CONTOUR MATCHING AND PLANAR ALIGNMENT USING OPTIMAL TRANSFORMATION PARAMETERS

[1]HALUK KUCUK, [2]EMRE CETIN, [3]ZEYNEP OZDEMIR GUNDUZ

[1]Department of Electrical & Electronics Engineering, Marmara University, [2]Altınay Robot Technologies, [3]Department of Mechatronics Engineering, Marmara University, Istanbul, Turkey

Abstract: In industrial automation systems, it is of immense importance to ensure precise and accurate positioning of a part to meet sustained quality requirements. The proposed algorithm minimizes planar translation and rotation errors during positioning of an object in a typical production process Disoriented object contour information was extracted using the existing image pre-processing methods. The proposed algorithm, determines the unknown planar translation and rotation parameters of the transformation matrix, that maps the template object contour points to the corresponding disoriented object points. Another algorithm for contour matching is coupled with parameter identification method to correct the arbitrary start location for the disoriented object contour points.

Keywords: Contour Matching, Object Alignment, Transformation Parameter.

I. INTRODUCTION

Contour analysis is one of the most common problems in modern computer vision applications. Contour matching is a study involving a wide range of methods, addressed in various contexts. The general approach consists of three steps. First, the critical points that determine the lines and curves of objects are determined. Second, matching points of two objects are identified. Third, in the light of information, matching points are sorted and the mapping is completed [1]. In this process, identifying matching points has been the most important topic of research in this area. The most popular approach is to create a matrix of values from the differences of all possible matches from two points. These difference values allow the matrix to easily calculate values such as the distance between two shapes [2]. This knowledge is the basis of this work. Among these approaches, there are three approaches that are most common and closest to this study. The first approach is based on assigning a local shape descriptor that captures spatial relationships to each critical point and to other critical points. This method uses labelled distance clusters to gather information about spatial relationships of critical points [2]. Labelled distance clusters and shaped contexts of critical points indicate as a robust method for capturing spatial relationships providing the formulation of the similarities of critical points [3, 4]. The second approach is the "structural graph matching" methods. A key feature of these methods is that efforts are made to maintain the spatial interactions of the critical points in the matching process [5]. This can be accomplished using graphical models with expected maximization or estimated diffusion algorithms. The third approach is defined as "contour matching" or "curve matching" methods. These methods are based on matching the points to extract critical points from the contours and then measuring the degree of similarity between the two shapes [6,7]. These approaches differ depending on the features used to characterize each curve and on the mapping algorithm used to determine the point matches. Typically, a dynamic programming algorithm, local region-based active contour model with morphology fitting energy [7], Gabor function based method [8], triangle similarity [9], two-component Gaussian Mixture (GM) distance map representation [10] are used for identification of features along the contour. Various methods are used to determine the critical points that characterize each curve. One of the simplest ways to represent the shape of an object is to create a N-point sequence that is determined according to several criteria in the image. Various difficulties arise when trying to compare the sequence of a reference and sequence of the detected points due to scale, shape, and starting point changes. Estimation of the object position and the scale from the matching points of two sets has been handled and resolved efficiently by many researchers.

The robust least squares technique is the best known example of this [11]. Shape deformation is a subject that has been studied extensively, especially in the context of active contours [12]. However, the estimation of the starting point is a less studied question. This estimation is usually accomplished by complex optimization procedures. In some cases, it needs manual correction. A simple method for starting point estimation is presented by using the scaling factor obtained by using the circular shift and the Fourier transform between the reference points and the perceived points [13]. In this study, a new algorithm is proposed to determine the disorientation parameters of an object.

II. PARAMETER IDENTIFICATION

An object contour points can be extracted and measured with respect to a fixed coordinate frame A (Fig. 1). This alignment of points measured in fixed frame A corresponds to template orientation of the object. Also lets assume a moving frame B attached to the object initially aligned with the fixed frame A. The misalignment of the object can be described by a translation and a rotation of frame B as S and θ° about z axis, respectively. During this misalignment circumferential point P measured with respect to the

fixed frame is then settles at point Q after the described transformation.

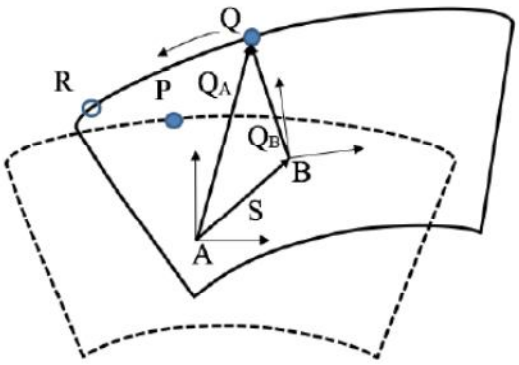


Fig.1. Template and disoriented view of the object.

Position of an arbitrary contour point Q, can be described as in the following equation

$$Q_A = S + Q_B \quad (1)$$

Here Q_A and Q_B are the coordinates of Q with respect to fixed frame A and moving frame B respectively. S is the translation of the origin of the moving frame B with respect to fixed frame A. Above equation in vector variables can be written in a matrix form as in Eq 2.

$$Q_A = {}^{A}T_B \, . Q_B \quad (2)$$

where ${}^{A}T_B$ describes the Transformation matrix from B to A.

$$ {}^{A}T_B = \begin{bmatrix} \cos\theta & -sin\theta & 0 & x \\ sin\theta & cos\theta & 0 & y \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

Substitution of Eq.3 into Eq.2 yields

$$\begin{bmatrix} {}^{A}Q_x \\ {}^{A}Q_y \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -sin\theta & 0 & x \\ sin\theta & cos\theta & 0 & y \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} {}^{B}Q_x \\ {}^{B}Q_y \\ 0 \\ 1 \end{bmatrix} \quad (4)$$

Here $\begin{bmatrix} {}^{A}Q_x \\ {}^{A}Q_y \\ 0 \\ 1 \end{bmatrix}$ and $\begin{bmatrix} {}^{B}Q_x \\ {}^{B}Q_y \\ 0 \\ 1 \end{bmatrix}$ represent coordinates of point Q with respect to frame A and Brespectively. Also one should remember that $Q_B = P_A$ and rewriting Eq.4 results in.

$$\begin{bmatrix} {}^{A}Q_x \\ {}^{A}Q_y \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -sin\theta & 0 & x \\ sin\theta & cos\theta & 0 & y \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} {}^{A}P_x \\ {}^{A}P_y \\ 0 \\ 1 \end{bmatrix} \quad (5)$$

Here the unknowns are θ, x and y variables. Simplifying the transformation matix as:

a = cosθ ; b = sinθ ; c = x ; d = y
resulting in Eq.6.

$$\begin{bmatrix} {}^{A}Q_x \\ {}^{A}Q_y \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} a & -b & 0 & c \\ b & a & 0 & d \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} {}^{A}P_x \\ {}^{A}P_y \\ 0 \\ 1 \end{bmatrix} \quad (6)$$

Expanding the above equation for the unknowns

$$ {}^{A}Q_x = a\,{}^{A}P_x - b\,{}^{A}P_y + c $$
$$ {}^{A}Q_y = b\,{}^{A}P_x + a\,{}^{A}P_y + d \quad (7)$$

and rewriting in matrix form results in the following equation:

$$\begin{bmatrix} {}^{A}Q_x \\ {}^{A}Q_y \end{bmatrix} = \begin{bmatrix} {}^{A}P_x & -{}^{A}P_y & 1 & 0 \\ {}^{A}P_y & {}^{A}P_x & 0 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \quad (8)$$

The above equation can be written for multiple contour points as in Eq.9.

$$\begin{bmatrix} ({}^{A}Q_x)_1 \\ \vdots \\ ({}^{A}Q_x)_i \\ ({}^{A}Q_y)_1 \\ \vdots \\ ({}^{A}Q_y)_i \end{bmatrix} = \begin{bmatrix} ({}^{A}P_x)_1 & -({}^{A}P_y)_1 & 1 & 0 \\ \vdots & & & \\ ({}^{A}P_x)_i & -({}^{A}P_y)_i & 1 & 0 \\ ({}^{A}P_y)_1 & ({}^{A}P_x)_1 & 0 & 1 \\ \vdots & & & \\ ({}^{A}P_y)_i & ({}^{A}P_x)_i & 0 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} \quad (9)$$

Solution of Eq.9 can be obtained using least squares algorithm as in 2.10.

$$\begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} ({}^{A}P_x)_1 & -({}^{A}P_y)_1 & 1 & 0 \\ \vdots & & & \\ ({}^{A}P_x)_i & -({}^{A}P_y)_i & 1 & 0 \\ ({}^{A}P_y)_1 & ({}^{A}P_x)_1 & 0 & 1 \\ \vdots & & & \\ ({}^{A}P_y)_i & ({}^{A}P_x)_i & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} ({}^{A}Q_x)_1 \\ \vdots \\ ({}^{A}Q_x)_i \\ ({}^{A}Q_y)_1 \\ \vdots \\ ({}^{A}Q_y)_i \end{bmatrix} \quad (10)$$

After solution of a,b,c and d unknowns the transformation parameters can be obtained as.

θ = atan2(b,a)
x = c
y =d (11)

Above computations rely on the assumption that the contour series on the disoriented object start with point Q, corresponding to the contour point series starting with P on the template object. After image pre-processing and contour extraction process, the starting point on the disoriented object may not always start with Q, in other words may shift to another arbitrary contour point R (Fig. 2). An algorithm to find the matching point on the template contour point series has been proposed, combined with the optimization algorithm to obtain the disorientation parameters, x, y and θ.

Starting from an arbitrary point R on the object and finding the Q point that matches with point P on the

template is searched by a minimization algorithm based on the min ($P_A - {}^{A}T_B R_B$) which is also coupled with computation of the planar disorientation parameters x,y and θ. The combined algorithm can be summarized as below.

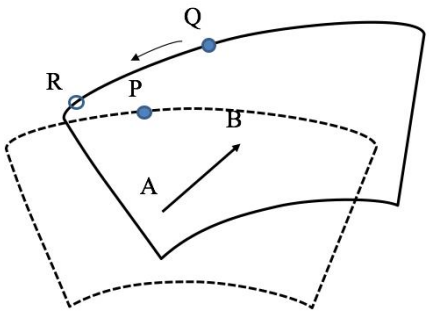


Fig.2. Correcting the contour sequence.

k=size(contour)

for i = k

⋮

θ = atan2(b,a)

x= c

y= d

$\varepsilon_i = (P_A - {}^{A}T_B R_B)$

$\delta_i = \Sigma (\Sigma \varepsilon_i^2)$;

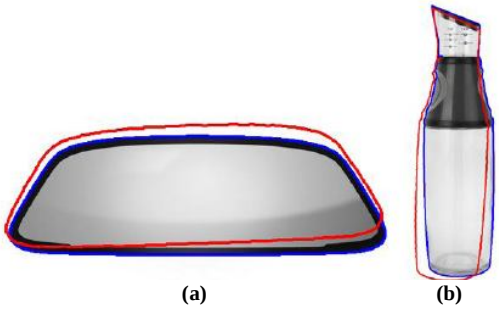
i=i+1

end

Fig.3. The Algorithm for Parameter Identification.

III. RESULTS AND DISCUSSION

The contour points object shown in Fig.4a were extracted after colour conversion and thresholding operations.



(a) **(b)**

Fig.4. Simulation Scenarios (a) windshield, (b) bottle.

The start of the disoriented object contour sequence, displacement and rotation values were selected randomly. Selected parameters were applied to the template object to obtain the disoriented object. Afterwards the optimization algorithm was executed. The preselected translation, rotation and shift parameters were obtained for the contour sequence providing 1.78×10^{-12} error. This sequence matched exactly the same contour sequence provided by the template view of the object. Another object was selected for the experimentation as in Figure 4b. The parameters were obtained for the sequence providing 4.0×10^{-12} error. Similarly the contour sequence of the disoriented object matched the sequence of the template object.

Case	shift	x	y	θ	min ($Q_A - {}^{A}T_B Q_B$)
1	143	10	5	2°	1.78×10^{-12}
2	1598	-5	10	-3	4.0×10^{-12}

Table1: Parameter Identification Experiments

Final scenario was if a portion of the disoriented object is in the view of the camera and if this partial contour sequence is enough to predict the disorientation parameters (Fig.5). The disorientation of the object was randomly selected to be x=7 units, y= 4 units and θ= -2° . The starting point of this sequence was randomly selected to be 48 units shifted and included 100 successive points on the contour. After executing the optimization algorithm, the contour segment match on the template was determined with 1.1885×10^{-12} accuracy, indicating the preselected translation and rotation parameters as x=7 units, y= 4 units and θ= -2°.

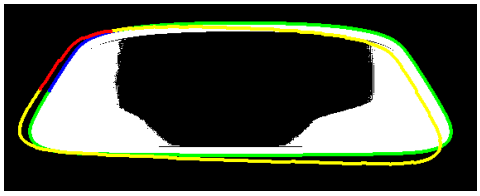


Fig.5. Partial contour matching and parameter identification.

Computation of the above described algorithm was accomplished using Matlab routines, as image pre-processing, Canny edge detection, contour extraction, and solution of Eq.9 by Matlab least squares algorithm.

CONCLUSIONS

A new algorithm is proposed to determine planar disorientation parameters of an object. The contour point sequence of the disoriented object was selected to start with an arbitrary point that may not always match with the template contour sequence. Another optimization algorithm was proposed to couple with the above method searching for the best sequence generally indicating the same starting contour point as in the template contour sequence. The proposed algorithm provided satisfactory results even if a partial segment of the disoriented object contour is provided.

REFERENCES

[1] C. Scott, R. Nowak. “Robust Contour Matching Via the Order-

[2] Preserving Assignment Problem”, IEEE Transactions on Image Processing, vol.15, no.7, pp. 1831-1838, 2006.

[3] C. Grigorescu, N. Petkov. “Distance Sets For Shape Filters And Shape Recognition”, IEEE Transactions on Image Processing, vol.12, no.10,pp.1274-1286, 2003.

[4] S. Belongie, J. Malik, J. Puzicha,“Shape Matching And Object Recognition Using Shape Contexts”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.24, no.4, pp. 509-522, 2002.

[5] H. Ling, D.W. Jacobs,“Using The Inner-Distance For Classification Of Articulated Shapes”, 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 20-25 June, San Diego,USA.

[6] J.M. Coughlan, S.J. Ferreira,“Finding Deformable Shapes Using Loopy Belief Propagation”, Computer Vision ECCV, 2352, 453-468.

[7] S. Wang, T. Kubota, T. Richardson,“Shape Correspondence Through Landmark Sliding”, Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 27 June – 2 July,

[8] K. Sun, Kaiqiong, Z. Chen, and S. Jiang,“Local Morphology Fitting Active Contour For Automatic Vascular Segmentation”, IEEE Transactions on Biomedical Engineering vol.59, no.2, pp. 464-473, 2012.

[9] Kovács, György, and AndrásHajdu, “A Self-Calibrating Approach For The Segmentation Of Retinal Vessels By Template Matching And Contour Reconstruction”, Medical image analysis vol.29, pp.24-46, 2016.

[10] Pun, Chi-Man, Caiping Yan, and Xiao-Chen Yuan, “Image Alignment-Based Multi-Region Matching for Object-Level Tampering Detection." IEEE Transactions on Information Forensics and Security vol.12, no.2, pp. 377-391, 2017

[11] H. Li, T. Shen, and X. Huang. "Approximately Global Optimization For Robust Alignment Of Generalized Shapes”, IEEE transactions on pattern analysis and machine intelligence vol.33, no.6, pp.1116-1131, 2011.

[12] R.M. Haralick, H. Joo, C. Lee, X. Zhuang, V.G. Vaidya, M.B. Kim, “Pose Estimation From Corresponding Point Data”, IEEE Transactions on Systems, Man, and Cybernetics, vol.19, no.6, pp.1426-1446, 1989.

[13] M. Kass, A. Witkin, , D. Terzopoulos,”Snakes: Active Contour Models”, International Journal of Computer Vision, vol.1, no.4, pp.321-331, 1988.

[14] J.S. Marques, A.J. Abrantes, “Shape Alignment – Optimal Initial Point and Pose Estimation”, Pattern Recognition Letters, vol.18, pp.49-53, 1997.

★★★