Efficient Geometric Matching with Higher-Order Features

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Abstract

We propose a new technique in which line segments and elliptical arcs are used as features for recognizing image patterns. By using this approach, the process of locating a model in a given image is efficient since the number of features to be compared is few. We propose distance measures to evaluate the similarity between the features of the model and that of the image. The model transformation parameters are found by searching the transformation space using cell decomposition.

1 Introduction

Locating instances of a known model in a given image is necessary in many applications such as industrial inspection, tracking and aerial image analysis [7]. The edge maps of the model and the image are represented using features and these features are compared in order to determine the transformation parameters of the model so that the transformed model features are in close correspondence with the part of the image containing the model object.

Huttenlocher et al. [5] have proposed a matching technique which is based on finding the transformations that minimize the Hausdorff distance between the model and image point sets. This technique can effectively deal with outliers and occlusions. Hausdorff distance-based matching has also been applied for line segment features in [11]. In this method, the line segments are treated as points in a 4-D space. The line matching problem then reduces to a 4-D point-matching problem under translation. The main disadvantage of this method is when there are breaks in line segments, the location of a line segment in the 4-D space changes, degrading the accuracy of matching [2]. Other techniques for matching line segment features have been proposed in [2, 8, 10].

In this paper, we propose a geometric matching methodology wherein not only line segments but also elliptical arcs are used as image features. We use these features since the representation of curved edges can be done optimally by incorporating these higher-order features [4, 9]. We propose distance measures for comparing the model and image features. These distance measures can be used for matching even when the features are distorted. The model is located by searching the transformation space using cell-decomposition [7]. In our approach, the number of features to be compared is considerably fewer than in the case of point-matching and line-matching techniques. Consequently, the proposed matching algorithm is generally much faster than the Hausdorff distance-based point matching technique [7]. We consider the model transformation to be 2-D translation and rotation. However, our technique can be extended to handle scale changes also.

2 Feature representation

We follow the technique described in [6] to obtain a representation of the edge map of images with line segments and elliptical arcs. In this method, the critical points (where the shape of edges change) present in the edges are initially detected. The edge map is then divided into edge segments at these critical points. These edge segments are represented by a combination of line segments and elliptical arcs using a least-squares approach [3, 6].

When conditions are not very controlled (as is the case in practise), features of the same object can change across different images due to occlusions, illumination variations or fragmented image data. In Figs. 1 (a) and (b) we show images of a mouse in different positions. We obtain their representation in terms of line segments and elliptical arcs. In Fig. 1 (c), we see that the mouse has been represented by one elliptical arc and few line segments (elliptical arcs are shown in pink colour and line segments are shown in green colour). On the other hand in Fig. 1 (d), we observe that the edge segments

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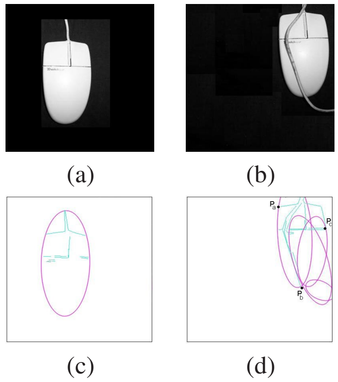


Figure 1. (a) and (b) Images of a mouse. Feature representations of (c) Fig. 1 (a), and (d) Fig. 1 (b).

between the points P_a and P_b, and between points P_b and P_c have been represented by two different elliptical arcs. This is due to the fact that the edge points between P_a and P_b, and the points between P_b and P_c are separated by the cable running over the mouse and are linked as separate edge segments. A matching algorithm should be robust to these feature distortions.

3 Matching features

In this section, we propose distance measures for comparing features of the model and the image. Let the feature sets of the given image and the model be denoted by I and M, respectively. Let I_L and M_L denote the line segments of the image and the model, and I_E and M_E denote the elliptical arcs of the image and the model, respectively.

We compare model line segments M_L with image line segments I_L using the distance measure D_L. Distance $D_L(M_L, I_L)$ is defined as

$$D_L(M_L, I_L) = \max_{m_l \in M_L} \left\{ \min_{i_l \in I_L} \left\{ d_l\left(m_l, i_l\right) \right\} \right\} \quad (1)$$

where d_l denotes the distance between a model line segment m_l and an image line segment i_l. We use the integrated squared perpendicular distance (ISPD) defined in [1] as the distance measure d_l. Distance $d_l(m_l, i_l)$ is given by

$$d_l(m_l, i_l) = \frac{1}{3}\left(v_{1im}^2 + v_{1im}v_{2im} + v_{2im}^2\right) \quad (2)$$

where v_{1im} and v_{2im} are the Euclidean distances between the infinitely extended model line m_l and the two end points of the image line segment i_l.

We need to compare the model elliptical arcs with image elliptical arcs. In some images, a part of the model elliptical arc can occasionally fit to a line segment when there are breaks. Hence, we also propose to compare model elliptical arcs with image line segments. We define the distance D_E to match the model elliptical arcs M_E with the image features I as

$$D_E(M_E, I) = \max_{m_e \in M_E} \left\{ \min_{i_e, i_l \in I} \left\{ d_e\left(m_e, i_e\right), d_{el}\left(m_e, i_l\right) \right\} \right\} \quad (3)$$

where d_e is the distance measure between a model elliptical arc m_e and an image elliptical arc i_e, and d_{el} denotes the distance measure between a model elliptical arc m_e and an image line segment i_l.

We derive the distance measure d_e using the algebraic distance [3] between an image ellipse point and the model ellipse. Consider a model ellipse m_e with center (h_m, k_m), major axis a_m, and minor axis b_m. The algebraic distance between a point on the image elliptical arc $p_i = (x_i, y_i)$ and the ellipse m_e is

$$d_{pe} = \frac{\left(x_i - h_m\right)^2}{a_m^2} + \frac{\left(y_i - k_m\right)^2}{b_m^2} - 1 \quad (4)$$

Distance d_e between m_e and i_e is obtained by integrating the square of d_{pe} along the image elliptical arc i.e.,

$$d_e\left(m_e, i_e\right) = \int_{<i_e>} d_{pe}^2\left(l\right) dl \quad (5)$$

On solving this, we get a closed form expression (not given here due to space constraints) for the distance measure d_e as a function of the model and image ellipse parameters.

Fig. 2 (a) shows a model consisting of an ellipse and Fig. 2 (b) shows an image in which the model ellipse broke into smaller arcs and is distorted. In the representation shown in Fig. 2 (c), we see that the image ellipses differ in dimensions from the original model due to breaks in the ellipse. The translation at which the distance between the model and image ellipses was minimized is shown in Fig. 2 (d) which is indeed correct. Thus, the distance measure d_e can be used to match elliptical arcs even in the presence of distortions.

We follow a similar approach to derive the distance measure d_{el} between a model elliptical arc and an image line segment. We integrate the square of the algebraic distance d_{pl} between a point on the image line segment and the model ellipse along the length of the line segment to get the distance measure d_{el} i.e.,

$$d_{el}\left(m_e, i_l\right) = \int_{<i_l>} d_{pl}^2\left(l\right) dl \quad (6)$$

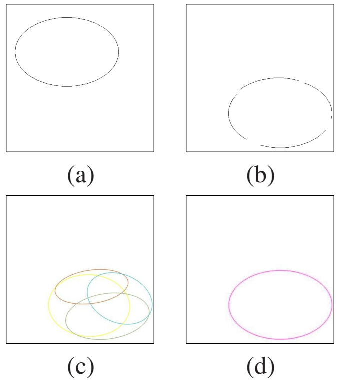


Figure 2. (a) Model ellipse. (b) Image containing a distorted model instance. (c) Features of the image. (d) Model located in the distorted image.

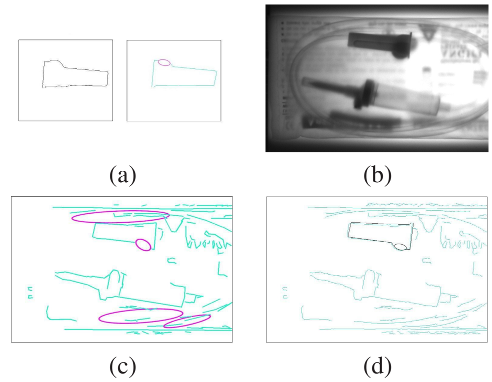


Figure 3. (a) Tube model. (b) Given image. (c) Image features. (d) The tube located in the image.

Distance d_{el} is obtained as a closed form expression (not given here as it is too long) in terms of line segment and ellipse parameters.

The distance measure D between the feature sets of the model and the image when a transformation $t(\cdot)$ is applied on the model is defined as

$$D\left(t\left(M\right), I\right) = \max\left\{D_L\left(t\left(M_L\right), I_L\right), D_E\left(t\left(M_E\right), I\right)\right\} \quad (7)$$

The distance $D\left(t\left(M\right), I\right)$ can be modified to handle outliers and occlusions.

4 Locating the model

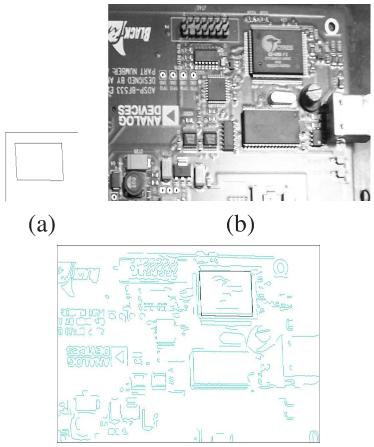
To locate the model, the transformation t^* that minimizes $D\left(t\left(M\right), I\right)$ in Eqn. (7) is to be found. In practical situations, due to feature distortions, only a fraction of the model features will match the image features. We use the length of features in terms of number of pixels as a cue for matching the model and the probe image. Let τ_n denote the fraction of the number of model edge pixels N_m to assert the presence of the model. Let I_f denote the set of image features that are close to the transformed model features when a transformation $t(\cdot)$ is applied on the model i.e., $I_f = \{i \in I | \exists\, m \in M \text{ such that } d\left(t\left(m\right), i\right) < \tau_d\}$, where τ_d is the distance threshold and d can be d_l, d_e or d_{el} depending on whether m and i are line segments or elliptical arcs. The number of image pixels that match the model is given by $N_{fi} = \sum_{i \in I_f} \text{len}\left(i\right)$, where len denotes the length of a feature. For $t(\cdot)$ to be a possible transformation, the condition to be satisfied is

$$\frac{N_{fi}}{N_m} > \tau_n \quad (8)$$

We use cell decomposition [7] to search the discretized 3-D transformation space and find the transformation for which the distance between features is minimum. Initially, the entire transformation space is regarded as an interesting cell. At each step, we divide the interesting cells into eight sub-cells, apply the transformation corresponding to the center of a sub-cell on the model features, evaluate the distance between features and check whether the condition in Eqn. (8) holds. Only those sub-cells that satisfy Eqn. (8) are likely to contain the actual transformation and are regarded as interesting cells. These cells are further sub-divided into eight smaller cells. The threshold τ_d is reduced as the cell size decreases. This process is continued recursively until the size of an interesting cell is sufficiently small whence we stop dividing it and evaluate the distance for all the transformations corresponding to that cell. Finally, we pick the transformation for which the distance between the features is minimized and Eqn. (8) holds.

5 Experimental results

For purpose of validation, we tested our algorithm on real images. We initially applied our algorithm to locate the instance of a model tube shown in Fig. 3 (a) in a pharmaceutical image shown in Fig. 3 (b). The model tube is translated and rotated in the probe image (Fig. 3 (b)). We set the value of threshold as $\tau_n = 0.9$. There were 553 pixels in the model and these were represented by one elliptical arc and seven line segments (Fig. 3



(a) (b)

(c)

Figure 4. (a) Model of a chip. (b) Image of a PCB. (c) The located instance of the chip in the PCB.

(a)). The image in Fig. 3 (b) had 6810 edge points and these were represented by four elliptical arcs and 140 line segments (Fig. 3 (c)). Our method correctly located the model tube in the image as shown in Fig. 3 (d) where the model is overlaid on the image edges.

We next tested the proposed algorithm when the model was to be located in a cluttered environment. A model of a chip (Fig. 4 (a)) was to be located in the image of a PCB shown in Fig. 4 (b). In the edge image of PCB (Fig. 4 (c)), we note that many irrelevant features tend to obscure the true features of the model thereby complicating the matching process. The model was compared against the image with $\tau_n = 0.9$. The chip was correctly located in the PCB as shown in Fig. 4 (c).

We have tested our algorithm on various images captured in the laboratory and found that the proposed method works well even under illumination variations, occlusions and clutter. The running time for an unoptimized implementation of our algorithm is of the order of one tenth of a second on a P-IV PC with a 2 G Hz processor and 256 MB RAM when translation alone is involved. When rotation is involved, the time taken is of the order of a few seconds. The proposed method generally performs two-to-three times faster than the point matching method in [7].

6 Conclusions

In this paper, we proposed a new technique which uses line segments and elliptical arcs as features for recognizing image patterns. In this technique, the number of features to be compared is much fewer than in the case of point-matching and line-matching schemes. We formulated distance measures for comparing the features and used cell decomposition to efficiently find the optimum transformations. The algorithm was tested on real images and was found to perform well under different conditions. It is much faster than the standard point-matching algorithm.

Acknowledgments

The second author is thankful to the Alexander von Humboldt Foundation, Germany for its support.

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