Object Detection Using Contour Fragments

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Abstract. In this paper, we present a novel object detection scheme using contour fragments. The template fragments are extracted by decomposing the template contour. The hinge angle, contour direction and partial Hausdorff distance (PHD) are used to match the fragments in the edge image. Then, the Multiclass Discriminative Field (MDF) is used to select the matches. With these selected matches and their corresponding template fragments, the contours of the objects can be obtained. The experiment on our postmark dataset shows that the proposed scheme is robust to detect a class of objects with different scales, directions and clutter edges.

Keywords: Object detection, contour feature, Hausdorff distance, Multiclass Discriminative Field.

1 Introduction

Contour feature is among the most distinctive object features. Similar to [1], we use a single template contour for object detection. The template contour is divided into fragments. The hinge angle, contour direction and partial Hausdorff distance (PHD) [2] are used to select candidates. Then, the matches are selected by the Multiclass Discriminative Field (MDF) [3] from the candidates. With these matches, the contour of the object can be composed. The experiment on our postmark dataset shows the effectiveness of the proposed method.

2 Object Detection Using Contour Fragments

Three features are used to select candidate matches of fragment $F_k$ in edge image $E$ ($E$ is gotten by Canny detector): hinge angle, contour direction and PHD.

The hinge angle and direction are proposed in [4]. $[0 \pi]$ is divided into $n$ equal parts. Then the hinge angle histogram is defined as

$$h_b(s, m_1) = n_{s, m_1}, \quad m_1 = 1, 2, \cdots, n,$$  \hspace{1cm} (1)

where $n_{s, m_1}$ is the number of the pixels whose angle is in $[(m_1 - 1)\pi/n, m_1\pi/n]$ and $s$ is scale (The original scale is 1). The direction histogram is defined as

$$h_d(s, m_2) = n_{s, m_2}, \quad m_2 = 1, 2, \cdots, 2n,$$  \hspace{1cm} (2)
where \( n_{s,m} \) is the number of the pixels whose direction is in \([\pi/n \cdot m \pi/n] \). Then, hinge angle difference \( D_h(F_k(s), E_i) \) and direction difference \( D_d(F_k(\theta), E_i) \) between the fragment \( F_k \) and the edge \( E_i \) (a part of \( E \)) are calculated by using their histogram differences.

To detect whether \( E_i \) contains \( F_k \), we use the PHD

\[
    h(F_k(s, \theta), E_i) = \frac{1}{N_{F_k(s, \theta)}} \sum_{p \in F_k(s, \theta)} d(p, E_i),
\]

where \( F_k(s, \theta) \) is the \( F_k \) with scale \( s \) and direction \( \theta \), \( d(p, E_i) = \min_{p_e \in E_i} \|p - p_e\| \) and \( \|\cdot\| \) is some underlying norm (in this paper, it is Euclidean distance).

Suppose fragment \( F_k(s, \theta) \) is expected to match the edge \( E_i \) at the position \( x \). The edge \( E_i \) should satisfy the following rules: (1) \( D_h(F_k(s), E_i) < T_1 \), (2) \( D_d(F_k(\theta), E_i) < T_2 \), (3) \( h(F_k(s, \theta), E_i) < T_3 \), (4) \( h(F_k(s, \theta), E_i) \) should be a local minimum, where \( T_1 \), \( T_2 \) and \( T_3 \) are thresholds.

In MDF, the association potential \( A \) is

\[
    A(x_i, y) = \sum_{k=1}^{C} \delta(x_i = k) \log P'(x_i = k|y),
\]

where \( C \) is the number of classes, \( \delta(x_i = k) \) is 1 if \( x_i = k \) and 0 otherwise, \( P'(x_i = k|y) \) is the probability of \( x_i \) belonging to class \( k \) under the observation \( y \). We describe \( P' \) as

\[
    \log P'(x_i = k|y) = \begin{cases} 
        1 & \text{if } h \leq T_4 \\ 
        0 & \text{otherwise} 
    \end{cases},
\]

where \( h \) is a PHD, \( T_4 \) is a threshold.

The interaction potential \( I \) is

\[
    I(x_i, x_j, y) = \sum_{k=1}^{C} \sum_{l=1}^{C} \nu_{kl}^T \mu_{ij}(y) \delta(x_i = k) \delta(x_j = l),
\]

where \( \nu_{kl} \) are the model parameters and \( \mu_{ij}(y) \) encodes the pairwise features. We define \( \mu_{ij}(y) \) as

\[
    \mu_{ij}(y) = \begin{cases} 
        (|s_i - s_j|, |\theta_i - \theta_j|)' & \text{if } |D - 1| \leq T_5 \\ 
        (0, 0)' & \text{otherwise} 
    \end{cases},
\]

where \( s \) is the scale, \( \theta \) is the direction, \( D = |D_{ij}/D_{kl}| \) denotes the difference between \( D_{ij} \) and \( D_{kl} \), \( D_{ij} \) is the difference between edge \( E_i \) and \( E_j \), \( D_{kl} \) is the difference between fragments \( F_k \) and \( F_l \), and \( T_5 \) is a threshold.

3 Experiments and Conclusion

To evaluate the valid of the proposed method, we apply it to detect the template on our postmark dataset. The postmark dataset has 80 envelope images.
which are categorized into two groups according to the complexities of their backgrounds. Each group has 40 images. The postmarks in the group (I) have similar scales and clean backgrounds, while the postmarks in the group (II), comparatively, have various scales and complex background. We measure the performance by \( F - \text{measure} \):

\[
F(F - \text{measure}) = \frac{2 \times P \times R}{P + R}.
\]  

(8)

where \( R(\text{Recall}) = \frac{\text{The number of correct detected objects}}{\text{The number of true objects}} \)

\( P(\text{Precision}) = \frac{\text{The number of correct detected objects}}{\text{The number of detected objects}} \).

The statistical results are shown in Fig. 1. We compare our method with the method using PHD in section 2. Two template are used: t1 and t2. t1 is a silhouette of one postmark in group (I) and has the similar scales with the postmarks in this group, while t2 from group (II). The parameters of MDF are trained by ten labeled images. Both of the two methods work well in group (I) with t1. Meanwhile, our method has relative high performances with both t1 and t2. The experiments show that our method is a practicable scheme. By using contour decomposition and the matching rules, our model, which requires only a sample contour, tolerates scale invariant, rotation, part of contour missing and complex backgrounds.

Fig. 1. Postmark detection performance.

References