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# A New Recognition Scheme for Orientation Determination

# (경사도 결정을 위한 새로운 인식방법)

禹東玟,* 白南七,* 金榮日,* 崔浩顯*

(Dong Min Woo, Nam Chil Paik, Young Il Kim and Ho Hyun Choi)

要 約

임의의 물체를 인식하고 그 위치 및 경사도를 결정하는 새로운 2차원 영상처리 방법이 본 논문에서 제시되었다. 물체와 모델의 비교가 주파수 영역에서 수행되며, 물체의 윤곽선에 대한 DFT가 모델성분과 잡음성분으로 분해되어 물체의 경사도 및 물체와 모델의 유사도가 추정된다. 이러한 방법은 알고리듬 자체가 윤곽의 잡음성분에 insensitive 하므로 윤곽에 대한 전처리 과정이 필요하지 않다. 또한 제시된 방법은 종래의 화상영역상의 상관계수 방법에 비해 많은 잇점을 나타내었다. 적은수의 sampling점들로도 효율적으로 훨씬 정확한 경사도가 추정되었다.

**Abstract**

In this paper, a new two dimensional processing method is presented, which determines the identity, position and orientation of a part. Matching between the object and model is performed in the frequency domain. The DFT of the object contour is decomposed to estimate the orientation of the object and to evaluate the similarity between the object and model. In this context, this new approach is very robust with respect to noise and no preprocessing of the contour is required. Also, this method has many advantages over the conventional correlation technique. With only a few uniformly sampled points, this method can estimate the accurate orientation in an efficient manner even in a noisy environment.

## I. Introduction

One of the first steps in an assembly task is grasping of the part in the workstation. In the grasping process, parts need to be identified and their precise position and orientation need to be known. Visual information, tactile pressure, or other sensory data can be used for recognizing three-demensional objects. In this paper, we are concerned with identifying and locating parts by using a single image from a 2-D camera.

Several studies have been reported on this problem. Much of the existing work has used image space domain methods incorporating template matching between the object and a model of the object in the image domain.

*正會員, 金星產電 研究所

(GoldStar Industrial System R & D)

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Perkins[1] used straight lines and circular arcs to represent the contours of parts and matched images with a two-dimensional image model to determain the identity, position and orientation of a part. Yachida [2] used the centroid and a polar representation of the boundary contour to identify and locate parts. The system presented in Dessimoz [3] is based on cross-correlation of the tangent angle or the curvature as functions of the curve length between the scene description and the models. These approaches have produced good results on some complex industrial scenes. However, they are computationaly intensive, since they require that many points be defined on the boundary contour of a part for recognition and accurate estimation of orientation. Another method by Again [4] and Gleason [5] is based on a sequential statistical pattern recognition approach using high-level features of the parts. This method is quite general, but it can be only used to identify parts and requires another technique to locate the part. More recently, Turney [6][7], Cyganski [8] and Ayache [9] have proposed new approaches to the problem.

Fourier descriptor methods reported by Cosgriff [10], Zahn [11] and Wallace [12] have been used to construct an invariant normalized representation with respect to translation and rotation of the contour. The Fourier series, or the Discrete Fourier Transform (DFT) are used. This invariant form has been successfully applied to the two-dimensional shape recognition problem. e.g. character recognition, airplane recognition, etc. The approach described in this paper uses a contour representation scheme similar to that of Wallace [12]. But, Fourier descriptor methods do not have the way of the orientation estimation, which is very important in part-recognition task. To estimate the orientation, in this paper, we decompose the DFT coefficients into model components and noise components rather than constructing a normalized form as in the Fourier descriptor methods. Noise components are minimized to estimate the optimal orientation of the object. This new approach has many advantage over the spatial domain methods. With only a few sampled points on the contour, this method can generate a more accurate orientation than the conventional correlation techniques.

This paper documents a complete system for identifying and locating a part which is in a stable pose located on the workstation. Each part is assumed to be isolated. In this case, the randomly placed object on the workstation has only three degrees of freedom: one for rotation and two for translation. A block diagram of the method is shown in Fig. 1. Boundary contours of parts are extracted out of an image of the workstation. A uniform sampling algorithm is used to extract uniformly sampled boundary contour to evaluate the DFT of the contour. The recognition scheme matches the object DFT with the model DFT to determine the identity, position and orientation. This new approach is very robust with respect to noise and no preprocessing of the contour is required, since the matching is performed in the frequency domain.

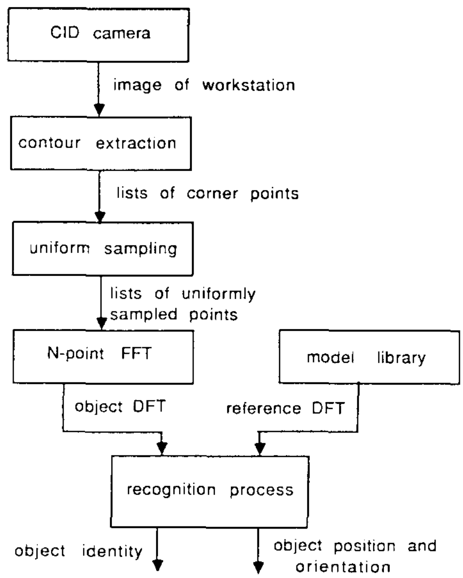



**Fig.1.** Block diagram of the part-recognition system.

## II. Representation of the Closed Contour

In representing the contour in the frequency domain, we use a scheme similar to the method of Wallace[12]. Consider a closed contour c in the complex plane, as shown in Fig.2. Trace this contour once with uniform velocity v. Then, we will obtain a parametrized representation of c as a cimplex function z(t), with parameter. t. Choose

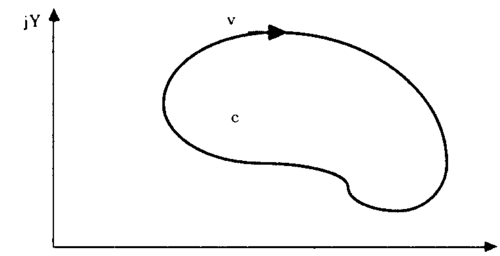



**Fig.2.** Representation of the closed contour in the complex plane.

v so that the time T required to traverse the contour is unity. If the contour is traced repeatedly, we get a periodic function, which may be expanded in a convergent Fourier series. We will define a Fourier descriptor of c to be the complex Fourier series expansion of z(t).

$$z(t) = \sum_{n=\infty}^{\infty} A(n) \exp(j2\pi nt)$$

$$A(n) = \frac{1}{2\pi} \int_0^{2\pi} z(t) \exp(-j2\pi nt)\, dt$$

This representation depends on both the shape of the contour and the starting point of z(t). Actually, c is taken from a digitized image, and thus z(t) is not available as a continuous function. If z(k) is a uniformly sampled version of z(t) of length N, the DFT provides the N lowest frequency coefficients A(i).

$$z(k) = \sum_{i=0}^{N-1} A(i) \exp(j2\pi nk/N)$$

$$A(i) = \frac{1}{N} \sum_{k=0}^{N-1} z(k) \exp(-j2\pi nk/N).$$

Then, $z(k) \underset{DFT}{\longleftrightarrow} A(i)$.

The computation of this representation is fairly straightforward. The contour of the image is represented as a sequence of N x-y coordinates which are derived from edge data. Here, we again remark that this contour be sampled uniformly. Thus, the length of the contour is computed first, and the contour is sampled at a spacing chosen to make the total number of samples, N, a prespecified number which is chosen to be a power of 2 for convenience. Then, the representation is computed by using an FFT implementation of the DFT of this sequence.

## III. Shape Matching

We investigate the matching between the reference contour and the object contour, when the object contour and the reference contour are not exactly the same, but similar enough to be identified as being of the same shape. Also, we assume that the object contour is randomly positioned and oriented, scale-changed and initialized from an arbitrary point.

Suppose that the object contour and the reference contour are represented as lists of uniformly sampled points, $\{b(k)\}_0^{N-1}$ and $\{r(k)\}_0^{N-1}$. Then the DFTs of the object contour and the reference contour are defined as $\{B(i)\}_0^{N-1}$ and $\{R(i)\}_0^{N-1}$, respectively. First, we normalize the position and the scale. To normalize position, we simply set the zero-coefficient of the DFT equal to zero. Then, the centroids of the object and reference contours are located at the origin of the coordinate system. Scale normalization can be accomplished by dividing each coefficient by the magnitude of the first coefficient. This yields normalized DFTs of the object contour and reference contour as follows:

$A(0) = 0$
$A(i) = B(i)/|B(1)|$ for i=1 to N-1
$M(0) = 0$
$M(i) = R(i)/R|R(1)|$ for i=1 to N-1

Suppose that $\{a(k)\}_0^{N-/1}$ is the inverse DFT of $\{A(i)\}_0^{N-1}$ and $\{m(k)\}_0^{N-1}$ is the inverse transformation of $\{M(i)\}_0^{N-1}$. Then, $\{a(k)\}_0^{N-1}$ is the normalized object contour and $\{m(k)\}_0^{N-1}$ is the normalized reference contour. In the spatial domain, we decompose the normalized object contour into the rotated and starting-point shifted versions of the normalized reference contour $\{m'(k)\}_0^{N-1}$ and the error sequence $\{e(k)\}_0^{N-1}$ In this case, the magnitudes of the error sequence are the distances between the uniformly sampled points of $\{a(k)\}_0^{N-1}$ and $\{m'(k)\}_0^{N-1}$. The error is minimum when the normalized reference contour is correctly rotated and starting-point shifted to fit into the normalized object contour. If we assume that error sequence $\{e(k)\}_0^{N-1}$ is a zero mean Gaussian white noise sequence independent of the sequence $\{m'(k)\}_0^{N-1}$ the problem of "optimal" can be formulated as a least square problem. Define:

$$a(k) = m'(k) + e(k) \text{ for } k = 0 \text{ to } N\text{-}1,$$

then the expectation of $\Sigma |e(k)|$ is minimized by proper choice of $\{m'(k)\}_0^{N-1}$ which is a contour synthesized by rotating the normalized reference contour by $\theta_r$ and shifting the staring point of the reference contour by $\beta$ points. We refer to $\{m'(k)\}_0^{N-1}$ as the optimally aligned version of the normalized reference contour according to the objective of minimum mean squared error. $\Sigma|e(k)|^2$ is the summation of the squared distances between uniformly sampled points of the normalized object contour and the optimally aligned version of the normalized reference contour. As such, the matching between the reference contour and the object contour is reduced to the estimation of the optimal orientation $\theta_r$ and the evaluation of $\Sigma\ |\ e(k)\ |^2$, which is a similarity measure between the object and the reference contour.

In the frequency domain, the decomposition is as follows:

$$M(i) = M'(i) + E(i) \quad \text{for } i = 1 \text{ to } N\text{-}1,$$

Due to Parseval's relation, the above equation minimizes $\Sigma\ |\ X(i)\ |^2$. Also, $\{M'(i)\}_0^{N-1}$ is the DFT of $\{m'(k)\}_0^{N-1}$. Using the properties of the DFT, we have the following relations:

$$|\ M'(i)\ | = |\ M(i)\ | \text{ and}$$

$$\arg[M'(i)] = \arg[M(i)] + \theta_r - 2\pi\beta i/N$$

$$\text{for } i=1 \text{ to } N\text{-}1$$

where $\theta_r$ is the optimal rotation and $\beta$ is the optimal starting point shift.

Since the starting point shift, $\beta$, is in the range of $\{0,N\text{-}1\}$, we may define $\theta_s = 2\pi\beta/N$, such that $0 \times \theta_s > 2\pi$. Then, we have

$$\arg[M'(i)] = \arg[M(i)] + \theta_r - \theta_s i$$

$$\text{for } i=1 \text{ to } N\text{-}1.$$

where $\theta_s$ is the optimal starting point angle.

Since $\{E(i)\}_0^{N-1}$ and $\{M'(i)\}_0^{N-1}$ are independent and orthogonal, $\{M'(i)\}_0^{N-1}$ can be interpreted as a minimum squared error approximation to $\{A(i)\}_0^{N-1}$. To evaluate the correct estimates of $\theta_r$ and $\theta_s'$ we have to select the two best approximations among N-1 approximations. Since the $\{E(i)\}_0^{N-1}$ are the DFT coefficients of the white noise error sequence, the phase angle of A(i) can be more accurately approximated by the phase angle of M'(i), when the magnitude of A(i) is large for a certain spatial frequency i. In other words, the DFT coefficient, whose magnitude is large, contains relatively less noise than the other coefficients.

To calculate the optimal orientation, two coefficients whose magnitudes of the object DFT are largest among the N-1 coefficients are selected as $A(f_1)$ and $A(f_2)$. Then, M' can be approximated as $M'(f_1)=A(f_1)$ and $M'(f_2)=A(f_2)$ and we have the following equations:

$$\arg[A(f_1)] = \arg[M(f_1)] + \theta_r - \theta_s f_1$$

$$\arg[A(f_2)] = \arg[M(f_2)] + \theta_r - \theta_s f_2.$$

From the above equations, we can solve for the optimum starting-point angle and the optimum rotation. Since $\theta_r$ and $\theta_s$ are $2\pi$ periodic, the solution is not necessarily unique. The solutions are:

$$\theta_s(j) = \theta_s(1) + \frac{2\pi(j-1)}{f_2 - f_1} \qquad \text{for } j=1 \text{ to } m,$$

where $m = \min(\ |\ f_1 - f_2\ |, N - |\ f_1 - f_2\ |\ )$

$$\theta_s(1) = \frac{\arg[A(f_1)] - \arg[M(f_1)] - \arg[A(f_2)] + \arg[M(f_2)]}{f_2 - f_1}$$

The corresponding solution of $\theta_r$ for each $\theta_s$:

$$\theta_r(j) = \arg[A(f_1)] - \arg[M(f_1)] + \theta_s(j) f_1$$

$$\text{for } j=1 \text{ to } m.$$

The next step is to select the optimal orientation among the m solutions given above. Thus, we evaluate a similarity measure between object contour and reference contour. We choose the similarity measure to be defined as $\Sigma\ |\ e(k)\ |^2$. To calculate this, we calculate M', based on the estimated $\theta_s$ and $\theta_r$.

$$\Sigma \mid e(k) \mid^2 = E \mid E(i) \mid^2$$

$$= \Sigma \mid A(i) - M'(i) \mid^2$$

where $M'(i) = \text{mag}[M(i)] \exp\{j(\arg[M(i)] + \theta_r - \theta_s i)\}$.

For each pair $(\theta_s, \theta_r)$, we calculate a similarity measure. Among these calculated similarity measures, we choose, of course, the least one. Also, the optimal orientation is $\theta_r$ for the least similarity measure.

## IV. Implementation

Fig. 3 shows the block diagram of the part-recognition system, based on our approach. The picture-taking and contour extraction are performed by the GE optomation system [13] and a list of corner points are extracted for each contour. To form the DFT representation, a uniform sampling algorithm is applied to the list of corner points. Also, for the global recognition of parts, contours are smoothed by windowing the DFT coefficients. Among the coefficients, the zero-frequency coefficient is saved as the position (centroid) of the part contour.

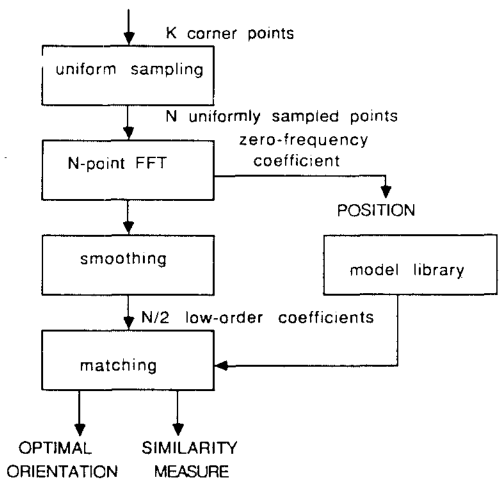



**Fig.3.** Diagram of vision processing.

### *1. uniform sampling*

The contour has been commonly represented by a chain code. However, approximating a continuous contour by a piecewise-linear function such as a chain code does not result in a uniform sampling of the contour, since portions of the actual contour which are not directly representable by a chain code are shorter than the perimeter of the corresponding chain code. This can be viewed as an error in sampling density, and can result in significant variation in performance as a function of the orientation of the picture. In this study, however, the contour is represented by a list of corner points. Then, we assume a straight line between the contiguous corner points and obtain approximately uniform sampling.

Suppose the contour is represented by a list of K corner points $\{(x_i, y_i)\}_1^k$. The idea to find the jth point on the uniformly sampled contour is such that the length from the starting point to the jth point is equal to the uniform spacing multiplied by j. The way to calculate the N uniformly sampled points $\{(xj', y_j')\}_1^N$ on the contour represented by $\{(x_i, y_i)\}_1^k$ is as follows:

The length of each line segment between corner points i and i+1 is,

$$D_i = \sqrt{(X_{i+1} - X_i)^2 + (Y_{i+1} - Y_i)^2}$$

for i=1 to k-1

The length from starting point to ith point

$$P_i = \sum_{j=1}^{i-1} D_j$$

Then, the perimeter of the contour is $P_K$. In order to find the uniformly sampled points on the contour, the first step is to calculate the uniform spacing of the uniformly sampled contour

$$d = P_K / N$$

Then, the following STEP A and B are repeated for j=1 to N with the initialization i=1.

STEP A If $D_i < j\,d$ then i=i+1 and go to STEP A else go to STEP B

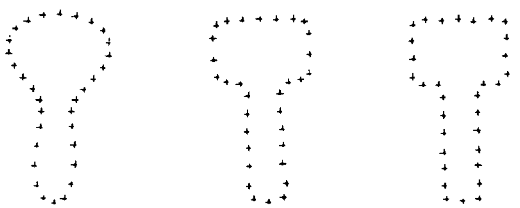
STEP B calculate the uniformly sampled points:

$$x_j' = \frac{j_d - P_{i-1}}{D_i}(X_i - X_{i-1}) + X_i$$

$$y_j' = \frac{j_d - P_{i-1}}{D_i}(Y_i - Y_{i-1}) + Y_i$$

*2. Contour Smoothing*

For the global recognition of parts, each shape should be smoothed using low pass filtering. In fact, the smoothing effect can be achieved by windowing the DFT. Shown in Fig. 4 are the contours derived from the inverse DFT transformation, respectively, using N/4, N/2 and 3N/4 low-order complex coefficients of the T-shaped object. In this experiment, we found that 16 coefficients ( ± 8 harmonics) were sufficient for the global recognition. Thus, when calculating the similarity measure, we use only N/2 low-order coefficients.



(a) 8 coefficients N/4 (b) 16 coefficients N/2 (c) 24 coefficients 3N/4

**Fig.4.** Contours obtained from inverse transforming the low-order coefficients of T-shape.

## V. Experimental Results

The accuracy of the estimated orientation was tested for various numbers of uniformly sampled boundary points. Fig. 5 shows contours of the U-shaped object with different numbers of contour sampling points. For this test, the object was relocated at several orientations (0, 30, ..., 330 degrees) by robot manipulator and contours were recognized using 4-point, 8-point, 16-point and 32-point contour samples. Table 1 shows the results of the test.

The use of 4 boundary points did not provide any reasonable estimate of the orientation. But, with 8 or more boundary points reasonable estimates of orientation were obtained. Even with 8 points, the average orientation error is only about 0.54 degrees. With 16 and 32 points, the accuracy slightly increased. The accuracy of the estimated orientation is very important because it is directly related to the accuracy of the similarity measure.

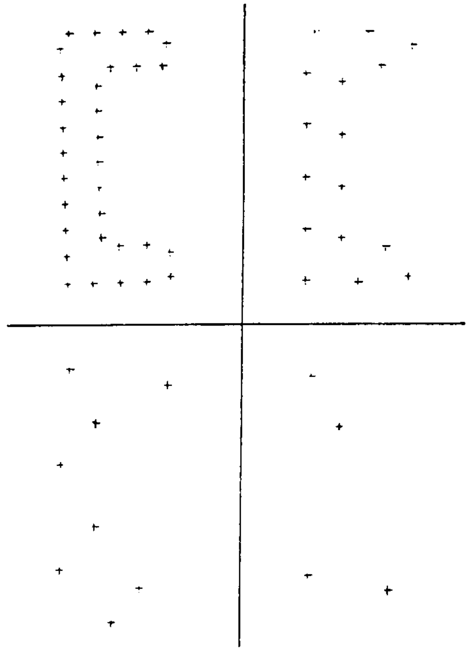


**Fig.5.** Contours of the U-shaped object, uniformly sampled by 32, 16, 8, 4 point.

Table 1. Estimation of the orientation by 4-point, 8-point, 16-point and 32-point boundary samples.

| rotation | estimated orientations | | | |
|---|---|---|---|---|
| | 4-point | 8-point | 16-point | 32-point |
| 30 | 34.94 | 30.31 | 29.43 | 28.45 |
| 60 | 50.14 | 59.22 | 58.87 | 60.31 |
| 90 | 68.95 | 90.80 | 90.19 | 89.26 |
| 120 | 96.98 | 121.31 | 121.01 | 120.50 |
| 150 | 118.30 | 149.90 | 150.62 | 149.83 |
| 180 | 68.41 | 179.77 | 179.78 | 179.65 |
| 210 | 267.97 | 211.02 | 210.57 | 209.95 |
| 240 | 279.25 | 240.61 | 239.48 | 239.37 |
| 270 | 191.17 | 270.17 | 269.67 | 270.14 |
| 300 | 223.98 | 299.40 | 300.33 | 300.14 |
| 330 | 244.08 | 330.21 | 330.29 | 329.73 |
| average error | | 0.54 | 0.50 | 0.43 |

Insensitivity of the estimation to the shape of object was tested by using an object with complex shape, shown in Fig.6. For 8-point, 16-point, 32-point contour samples, each average error of estimated orientations was shown as 3.21 degrees, 0.58 degrees, 0.43 degrees, respectively. Through

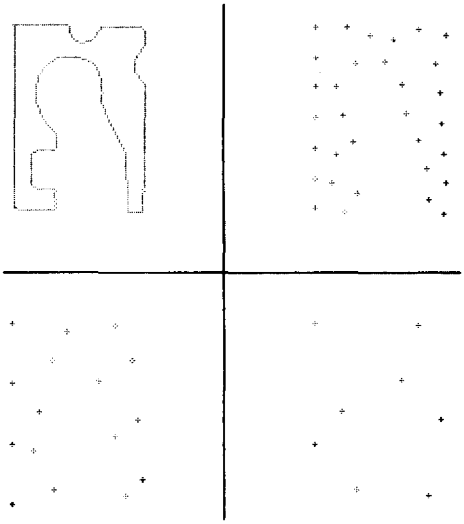


**Fig.6**. Contour of a complex object and its uniform sampling by 32, 16, 8 point.

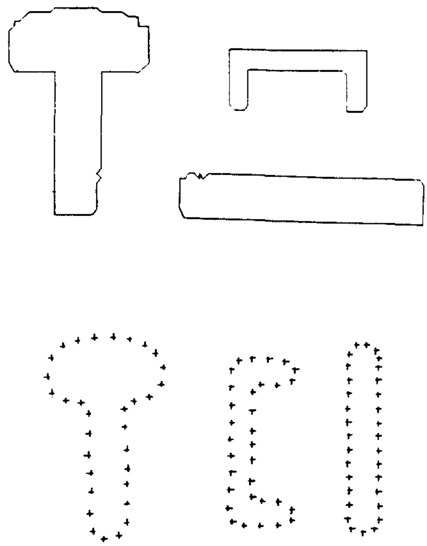


**Fig.7**. Three test objects for the similarity measure and their Contours after Smoothing.

this test, the performance of the algorithm was proved to be almost insensitive to the shape of an object.

The similarity measure between objects were tested next. Fig.7(a) shows the four objects used in this test: a T-shaped objects, a block and a U-shaped object. In the identification process, only the low-order coefficients of the DFT are used for global recognition. Thus, the object shapes actually matched are shown in Fig.7(b). The contours are efficiently smoothed by this simple method. For the test, the objects were reoriented several times (0, 30, ..., 330 degrees) and were matched to the model of T-shaped object. Table 2 shows the values of the similarity measures $\Sigma \mid E(i) \mid^2$ between the three objects and the model for 8-point, 16-point and 32-point boundaries, where the 8-point 16-point and 32-point contours use only 4, 8 and 16 low order DFT coefficients, respectively. The relative similarity ratio is calculated as $\Sigma| A(i) | / \Sigma| E(i)|$. As shown in the results, the T-shaped object showed high similarity to the model T-shape, while the block and the U-shaped object had low similarity. 8-point, 16-point or 32-point contour could be used to recognize the shape, but the similarity measures for 8-point contour were very inconsistent. This inconsistency probably resulted from inaccuracies in calculating the object centroid. With only 8 points, the centroid of the contour is very sensitive to the selection of the uniformly sampled points and in turn, the object contour is not appropriately aligned with the model shape in the matching process. The 32-point contour had the most consistent similarity measures. The 16-point contour showed fair performance. If speed is the most important factor, 16 points might be best to use.

The recognition system was implemented on an IBM AT. The speed of the matching process was independent of the complexity of the shape, but the speed of the uniform sampling process was dependent on the number of object corner points. Table 3 shows the computational speed of the uniform sampling and the recognition system.

## VI. Conclusions

To identify and locate parts, a new two dimensional processing method was developed. Shape matching between the part and the model is performed in the Fourier domain. The DFT of the object contour is decomposed to estimate the orientation of the object and evaluate a similarity

Table 2a. Similarity measure of the test objects to T-shape by 8-point boundary samples.

| | T-shaped | Key | Block | U-shaped |
|---|---|---|---|---|
| Similarity measure | | | | |
| average | 0.064 | 0.077 | 1.54 | 1.63 |
| maximum | 0.175 | 0.160 | 1.54 | 1.74 |
| minimum | 0.019 | 0.041 | 1.49 | 1.50 |
| deviation | 0.044 | 0.039 | 0.03 | 0.08 |
| Relative similarity ratio | | | | |
| average | 13.31 | 11.54 | 2.39 | 2.32 |
| maximum | 21.56 | 14.68 | 2.42 | 2.42 |
| minimum | 7.07 | 7.33 | 2.35 | 2.24 |
| deviation | 3.81 | 2.51 | 0.02 | 0.06 |

Table 2b. Similarity measure of the test objects to T-shape by 16-point boundary samples.

| | T-shaped | Key | Block | U-shaped |
|---|---|---|---|---|
| Similarity measure | | | | |
| average | 0.055 | 0.064 | 1.56 | 1.76 |
| maximum | 0.076 | 0.110 | 1.60 | 1.88 |
| minimum | 0.044 | 0.036 | 1.49 | 1.67 |
| deviation | 0.015 | 0.025 | 0.05 | 0.07 |
| Relative similarity ratio | | | | |
| average | 12.89 | 12.20 | 2.37 | 2.24 |
| maximum | 14.19 | 15.30 | 2.44 | 2.30 |
| minimum | 10.78 | 8.74 | 2.34 | 2.17 |
| deviation | 1.21 | 2.34 | 0.04 | 0.04 |

Table 2c. Similarity measure of the test objects to T-shape by 32-point boundary samples.

| | T-shaped | Key | Block | U-shaped |
|---|---|---|---|---|
| Similarity measure | | | | |
| average | 0.076 | 0.135 | 1.94 | 2.16 |
| maximum | 0.088 | 0.160 | 1.96 | 2.35 |
| minimum | 0.064 | 0.098 | 1.91 | 2.09 |
| deviation | 0.008 | 0.023 | 0.02 | 0.04 |
| Relative similarity ratio | | | | |
| average | 11.28 | 8.52 | 2.23 | 2.11 |
| maximum | 12.30 | 9.93 | 2.25 | 2.15 |
| minimum | 10.47 | 7.75 | 2.22 | 2.07 |
| deviation | 0.58 | 0.78 | 0.01 | 0.02 |

Table 3a. Computation speed of the uniform sampling per one object.

| number of corner points | 16-point | 32-point |
|---|---|---|
| 10 | 14ms | 24ms |
| 20 | 22ms | 30ms |
| 30 | 28ms | 36ms |
| 40 | 34ms | 42ms |

Table 3b. Computation speed of the recognition system per one object.

| | 16-point | 32-point |
|---|---|---|
| FFT | 38ms | 92ms |
| matching | 14ms | 25ms |

measure. In this context, the method appears to be insensitive to noise and does not require preprocessing of the boundary contour. Also, by using an FFT implementation of the DFT algorithm the recognition speed is very rapid. The experimental results indicate that the algorithm is very accurate in estimating orientation. With only 8 uniformly sampled points, we estimated orientation more accurately than with conventional correlation methods in the spatial domain. Since the approach is based on matching in the frequency domain, it is effective for the global recognition of the object shape. Also, the speed is fast enough for many real-time part handling tasks.

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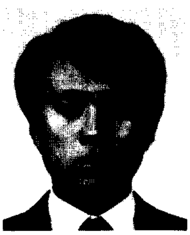
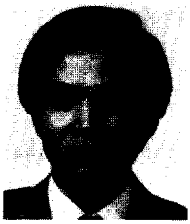
## 著 者 紹 介



**禹 東 玟**(正會員)

1958年 2月 6日生. 1980年 연세대학교 전자공학과 졸업, 1982年 연세대학교 대학원 전자공학과 졸업. 1987年 美 Case Western Reserve University. Electrical Engineering and Applied Physics 공학박사학위 취득. 현재 금성산전 연구소 선임연구원, 주관심분야는 Computer Vision, Pattern Recognition, AI 등임.

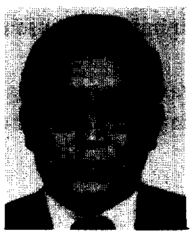


**白 南 七**(正會員)

1951年 8月 4日生. 1974年 연세대학교 전기공학과 졸업, 1979年 연세대학교 대학원 전기공학과 졸업, 1988年 연세대학교 대학원 전기공학과 공학박사학위 취득. 1984年 금성계전연구소 선임연구원, 현재 금성산전 연구소 제4연구실장. 주관심분야는 Machine Vision을 이용한 공장자동화, Image Processing등임.

**金 榮 日**(正會員)

1952年 10月 27日生. 1981年 숭실대학교 전기공학과 졸업. 1985年 연세대학교 대학원 전기공학과 졸업, 현재 연세대학교 대학원 전기공학과 박사과정, 금성산전 연구소 주임연구원. 주관심분야는 자동제어, Machine Vision, Signal Processing 등임.



**崔 浩 顯**(正會員)

1932年 8月 17日生. 1957年 해군사관학교 졸업. 1964年 미 해군공과 대학원 졸업. 1969年 Canada, Univ. of Saskatchewan 대학원 공학박사 학위 취득, 1964年~1967年 해군사관학교 전기공학과 조교수. 1969年~1971年 Canada, Saskatchewan 대학원 post doctoral Research Fellov(non-linear system control and stability에 관한 연구 수행), 1971年~1972年 해군본부 함정감 기술보좌관. 1972年~1982年 국방 과학연구소 책임 연구원. 1983年~1987年 금성계전 연구소 소장. 현재 금성산전 연구소 소장 주관심분야는 자동제어 Robotics 등임.