CHARACTERISTIC VIEWS: OBTAINING 2-D RECONSTRUCTIONS FROM COLOR EDGES

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ABSTRACT

This article presents a complete hybrid object recognition system for three-dimensional objects using the characteristic view (ChV) idea. High-quality 2-D reconstructions have to be generated from intensity or color data, respectively, to integrate the ChV representation method into a recognition system. First, we present an approach for obtaining edges and gradient information from color images. Second, we present an adaptive edge linking process that transforms the image data into a suitable form. The edge linker uses an energy function to combine data from the edge detector and color gradient information to improve the results of the edge detector for the 2-D reconstruction. Results are presented for real color images.

I. INTRODUCTION

Viewer-centered approaches use models that represent the visible information from a defined view point. We introduce an adaptive hybrid matching framework and show results with real data. Image features are converted in a symbolic description (a labeled edge structure graph, that is compared with the descriptions in the model base. Our method combines model- and data-driven strategies to a hybrid system, see [1, 2] and Fig. 1. The data driven feature indexing module generates the best fitting hypotheses that are localized and verified by an object driven localization module. Our work focuses the following aspects, that are described in [3]:

- 1) computing an appropriate ChV representation
- 2) developing a generic data base
- 3) implementing an adaptive data-driven matching procedure
- 4) developing a localization and verification tool
- 5) implementing a color edge based segmentation and an adaptive edge linking approach to transform the image data into a suitable form.

Especially the fifth aspect is described in this paper.

1) The system generates either ChV sets of arbitrary shaped objects or aspect graphs of planar objects. Edge structure graphs based on vertex, edge and face data specify instances of both models.

2) The exact classification of scene objects and the efficient access to complex model data -generally independent from amount of the ChVs- are goals of a recognition system. The use of "a priori" knowledge as the

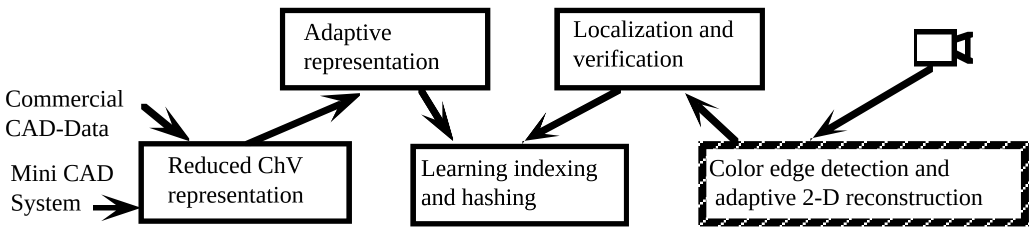

Figure 1: Modules of the presented recognition system.

feature distribution in the data base supports the recognition realization [2].

3) An adaptive hierarchical indexing module is employed that adjusts the indexing dependent to the sensor behavior [2]. Additionally, a hashing algorithm, which applies a local topological feature, has been developed [1].

4) The successive localization and verification module uses an object driven strategy. An ordered list of best fitting hypothesis is generated by the the indexing or hashing. The candidates of the list are verified until a certain fitting degree is reached [2].

5) Edges and gradient information are detected in color images employing the Cumani approach [4]. The results are combined to support an edge-linking process.

The edge-linker has two main properties. These are, first, the adaptive integration of gradient information into the results of the mentioned color edge detector and, second, the ability to distinguish between straight and curved edges. As result of the edge-linking the approach generates a labeled structure graph [2].

II. COLOR EDGE DETECTION

During the past few years, the interpretation of color information for object recognition has been a subject of considerable research activity. Color information is used to support object recognition, e.g., by computing color histograms [5], generating color adjacency graphs [8] or grouping object colors [10]. However, the detection of color edges, that can be employed to generate 2-D reconstructions, has received much less attention of the scientific community. Since color images provide more information than gray value images, more detailed edge information is expected from color edge detection. Novak and Shafer found [9] that 90 percent of the edges are about the same in gray value and in color images. Consequently, there are still 10 percent of the edges left that may not be detected in intensity images. These 10 percent may be important for a consecutive object recognition process. It has to be pointed out that no edges will be detected in gray value images when neighboring objects have different hues but equal intensities. Such objects can not be distinguished in gray value images. They are treated like one big object in the scene. This may become crucial for the task of object recognition. Additionally, edge detection is sometimes difficult in low contrast images but rather sufficient results can be obtained in color images. Thus, a robust approach to color edge detection is needed that provides high quality results.

We applied different approaches for color edge detection to several synthetic and real images [7]. The approaches were based on the Sobel operator, the Laplace operator, the Mexican Hat operator, and different realizations of the Cumani operator [4]. As a result, we found that the edges are determined with the best quality in this comparison when the Cumani operator was applied. However, the results obtained from color images were always better than the results obtained from intensity images. Additionally, we found that the quality of the results increased if Gaussian masks of larger width are used in the derivation process instead of simple 3 x 3 masks [7]. From these observations, we use the Cumani operator in our object recognition system. A brief description of the Cumani operator is given below.

A color image is considered as a two-dimensional vector field $\boldsymbol{f}(x,y)$ with three components, Red, Green, and Blue. The squared local contrast $S(P;\boldsymbol{n})$ of a point $P = (x,y)$ is defined [4] as squared norm of the directional derivative of $\boldsymbol{f}$ in the direction of the unit vector $\boldsymbol{n} = (n_1, n_2)$ by

$$S(P;\boldsymbol{n}) = \frac{\partial \boldsymbol{f}}{\partial x} * \frac{\partial \boldsymbol{f}}{\partial x} \cdot n_1 \cdot n_1 + 2 \cdot \frac{\partial \boldsymbol{f}}{\partial x} * \frac{\partial \boldsymbol{f}}{\partial y} \cdot n_1 \cdot n_2 + \frac{\partial \boldsymbol{f}}{\partial y} * \frac{\partial \boldsymbol{f}}{\partial y} \cdot n_2 \cdot n_2 = E \cdot n_1^2 + 2 \cdot F \cdot n_1 n_2 + H \cdot n_2^2$$

using shorthand notations

$$E = \frac{\partial \boldsymbol{f}}{\partial x} * \frac{\partial \boldsymbol{f}}{\partial x}, F = \frac{\partial \boldsymbol{f}}{\partial x} * \frac{\partial \boldsymbol{f}}{\partial y} \text{ and } H = \frac{\partial \boldsymbol{f}}{\partial y} * \frac{\partial \boldsymbol{f}}{\partial y}.$$

The eigenvalues λ of the 2 x 2 matrix $\begin{pmatrix} E & F \\ F & H \end{pmatrix}$ coincide with the extreme values of $S(P;\boldsymbol{n})$ and are attained when $\boldsymbol{n}$ is the corresponding eigenvector. An edge point in the color image is considered as the point P where the first directional derivative $D_S(P;\boldsymbol{n})$ of the maximal squared contrast $\lambda(P)$ in the direction $\boldsymbol{n}(P)$ of maximal contrast is zero [4]. The directional derivative $D_S(P;\boldsymbol{n})$ mentioned above can be written as:

$$D_S(P;\boldsymbol{n}) := \nabla\lambda \cdot \boldsymbol{n} = E_x n_1^3 + (E_y + 2F_x) n_1^2 n_2 + (H_x + 2F_y) n_1 n_2^2 + H_y$$

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where indices x and y denote the corresponding derivatives with respect to x and y, respectively. Edge points are detected by computing zero-crossings of $D_S(P;\boldsymbol{n})$. Although $D_S(P;\boldsymbol{n})$ can be efficiently obtained without explicitly computing E, F, and H [7], we have to compute these directional derivatives in this approach, because we use the gradient information from $S(P;\boldsymbol{n})$ for a consecutive refinement of the edge detection result.

III. ADAPTIVE 2-D RECONSTRUCTION

The adaptive 2-D reconstruction bases of an approach for the edge finetunig. This approach improves the results of the mentioned edge detector. Additionally an algorithm that distincts between straight and curved lines is implemented.

A. Refinement of Edge Detection Results

Figure 2: Gradient maximum search

The edge finetunig approach performs a gradient maximum search (jittering) to improve the results of the line approximation. The approach gains to eliminate artifacts in binary images. Artifacts are displacements of the edges, gaps and displacements of the edge endpoints.

The gradient maximum search combines a color gradient image with the result of the mentioned edge detector. First, the results of the edge detector are polygonaly approximated. Then a line generating algorithm similar to the well-known Bresenham algorithm is applied. The following energy function integrates the gradient data and the polygonal data.

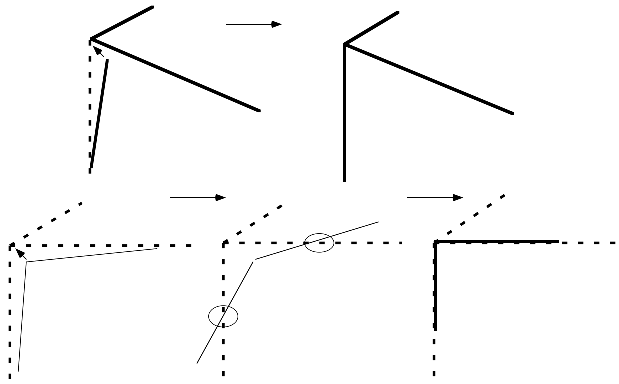

Figure 3: Results of the polygon edge correction. First row, the polygon edge is adapted on the correct edge. Second row, correction of a vertex that generates wrong spikes in the energy function.

$$Max = \frac{\sum Bres\_Gradient}{len} + K \bullet \frac{1}{dist},$$

where *len* denotes the line length, that is generated by the line generating algorithm, K denotes a constant and *dist* denotes the distance to the next polygon point. The nearest polygon point is chosen as candidate for a edge endpoint. The gaussian is used as weighting function for the endpoints, which have to be corrected. The function *Bres_Gradient* calculates the values of these points in the gradient image that are placed at the same position as the already calculated line. The approach assumes the same position of the gradient and the polygon values. The polygon weighting bases on the sum of the gradient values that are situated „under“ the polygon edge. For the position fitting the 8-neighbouring of the polygon endpoint is searched to maximize the energy function of the to polygons. The energy function expects the coordinates of the two polygon edges and calculates the energy of the interesting gradient values. The sum of these values is normalized by the length of the polygon edges. The algorithm terminates if there are no more connected gradient points, see fig 2.

Fig. 3 shows examples of possible applications of the algorithm.

B. Distinction between curved and straight edges segments

To distinct between curved and straight edge segments a circle is fitted on two segments that has to be combined. The fitting is done by a least square algorithm.

Three points of each segment are analyzed by comparing their distances to the circle center. Fig. 4 shows a schematic drawing of the algorithm. The start, middle and end point of the segment are chosen to be the three analyzed points. Three points are necessary to detect a change in the curvature direction as shown in the figure.

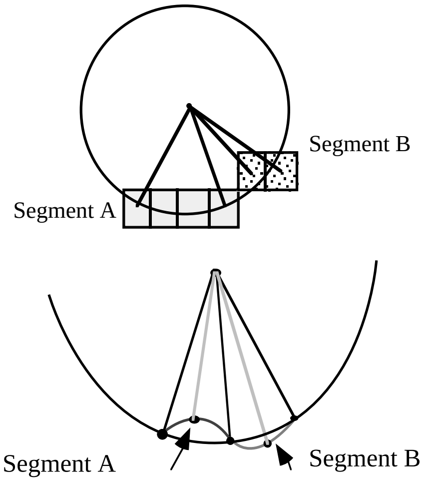

Figure 4: The distances of selected points to the center of the fitted circle are the criterion to clue together the edge segments

Two segments are combined if the distances between regarded points and circle center are below a dynamic threshold, that depends on the square of these distances and the two segments show the same curvature direction. The dynamic threshold is an improvement to Etemadi [6] which is strongly related to our approach. Etemadi chooses a fixed threshold of 1.4 as maximal distance.

IV. EXPERIMENTAL RESULTS

Fig. 5 shows results of the two described features of the 2-D reconstruction algorithm.

Seventy images have been investigated to evaluate the implemented approaches (see Table 1). Twenty-five of these images have contained curved edges. Principially it exists no objective criteria to classify edges into curved and straight lines.

Additionally, to evaluate the the curved/straight distinction algorithm, the curved edges have been classified manually. The results of the algorithm have been compared with the results obtained by manual classification.

Detected edges	Optimization using color to detect edges	Optimization of the corner position in grayscale images	Optimization of the corner position in color images
58.4%	180%	52.2%	73.5%

Table 1: Results of the approach (testing 70 images)

The Euclidean distances between the real and the detected corner position algorithms are normalized and compared to evaluate the results of the corner optimization. The detected corners of all images have been evaluated.

V. CONCLUSION

To recognize and locate 3D-objects in space the accurate position estimation of object corners and edges and the edge type distinction is obvious. Especially the position estimation of corners needs the precise localization of the edges that are extremely dependent from the chosen edge detector. A system based on grayscale was implemented in [3]. In the presented work we demonstrate an improved version, using color information contained in 24 bit RGB images.

The number of real object edges (generated by surface discontinuities) is a determinative feature for the object classification. Therefore the distinction between straight and curved object edges, that mostly not are caused by surface discontinuities, improves the matching accuracy.

The combination of color information, corner position estimation and curved edge detection seems to be a promising approach to improve the generation of labeled edge structure graphs, that are essential for a feature based object recognition system.

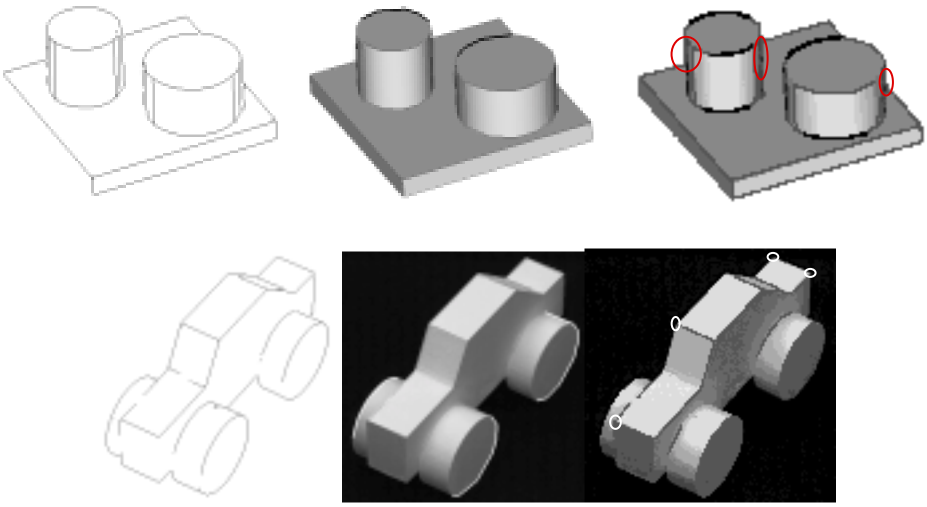

Figure 5: Results of the polygonal approximation and the detection of straight and curved edge segments. Left image edge image; middle image result of the line approximation; results with applying the energy function.

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