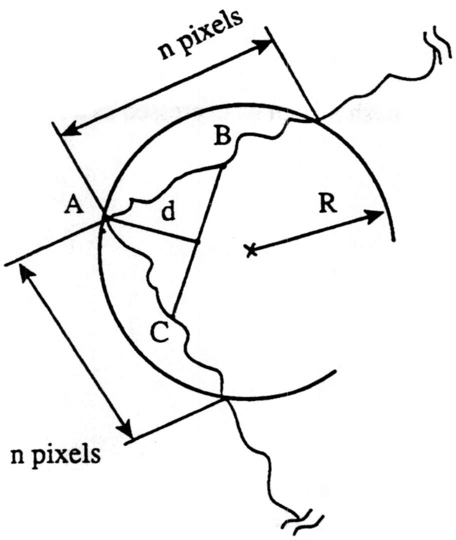


Fig. 3 Typical Machine Components

Feature points representing a silhoutte such as corners and locations of high curavature cannot be obtained reliably from the curvature functions due to quantization noises and rough surface finish of the raw machine component. Thus, a few neighborhood pixels are averaged for feature point selection. Fig. 4 illustrates a typical section of the digitized boundary, where B and C are the average values of n neighbor pixels on each side of the pixel A along the boundary. The average value of n is chosen based upon the expected level of noise to reduce the noise effect in the determination of feature points. The length of the median, which is relatively simple to obtain, can be used to characterize the curvature. The feature point is defined here as the pixel which has a median length exceeding a certain threshold. From the candidate feature pixels, the pixel with the maximum median length in a 2n-pixel neighborhood is chosen as shown in Fig. 4. The method is effective for locating feature points such as corners and locations of high curvature. A typical outline of the example component is shown in Fig. 5.



A = Point under consideration
B = Average location of n pixels on one side
C = Average location of n pixels on the other side
d = length of the median
A is a critical point if d > threshold distance, and
d is maximum in a neighborhood of '2n' pixels.

Fig. 4 Feature Point Selection

Object Identification

In general, the n features points, denoted by P_1, P_2,..., P_n, represent the concatenation of the line segments from P_1 to P_2, P_2 to P_3,..., and P_n to P_1 such that a closed boundary is formed. The signatures of the template and the image represents the median-length distribution function which graphically shows the median-length along a closed boundary. Disturbances such as shadows, highlights, missing marks, and partially overlapped parts are particularly problematic in part-presentation since they may introduce undesired features or result in missing some of the features. Thus, the matching procedure begins with a search for three or more reliable features from the image such that the triangle formed by these three points is similar to that of the corresponding triangle of the template.

Note that the similarity of triangles requires the following two constraints to be satisfied: (1) The angle subtended at the feature point with two other points of the silhouette is equal to that of the corresponding angle of the template. (2) The respective ratios of the corresponding sides of the two triangles are equal. The constraints are expressed as $\Phi_i = \phi_i$ where Φ_i and ϕ_i are the angles subtended at the i^{th} feature point of the template and the silhouette, respectively, and $L_i/L = \ell_i/\ell$, where L,l are the largest sides and, L_i and l_i, i = 1 and 2, are the other two sides of the triangles ABC and abc respectively, as shown in Fig. 6. However, the location of the points in a typical real image is known only approximately. To account for the positional variations in the real image, a similarity threshold ϵ_i is defined such that the two triangles are regarded as similar if the following inequality is satisfied:

$$\left|\frac{L_i}{L} - \frac{\ell_i}{\ell}\right| < \epsilon_i, \qquad i=1,2. \tag{1}$$

where L and ℓ are the largest sides of the triangles ABC and abc respectively. Note that an exact similarity of the two triangles would yield

$$k = \frac{\ell_i}{L_i} = \frac{\ell}{L} \tag{2}$$

where k is a scaling factor of the template with respect to the silhouette. Let the bound of the error in the distance between any two adjacent feature points of the object silhouette (real image) be defined by Equation (3):

$$\rho = \frac{|\delta|}{\ell} = \frac{|\delta_i|}{\ell_i} \qquad i = 1, 2, \ \rho > 0\,. \tag{3}$$

where δ and δ_i the maximum errors of ℓ and ℓ_i, respectively. The similarity threshold can be expressed as a function of the error bound ρ:

$$\epsilon_i = \frac{2\rho}{1-\rho}\,\frac{\ell_i}{\ell} \tag{4}$$

The selection of ρ is discussed in Section 3.

2.3 Matching Procedure

As explained in the previous section, triads of feature points of the template and that of the silhouette are compared and if the triangles formed are similar, the parameters which allow the template to be scaled and mapped onto the object are determined. The remaining matching procedure consists of two parts; namely, the determination of the transformation parameters to map the template onto the image plane, and the determination of the best match. The procedures are detailed as follows:

Determination of Transformation Parameters

The transformation parameters are determined using a set of feature points which satisfy the similarity criterion of the two triangles formed by the template and the silhouette.

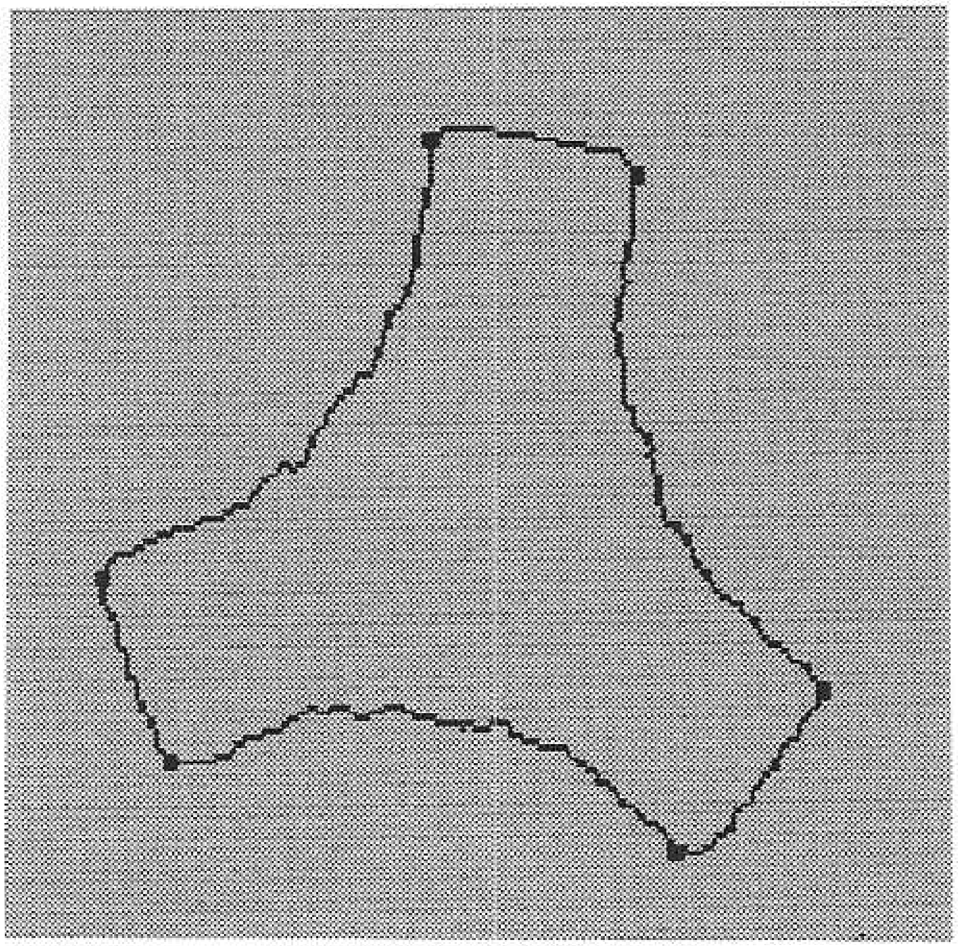


Fig. 5 Typical Outline and Selected Feature Points
of the Machine Components

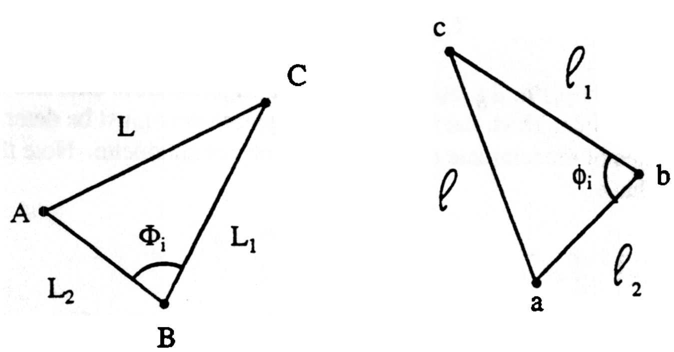


Fig. 6 Nomenclature Used in Illustrating Similarity

The coordinate systems used in the matching procedure is defined in Fig. 7. The image coordinate frame X-Y is treated here as a coordinate frame of reference. A local coordinate frame x-y is assigned at the center of the object silhouette, c, where the x and y axes of the coordinate frame are parallel to the X and Y axes, respectively. The i^{th} point of the object silhouette with respect to the x-y frame are denoted as its coordinate (x_i, y_i). Similarly, a second local coordinate frame x_t-y_t is fixed at the center of the template (model). Unlike the object silhouette which is stationary with respect to the X-Y frame, the template can be scaled, rotated, and translated. The coordinates of the j^{th} point of the template is given with respect to the x_t-y_t frame as (x_{tj}, y_{tj}).

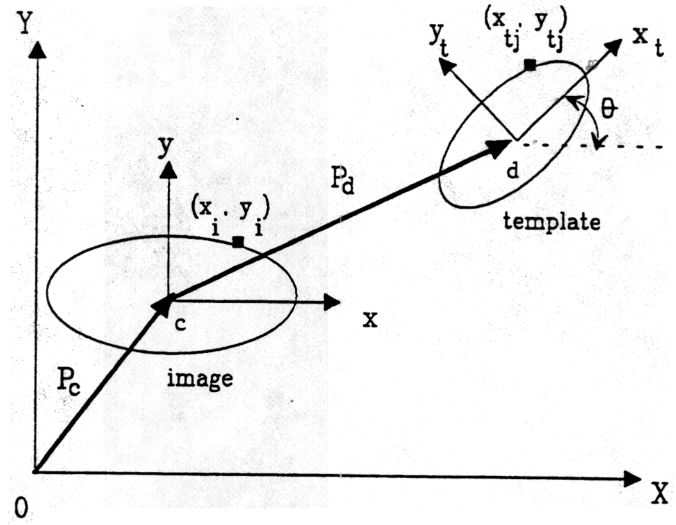


Fig. 7 Parameters of the Coordinate Transformation

Let the position vectors $\mathbf{P_c} = [X_c \;\; Y_c]^T$ and $\mathbf{P_d} = [x_d \;\; y_d]^T$, where the coordinates (X_c, Y_c) refer to the center of the object silhouette and (x_d, y_d) refer that of the template. The coordinate of the j^{th} point of the template can be expressed with respect to the X-Y coordinate frame by using Equation (5):

$$\begin{bmatrix} X_{tj} \\ Y_{tj} \end{bmatrix} = k \begin{bmatrix} C_\theta & -S_\theta \\ S_\theta & C_\theta \end{bmatrix} \begin{bmatrix} x_{tj} \\ y_{tj} \end{bmatrix} + \begin{bmatrix} X_c + x_d \\ Y_c + y_d \end{bmatrix} \tag{5}$$

where θ be the angle rotated by the template; S_θ and C_θ denote the trigonometric sine and cosine functions of the angle θ; and k is the scaling factor of the template. Thus, the following four parameters must be determined, namely, k, θ x_d, and y_d, in order to transform the coordinates of the template onto that of the object silhouette. Note that if the scaled template ideally matches the object silhouette, we have

$$\begin{bmatrix} X_{tj} \\ Y_{tj} \end{bmatrix} = \begin{bmatrix} X_j \\ Y_j \end{bmatrix} \tag{6}$$

Let the template be characterized by m points. An overdetermined system of 2m equations can then be obtained from Equations (5) and (6) in the form:

$$\mathbf{R} = \underline{\mathbf{A}}\,\mathbf{Q}\,, \tag{7}$$

where

$$\mathbf{R} = [X_1\ Y_1 \quad X_2\ Y_2 \qquad\qquad X_m\ Y_m]^T,$$

$$\mathbf{Q} = [q_1 \quad q_2 \quad q_3 \quad q_4]^T \quad \text{where,}$$

$$q_1 = k \cos\theta,$$
$$q_2 = k \sin\theta,$$
$$q_3 = X_c + x_d,$$
$$q_4 = Y_c + y_d,$$

$$\underline{\mathbf{A}} = \left[\begin{array}{cc|c} x_{t1} - X_c & -y_{t1} + Y_c & \underline{\mathbf{I}} \\ y_{t1} - Y_c & x_{t1} - X_c & \\ \hline x_{t2} - X_c & -y_{t2} + Y_c & \underline{\mathbf{I}} \\ y_{t2} - Y_c & x_{t2} - X_c & \\ \hline \vdots & & \vdots \\ \hline x_{tm} - X_c & -y_{tm} + Y_c & \underline{\mathbf{I}} \\ y_{tm} - Y_c & x_{tm} - X_c & \end{array}\right] \tag{8}$$

and $\underline{\mathbf{I}}$ is a 2 x 2 identity matrix.

The overdetermined system can be solved by using the pseudo-inverse method for the four unknowns, q_k, k=1,....,4, which yields

$$\mathbf{Q} = [\underline{\mathbf{A}}^T \underline{\mathbf{A}}\,]^{-1}\ \underline{\mathbf{A}}^T\ \mathbf{R}. \tag{9}$$

Hence, we have

$$k = +\sqrt{q_1^{\,2} + q_2^{\,2}}$$
$$\theta = \tan^{-1}(q_2/q_1)\ ,$$
$$x_d = q_3 - X_c\,,$$

and $$y_d = q_4 - Y_c\,.$$

Determination of the best match

With the estimated values of the transformation parameters, the template is mapped onto the object. The mapping results in a description of the scaled template in terms of the feature point coordinates with respect to the reference frame X-Y. Let the feature point coordinates of the scaled and transformed template be (x_{t1}, y_{t1}), .. (x_{tj}, y_{tj}), .. (x_{tm}, y_{tm}) where m is the number of feature points in the template. Similarly, let the feature point coordinates of the object be (x_1, y_1), .. (x_i, y_i) .. (x_n, y_n) where n is the number of the object silhouette.

Points (x_{tj}, y_{tj}) and (x_i, y_i) are regarded as a matching pair if the following two inequalities are satisfied:

$$\sqrt{(x_i - x_{tj})^2 + (y_i - y_{tj})^2} \quad < \epsilon_m ,$$

and
$$\left[\tan^{-1} \frac{y_c - y_{tj}}{x_c - x_{tj}} - \tan^{-1} \frac{y_c - y_i}{x_c - x_i} \right] < \epsilon_\theta ,$$

where ϵ_m and ϵ_θ are the tolerances in the location and orientation of the part, respectively. In other words, the closeness of the match is determined by the tolerance in the location and orientation of the part. The optimal match is defined as the match with a maximum number of matching pairs. For multiple solution, the match with a minimum error E defined by Equation (11) is chosen.

$$E = \sum_{i=1}^{k} \sqrt{(x_{ti} - x_i)^2 + (y_{ti} - y_i)^2} ,$$

where k is the number of matching pairs.

3. IMPLEMENTATION CONSIDERATIONS

For real-time implementation, the part-presentation computation must be efficient and robust to disturbances of various nature causing unwanted or missing features. In this section, the factors influencing the computation of the part-presentation are discussed.

Let m and n be the number of feature points of the template and the image respectively. The number of triangles in the template to be computed is $\binom{m}{3}$ and that in the image is $\binom{n}{3}$. The maximum number of comparisons between the triangles of the template and the image is of the order of m^3n^3. Hence, in the worst case, the computing time grows significantly with the number of feature points.

The number of matching triangles depends, however, on the choice of the similarity threshold ϵ_i. A tighter threshold implies a much closer match between any two similar triangles than a loose one. In other words, a tight threshold would allow only features that are subjected to small deviation be selected during the search of similar triangles. In Section 2, the similarity threshold has been expressed as a function of the allowable proportional variation in the sides of the triangle, ρ. Often it is desirable to specify the dimensional tolerances on the location and orientation of the final match. Thus, a relationship between the tolerance specification and ρ is derived as follows. The transformation parameters obtained using a least-square fit in Equation (9) are affected by noise in the real images. Let the orientation tolerance on the angle θ be $\delta\theta$, the positional tolerance on the translation denoted by x_d, y_d be δx_d and δy_d respectively. Thus, the allowable variation in the vector **Q** can be expressed as

$$\Delta Q = \begin{bmatrix} k\ \delta C_\theta \\ k\ \delta S_\theta \\ \delta x_d \\ \delta y_d \end{bmatrix}$$

where δC_θ and δS_θ are defined as the maximum of $[\,|\cos(\theta \pm \delta\theta) - \cos\theta|\,]$ and $[\,|\sin(\theta \pm \delta\theta) - \sin\theta|\,]$ respectively. corresponding bound on **R** is derived to be

$$R' = \underline{A}\ (Q \pm \Delta Q)$$

where $\mathbf{R}' = [x_{z1}\ y_{z1} \mid x_{z2}\ y_{z2} \mid \ldots \mid x_{zn}\ y_{zn}]^T$. The vector $\mathbf{R}'$ represents the allowable variation of n points (x_{z1}, y_{z1}), ..., (x_{zn}, y_{zn}) characterizing the silhouette. Let the distance between the i^{th} and j^{th} features of the template be L_{ij}. A set of $\binom{n}{2}$ equations can be constructed as given by Equation (14):

$$L_{ij}\,(1 + \rho_{ij}) = P_{ij}$$

where ρ_{ij} is an apparent error bound on L_{ij} and P_{ij} is the distance between the i^{th} and j^{th} features of the polygon formed by the n points of the $\mathbf{R}'$ vector. The maximum of the $\binom{n}{2}$ values of ρ_{ij} is chosen to be the characteristic error bound ρ:

$$\rho = \mathrm{Max}\,(\rho_{ij}) \qquad i \neq j,\ i, j, = 1, 2, \quad n$$

Equations (12) to (15) provide a means to determine the similarity threshold for a given tolerance specification from which from ϵ_i can be obtained off-line for a number of selected parts.

4. EXPERIMENTAL INVESTIGATION

The model-based part-presentation is experimenatlly investigated using GRIPPS, the Generic Retroreflective Part Pick-up System, which has been developed as a low-cost robotic part pick-up system. GRIPPS is desrcibed in greater detail in Lee et al. [10]. Here we review the basic experimental setup used in the investigation.

GRIPPS uses a charge-coupled-device (CCD) to capture an image, electronically samples the imaging signal through an analog-to-digital (A/D) converter, and the resulting array is then processed directly using the software embedded in an on-board based microcomputer. The illumination system consists of twelve light-emitting-diodes (LEDs) mounted in a ring of one-inch diameter around a 16mm standard C-mount lens. The LEDs emitting light in a norrow cone of 7°. In this investigation, all computations have been performed on a 33 MHz Intel-486 based personal computer.

The experimental results are organized in two parts: The first part examines the sensitivity of the design parameter ρ on the computation load in an environment where the image is contaminated with unwanted or missing features. The second part experimentally predicts the shop-floor performance of the algorithm using two typical real images, which are obtained by taking advantage of the dramatic contrast offered by the retroreflective material.

4.1 Sensitivity of the design parameter ρ

The number of triangles involved in the matching procedure depends on (1) the number of feature points, (2) the selection of the design parameter ρ which defines the closeness of the similarity between any two triangles, and (3) the quality of the image. As an illustration, consider the template of the instrument cluster described in Fig. 8(a). The template consists of eleven feature points.

Fig. 8(b), denoted here as image 1, shows the feature points of the corresponding image obtained from the same instrument cluster. The image has three "noisy features" which appear as a result of unexpected highlights, and three missing features which may result from partial overlapping of parts, poor lighting, or physically missing landmarks. Several values of ρ were tested to illustrate the sensitivity of the design parameter ρ. For each value of the design parameter, the algorithm finds all possible matching configurations for a pre-specified tolerance and determines the location and the orientation from the best match. The same optimal match was found in all cases but the execution time, however, increases significantly with the value of ρ. The "best match" is displayed in Fig. 8(c). The number of matches and the execution time to locate the part are plotted as a function of the design parameter ρ in Figs. 9 and 10 respectively, where the results computed on the image shown in Fig. 8(b) are denoted as "image I" on both plots. Notice that the execution time varies from 0.4 second to 2.5 seconds corresponding to approximately 10 to 300 matches.

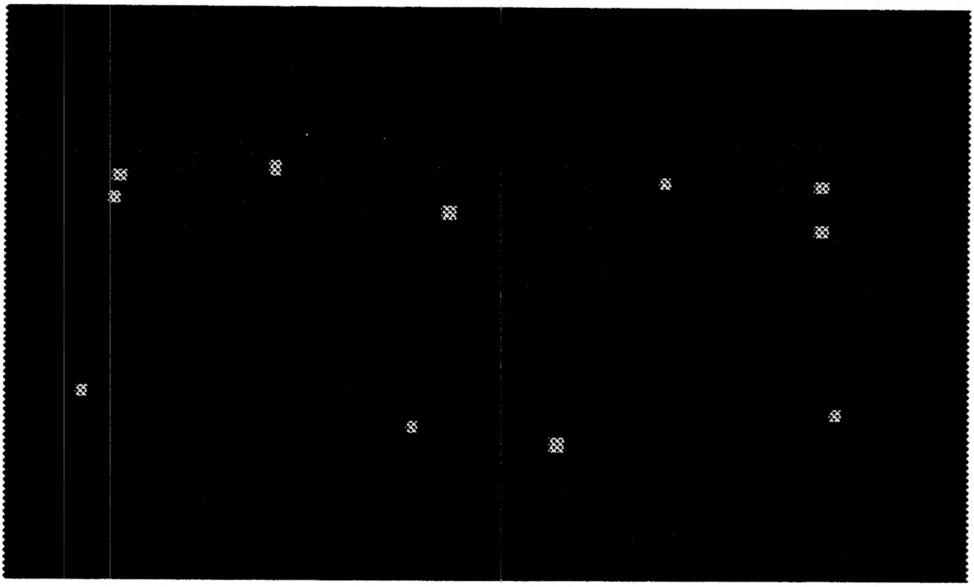


Fig. 8(a) Template Characterizing the Instrument Cluster

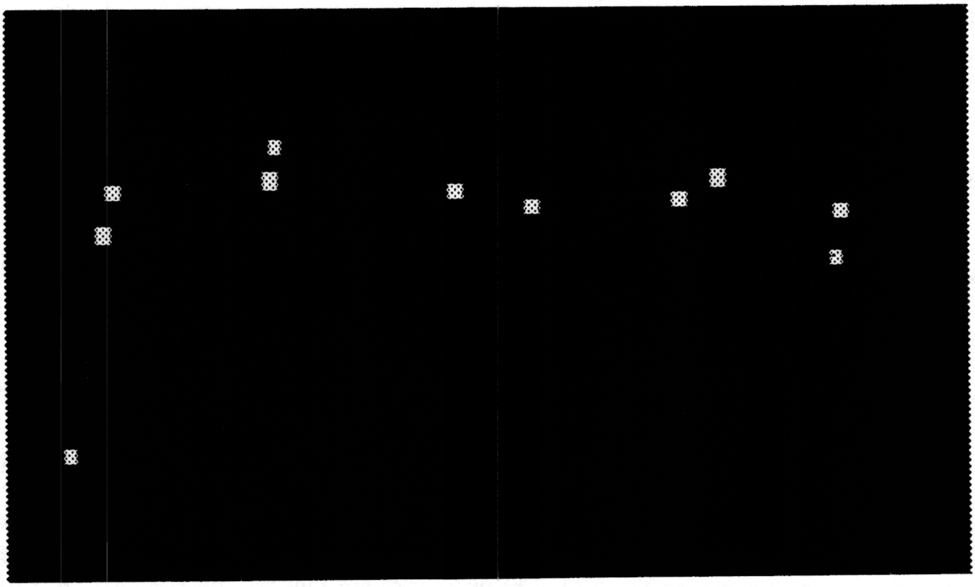


Fig. 8(b) Feature Points Obtained From a Contaminated Image
of the Instrument Cluster

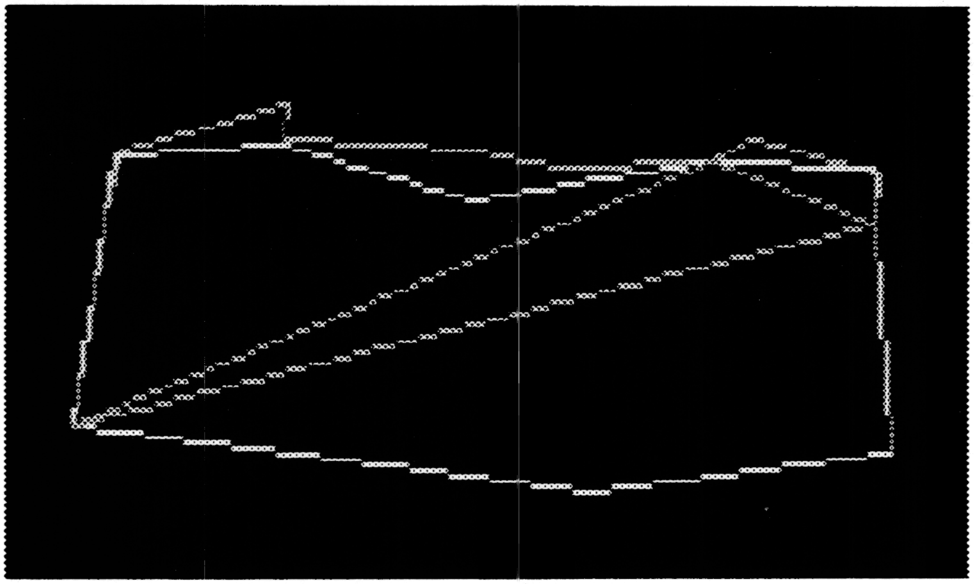


Fig. 8(c) Final Match Between the Template and the Contiminated Image

Fig. 2(b) shows the second image, denoted as image 2, which was taken on a portion of the same instrument cluster with a retroreflective background as described in Section 2.1. By using a relatively small field-of-view and taking advantage of the dramatic contrast between the retroreflective landmarks and the object/background, the feature points can be reliably located. The results as denoted by image 2 are summarized as a function of ρ in Figs. 9 and 10. As in the case of image 1, the same final match between the template and the object to be located is obtained. Fig. 11 displays the result of the final match. It is noted that the number of matches is rather insensitive to the design parameter ρ. The small number of feature points and the ability to locate them accurately results in a fast execution of 0.25 to 0.4 second. Clearly, if the images are "reliable" and the pattern of the feature points are "intelligently" designed, the number of matches and hence the computation time can be drastically reduced by using a small value of ρ.

4.2 Sensitivity of feature representation

The pre-casted or pre-formed materials often contain some irregular spruce-like edges prior to the machining processes. The spruce-like edges often make the reliable extraction of the feature points a difficult task. The pre-processed machine component as described in Fig. 3 is used to investigate the sensitivity of the feature representation in the determination.

A template of the machine component was prepared by obtaining the silhouette and the feature points were selected using the methods as described in Section 2. The template consists of six feature points. The feature points of the images are determined using the same technique as that of the template. A typical contour and the feature points are given in Fig. 5. The value of $2\rho/(1-\rho)$ was selected to be 0.1 in all the following tests.

The images of the part are taken at a height of 0.6 meters (2 feet) about an ANORIDE X-Y table which has an accuracy of ± 0.0001 inch per inch of travel and 0.00005 inch/inch of repeatability. For the determination of object orientation, the part was placed on a manually operated rotary table with typical accuracy with 0.1°. Tests were run for several displaced and rotated part, and the results are tabulated in TABLE 1 and II respectively. Since the algorithm searches for three of the "best" feature points, it successfully matches the template onto the object to be located in all displaced locations being tested. A typical match is given in Fig. 12.

The accuracy of the algorithm depends somewhat on the ability to obtain at least three accurate points. The narrow cone of the LEDs used in the collocated illumination results in some non-uniformity in the field-of-view. In the non-uniform region, the poor edge-detection along with the quantization noises may result in relatively poor feature points. Typical accuracy with uniform illumination is approximately 0.5 mm and less than 1° computed in the order of one-third of a second. When a portion of the object is displaced outside the region of uniform illumination, the locations of some feature points are sensitive to the threholding and edge-detection techniques. The accuracy is degraded due to the lack of sufficient accurate feature points. A computer-aided design algorithm for uniform illumination and feature point selection is being studied under a separate project [11].

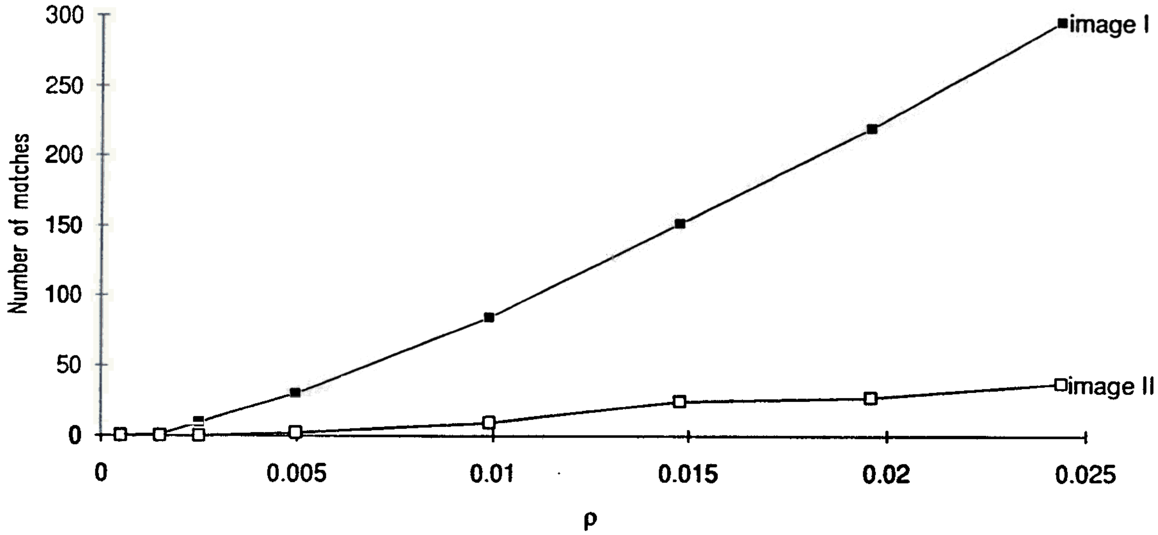


Fig. 9 Number of Matches as a Function of the Error Bound ρ

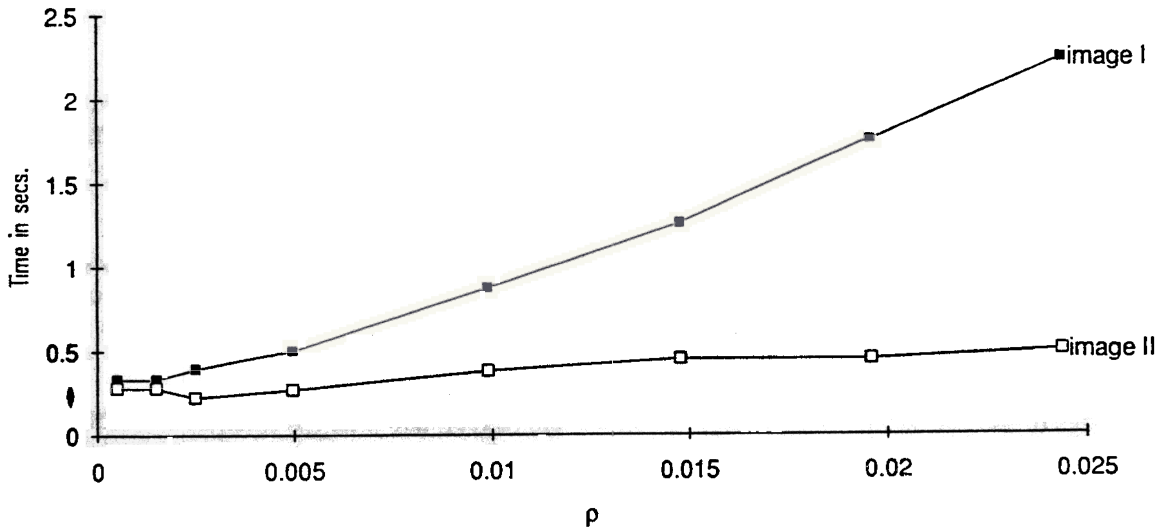


Fig. 10 Computation Time as a Function of the Error Bound ρ

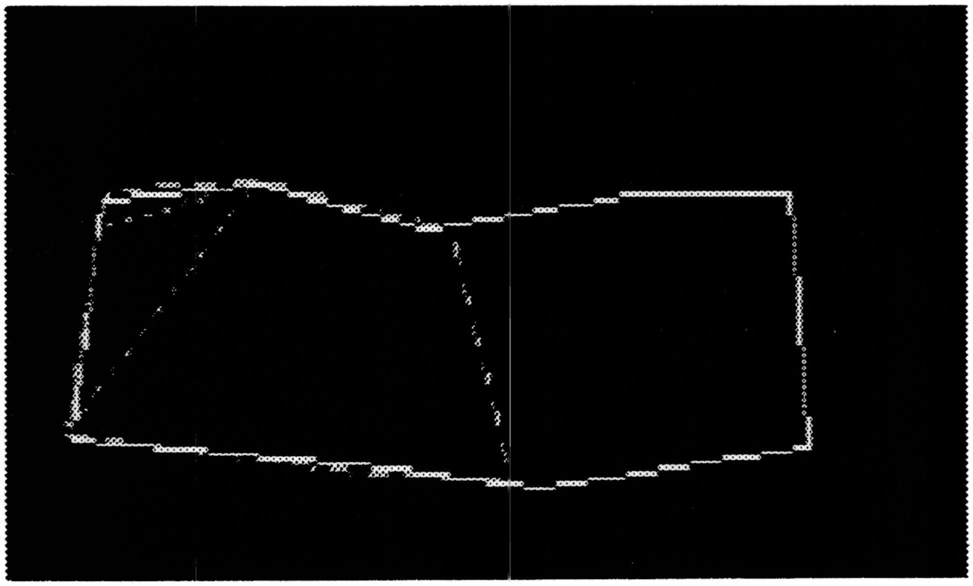


Fig. 11 Final Match Between the Template and the Retroreflective Landmarks (Portions of the Instrument Cluster are Imaged)

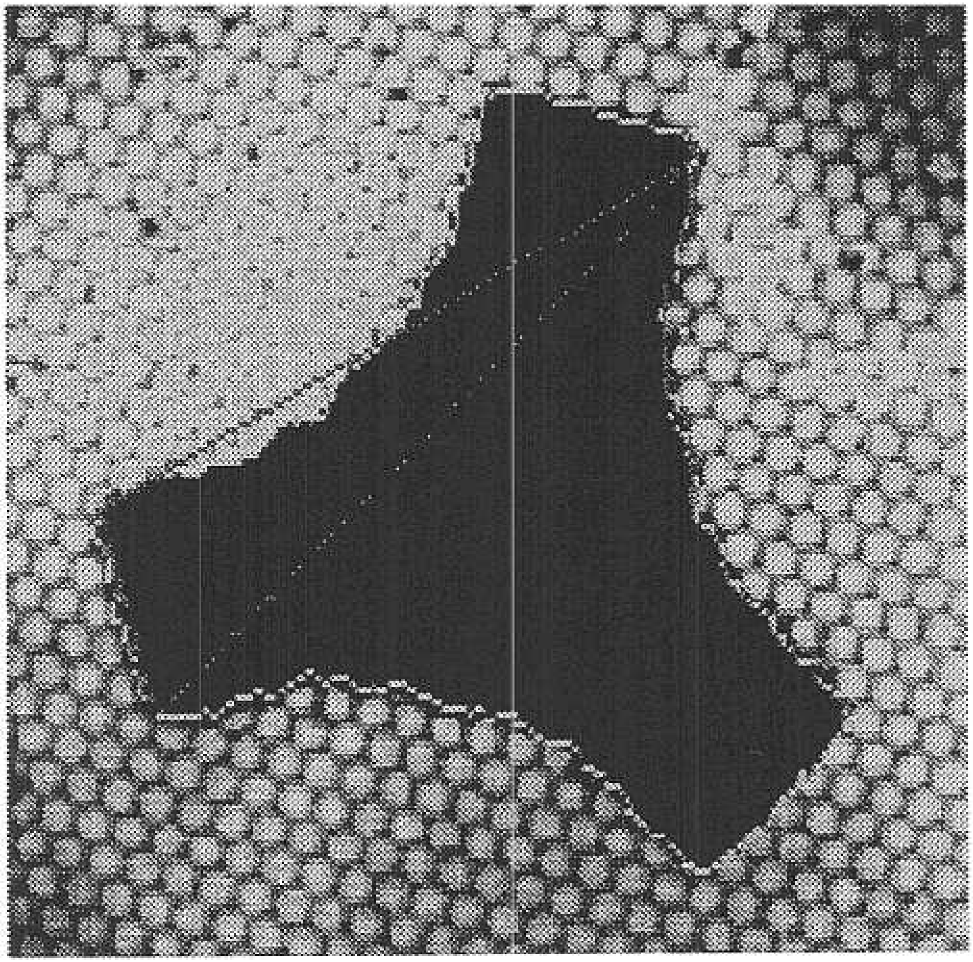


Fig. 12 Final Match Between the Template and the Image of the Machine Component

Table 1

Actual Displacement (in mm)		Absolute Displacement Error from Matching (in mm)		# Matched Points	Error (pixel)	Time (secs)
x	y	x	y			
-6.35	0	0.381	0.000	6	3.96	0.39
-10.16	0	0.051	0.152	6	3.71	0.33
+6.35	0	0.483	1.168	6	4.89	0.28
+19.05	0	0.381	1.981	6	3.47	0.28
0	-6.35	0.483	0.000	6	3.48	0.27
0	-12.7	0.406	0.645	4	3.28	0.27
0	+6.35	0.315	0.356	5	4.74	0.27
0	+12.70	0.0483	0.328	3	4.19	0.27

Table 2

Angular Displacement (degrees)	Absolute Error (degrees)	# Matched Points	Error (pixel)	Time
10.0	0.44	6	2.31	0.27
20.0	0.65	6	3.68	0.26
30.0	0.46	6	2.78	0.28
40.0	0.04	6	1.93	0.28
50.0	1.02	6	3.07	0.26

5. CONCLUSIONS AND FURTHER WORK

An algorithm based on the search of "best feature points" has been developed for identifying and locating industrial parts. It has been demonstrated that both the feature points in the data base and the object in the scene can be characterized using the same algorithm. The algorithm which can deal with parts with partial overlapping, missing or unwanted features, and scale changes effectively excludes noisy feature points from the computation of the part's location and orientation. The computation load can be minimized in an off-line process for real-time implementation using a low-cost machine such as a personal computer.

Although the approach structure surface reflectance is not a strictly necessary prerequisite to the use of the algorithm, as it has been demonstrated, this ability allows us to generate reliable silhouettes using a low-cost collocated illumination despite the ambient lighting conditions, thereby, using some simple procedures to reliably extract feature points.

The present implementation is restricted to parts that exhibit "sharp" corners and/or "high" curvature. This needs to be extended to describe a variety of parts using shapes and other features such as holes and color patches. Reliability analysis can be performed on specific environments to evaluate a match. A high reliability means that further search can be terminated and the parameters obtained from the present match can be used.

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