Object Recognition Using Distributions of Edge Information on Gaussian Spheres

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Abstract: In this paper, we present a recognition method of polyhedral objects using distributions of edge information on Gaussian spheres. This method compares a distribution of edge vectors on a Gaussian sphere that is obtained from a camera image with that of 3-D object models in order to recognize the category of objects and to determine their orientations. The matching procedure has three steps. The first step searches candidates of category and orientation based on distributions of edge information on a Gaussian sphere. The second step ascertains the validity of candidates based on relationship concerning vertex information so as to find which is correct. The third step makes accuracy higher. The proposed method can recognize objects whose edges are partly lacked with image noise. Simulation results show the effectiveness of the method.

Keywords: Computer Vision, Object Recognition, Gaussian Sphere, Edge Information, Polyhedral Object

1 Introduction

One of the demanded techniques in the factories is to recognize moving parts on belt conveyors (Fig.1). It is important for parts recognition to examine the category of parts and their orientations. A parts feeder can sort different kinds of parts and align their posture. However, this machinery cannot accommodate in all situations of parts position. It has high costs and takes long times when parts feeders change to cope with new kinds of parts. To solve these problems, the object recognition in the field of the computer vision is an effective method. In this paper, we propose a method that can recognize the category of parts and determine their orientations using an image processing technique.

Recently, there are a lot of studies about the 3-D object recognition [1,2,3]. The categories and the orientation of parts can be determined to compare predefined object models with image data in general. However, there are problems about the long processing time and the susceptibility to image noises. One of the subjects to resolve the problems is to reduce candidates of matching.

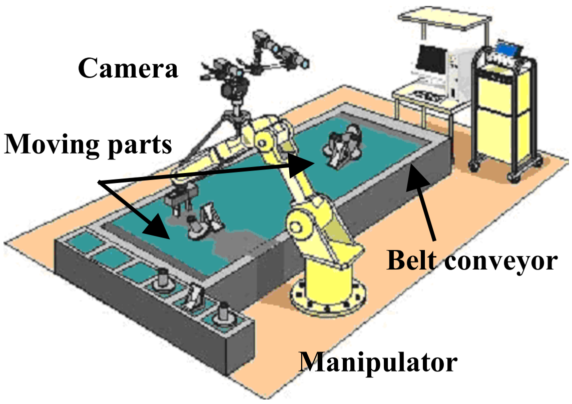


Fig.1: The camera system recognizes moving parts on the belt conveyor and the manipulator handles them.

Therefore, the purpose of this paper is a construction of a new method to recognize polyhedral objects robustly and process fastly. Robust recognition means to recognize objects whose edges are partly lacked with image noise. A method using 3-D edge information can realize the robust recognition [2].

The matching procedure of this method has three steps. The first step searches candidates of object’s category and orientation based on distributions of edge information on Gaussian spheres. The second step ascertains the validity of candidates based on relationship concerning vertex information so as to find which is correct. The third step makes accuracy higher. This method can recognize objects when only two straight edges are extracted from a camera image. Thus, the method is robust against errors that edges are partly lacked with image noise.

2 Theory

2.1 Assumption

There are some assumptions for the object recognition shown as follows:

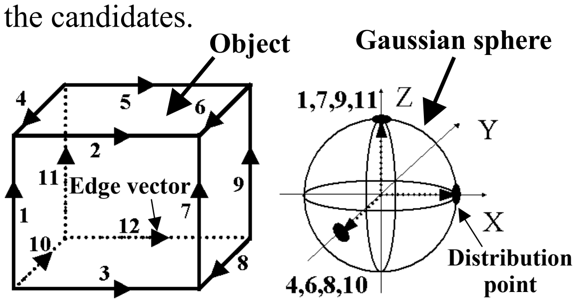
1. This method has already made several image processing: the edge extraction from camera images, the detection of line segment and vertex intersection, and the 3-D measurement of the edge positions.

2. This method defines object models for recognition in advance. The object models have various ideal features: edge vectors, vertex position, and the relationship between edges and vertex.

3. Image data are the features generated from assumption 1. Image data consist of edge vectors, vertex position and their relationship as well as object models. However, image data do not have invisible feature that are hidden from the point of view.

2.2 Description using Gaussian spheres

The edge vectors in image data are distributed on Gaussian spheres. Several processes make the distribution of the vectors. Firstly, each vector is normalized to a unit vector. Secondly, the vector's start point is transfer to Gaussian sphere's center point. Finally, the end point is set on the surface of Gaussian sphere. Figure 2 (a) shows examples of edge vectors and Fig.2 (b) shows the distribution of these vectors on a Gaussian sphere in the case of a rectangular object. However, Gaussian sphere represents the same distributions when the lengths and positions of edge change. The purpose of the matching using Gaussian spheres is to make a short list of the candidates.



(a) Edge vectors. (b) Gaussian sphere.

Fig.2: Distribution using edge vector.

2.3 Relation concerning vertex position

This method uses the vertex position because the matching using only edge vectors represent incorrect results of the same distribution.

The relation concerning vertex position generates shape vectors. The shape vectors are outer products obtained from two edge vectors that construct one vertex (Fig.3). When three edge vectors that construct one vertex are detected, three shape vectors of the vertex is generated. When only two edge vectors are detected, one shape vector is generated. The matching using the shape vectors makes the object recognition more robust.

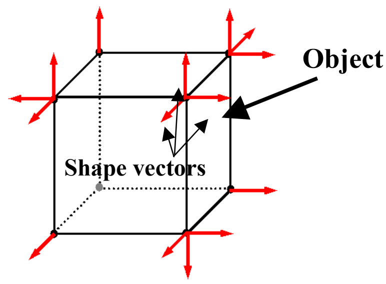


Fig.3: Shape vector. The solid line is a visible one and the dashed line is an invisible one.

3 Recognition algorithm

In this section, object recognition that an algorithm has a preprocessing and three matching steps is shown.

3.1 Preprocessing

Firstly, forms of image data are converted to effective forms for matching. The edge vectors are distributed on Gaussian sphere to realize the effective matching. Additionally, neighborhoods of distribution points are integrated into one point. This conversion can decrease the number of the distributed points and may result in the decrease of the processing time.

3.2 1st step: Searching candidates

The first step compares the converted distribution of image data on a Gaussian sphere with that of multiple object models (see Fig.4), and obtains the candidates of the category and the orientation. The candidates are generated by the following procedures:

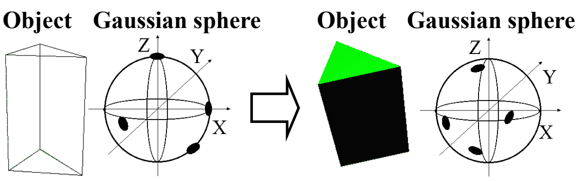
1. The 3×3 rotation matrix R can rotate the Gaussian sphere of the object model as two arbitrary distribution points of object model coincide with that of image data. A rotation matrix R is calculated.

2. After rotating the Gaussian sphere of the object model, the corresponding points in image data are searched with points in object models.

3. If the distribution of the object model differs apparently from that of the image data, the points in the object model and in the image data satisfy Equation (1).

$$\frac{1}{d}\sum_{p=1}^{d} E_p < \theta \, , \tag{1}$$

   where d is the total number of corresponding distribution points, and E_p is the distance of corresponding distribution point p between image data and object model. θ is the threshold to ascertain candidates of matching.



(a) Object model (b) Image data

Fig.4: Object model and image data.

In this way, the candidates of the category and orientation of object are obtained from above.

3.3 2nd step: Candidate reduction

The second step ascertains the validity of candidates i ($1\leq i\leq k$; k: the total number of candidates) obtained from the first step using shape vectors of all vertices. As comparing a shape vector N_l in the image data with a shape vector B_l in the object model, the validity of candidates is ascertained. A performance function P_i realizes ascertainment.

$$P_i = \frac{1}{h}\sum_{j=1}^{h} G_j \, , \tag{2}$$

$$G_j = \frac{1}{a_j}\sum_{l=1}^{m_j}\left(N_l \bullet B_l\right), \tag{3}$$

where h is the total number of image data's vertex, and G_j is the performance function that represents the correlation value concerning shape vectors of the vertex j. a_j is the number of image data's shape vector in the vertex j, m_j is the number of obtained shape vector in the vertex j, and $\bullet$ is the operator of the inner product.

The performance function P_i represents the correlation value between the image data and the object model. Concerning the image data that correspond completely the object model, P_i takes 1.0. However, P_i may not take 1.0 when the vertices are detected from a camera image.

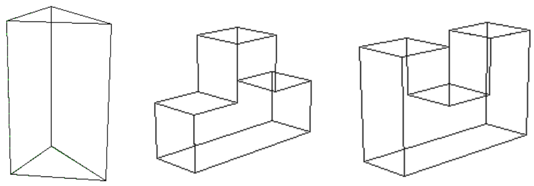
3.4 3rd step: Fine adjustment

The third step rotates slightly the candidates selected in the second step and makes accuracy higher. This fine adjustment process rotates angles α, β, γ around X-axis, Y-axis, Z-axis using a rotation matrix S and selects the candidate whose the average distances between corresponding vertices are calculated minimum.

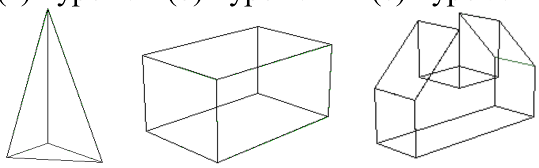
Consequently, a rotation matrix T (T=SR) obtained from three steps matching represents the best orientation of object model comparing with image data's features, and finishes the recognition process.

4 Simulation

The effectiveness of our method is shown using arbitrary polyhedral objects through simulation results. The spec of our computer is as follows; CPU: PentiumⅢ 500MHz, Memory: 256MB. The resolution of angles α, β, γ are 0.1deg.The predefined object models of simulation are shown in Fig.5.



(a) Type 1. (b) Type 2. (c) Type 3.



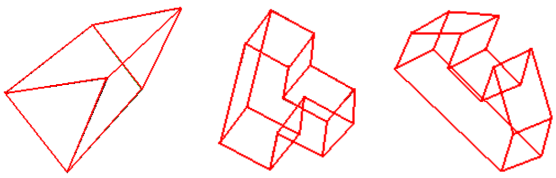
(a) Type 4. (b) Type 5. (c) Type 6.

Fig.5: Object models.

4.1 Containing no error

Image data containing no error (a), (b) and (c) in Fig.6 show the objects rotated model 1,2 and 6. When threshold θ equals 0.1 in the case of Fig.6 (a), the total number of candidate k is 212 and the performance function P_i equals 1.0. The recognition time t took 0.26 seconds. In (b), θ=0.1, k=340, P_i=0.41, and t=0.41 sec. In (c), θ=0.1, k=310, P_i=0.89, and t=0.55 sec.

In this simulation, the categories and the orientation of the objects can determine correctly. However, P_i did not get 1.0 because image data has invisible vertices.



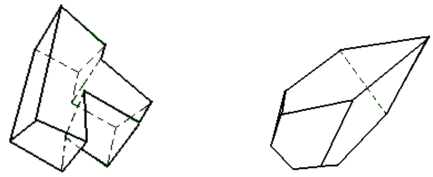
(a) Data 1. (b) Data 2. (c) Data 3.

Fig.6: Recognition results of containing no error.

4.2 Containing error

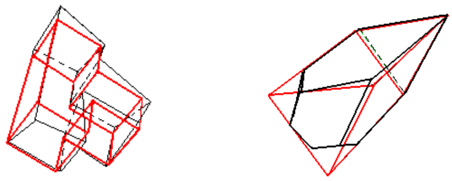
The cases that the features in image data contain error are shown in Fig.7. Figure 8 shows recognition results. In Fig. 8 (a), θ=0.5, k=7994, P_i=0.38, and t=2.21 sec. In (b), θ=0.1, k=304, P_i=0.59, and t=0.75 sec.

As shown in Fig.8, image data containing error comported about the category and the orientation with the rotated object model. However, the result in Fig.8 (a) was not obtained in the case θ is below 0.5. Because each edge contains large error, each distribution in the image data does not correspond with that of the object model.



(a) Data 4. (b) Data 5.

Fig.7: Image data containing error. (a): The object in Fig.6 (b) whose edges and vertices contain error. (b): The object in Fig.6 (a) whose vertices are partly lacked.



(a) Result 4. (b) Result 5.

Fig.8: Recognition results of containing error. (a): The case that θ is above or equal 0.5. (b): The case that θ is above or equal 0.1.

5 Conclusion

In this paper, we proposed an object recognition method using the distribution of edge information on Gaussian spheres. When the features in the image data contain large error, this method was confirmed to recognize the category and the orientation of objects. In other words, this method could recognize robustly.

The future works are to recognize objects having more complicated shape and resolve some problems, such as determination of the threshold θ, more accurate correspondence in each step.

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