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Oriented Hausdorff Similarity Measure for Object Matching

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Abstract

This paper proposes an oriented Hausdorff similarity measure for object matching. The oriented Hausdorff distance (HD) measure is introduced by replacing the distance concept of conventional HD algorithms by a similarity measure. The orientation at each pixel is used for removing incorrect correspondences. Various experiments show that the performance of the proposed algorithm is better than that of conventional HD algorithms considered.

1 Introduction

Object matching in two-dimensional images has been an important topic in computer vision, object recognition, and image analysis. The performance of the matching method depends on the properties of the features and the matching measure used. A distance transform (DT) and a Hausdorff distance (HD) have been widely investigated because they are simple and insensitive to changes of image characteristic [1]. However, their performance is severely degraded for noisy image data with severe distortion and deterioration.

Borgefors proposed a chamfer matching algorithm based on the chamfer DT, in which optimal polygon vertexes were detected in the closed contour objects [2]. The HD matching scheme proposed by Huttenlocher *et al.* [1] does not require to establish correspondences, i.e., it does not need to find feature points such as polygon vertexes, only using a set of points extracted by an edge operator. They proposed a partial HD measure based on the ranked order statistics to estimate the similarity between two sets of edge points extracted from the object model and the test image in the presence of occlusion. Also a censored HD (CHD) measure based on the ranked order statistics was proposed by Azencott *et al.* [3]. The CHD yields a good efficiency for luminance change of noisy gray level images contaminated by additive Gaussian noise. Dubuisson

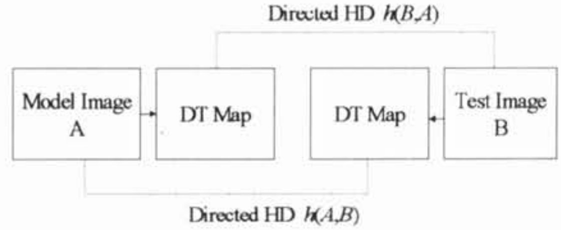

Figure 1: Block diagram for the Hausdorff distance algorithm

and Jain [4] analyzed the properties of the HD measures, and proposed the modified HD (MHD) based on the average distance to estimate the similarity between two objects. They also showed that the MHD yielded a good efficiency for different types of binary noise models.

This paper proposes an oriented Hausdorff similarity measure for object matching. By adopting the robust similarity function, the proposed algorithm is robust against outliers. The orientation at each pixel is also used for eliminating wrong correspondences. The rest of the paper is structured as follows. Some conventional algorithms are addressed in Section 2. In Section 3, the proposed algorithm is introduced. In Section 4, experimental results are shown with various images and varying noise level. Finally, conclusions are summarized in Section 5.

2 Conventional HD Algorithms

The HD measure computes a distance value between two sets of edge points extracted from an object model and a test image. The classical HD measure between two point sets $A = \{a_1, ..., a_{NA}\}$ and $B = \{b_1, ..., b_{N_B}\}$ of sizes N_A and N_B, respectively, is defined as

$$H(A, B) = max(h(A, B), h(B, A))$$

where $h(A, B)$ represents the directed distance between two sets A and B. Two point sets A and B are obtained by an edge detection algorithm from two images **A** and **B**, respectively. The directed distance $h(A, B)$ is defined as

$$h(A, B) = max_{a \in A} min_{b \in B} ||a - b||$$

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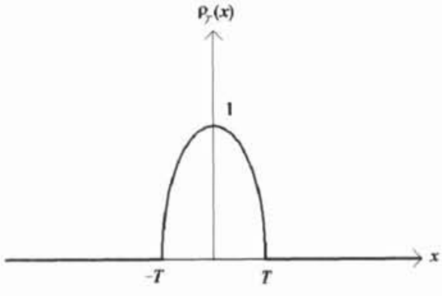


Figure 2: Similarity function

where $||\cdot||$ represents any norm. This Hausdorff distance value is calculated according to a block diagram shown in Fig. 1. This classic HD measure is sensitive to degradation such as noise and occlusions because of employment of the max operator, so improved methods have been proposed for image or object matching. Dubuisson and Jain proposed the MHD based on the average distance value [4]. The directed distance of the MHD is defined as

$$h_{MHD}(A,B) = \frac{1}{N}\sum_{a\in A} min_{b\in B}||a-b||.$$

However, this algorithm is not robust to severe distortion. So, Huttenlocher *et al.* proposed the partial HD measure based on the robust statistics in comparing partial portions of images containing severe occlusions or degradation [1]. The directed distance of the partial HD is defined as

$$h_K(A,B) = K^{th}_{a\in A} min_{b\in B}||a-b||$$

where K denotes the Kth ranked value. But it is justified that this algorithm can not cope well with noisy images containing a large percentage of outliers of input observations [1][5].

3 Proposed Oriented Hausdorff Similarity (OHS)

The proposed oriented Hausdorff similarity (OHS) is based on a similarity while the conventional HD algorithms are based on the distance between two images [1][4][6]. The proposed OHS is defined as

$$H_{OHS} = min(h_{OHS}(A,B), h_{OHS}(B,A))$$

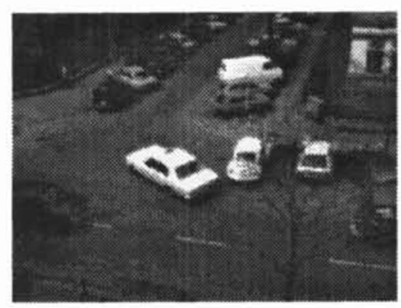
where $h_{OHS}(A,B)$ denotes the directed OHS. The directed OHS is defined as

$$\begin{aligned} h_{OHS}(A,B) &= \sum_{a\in A} d_{A(a)}\cdot d_{B(a)}\rho_T(d_B(a)) \\ &= \sum_{a\in A} s(a)\rho_T(d_B(a)) \end{aligned}$$

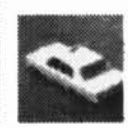
where an orientation vector $d_{A(a)}$ represents a unit gradient vector of a gray level image **A** at position a, $s(a) = d_{A(a)}\cdot d_{B(a)}$ is the dot product of

(a) Input image (Crowd)

(b) Model image



(c) Input image (Taxi)



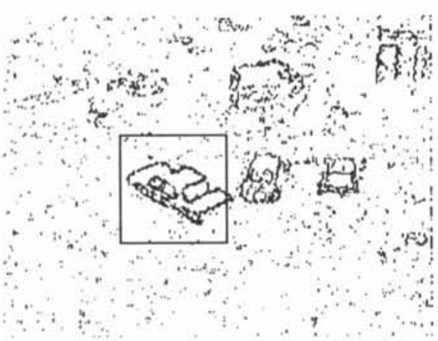
(d) Model image

Figure 3: Input and model images

two gradient vectors obtained from two images, and $d_B(a) = min_{b\in B}||a-b||$ is the distance map [7] value of image **B** at position a. The Huassdorff distance algorithm can be accelerated by using the distance map. The symmetric threshold function, $\rho_T(x)$, is shown in Fig. 2. Because the proposed algorithm makes use of the distance value, it considers the number of matching points as the Hough transform does. As a result, the proposed algorithm becomes robust to severe noise. Furthermore, because the orientation information is used, the point that has a small DT value with different orientation can be removed. The conventional algorithms are based on only the distance map so that they could be disturbed by edges having different orientations.

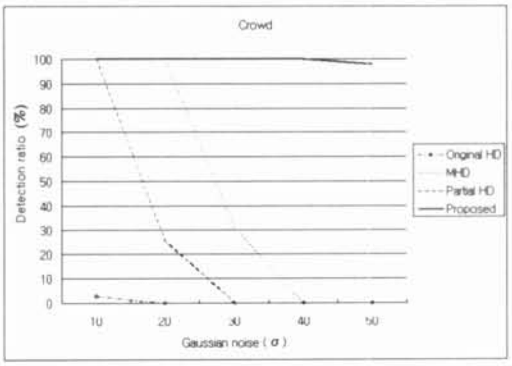
The proposed algorithm does not require any sorting operation as in Huttenlocher *et al.*'s partial HD. The computational complexity is similar to that of the original HD algorithm. $O(A_xA_y + B_xB_y)$ addition and comparison operations are required for calculating the distance map, where A_xA_y and B_xB_y denote the sizes of images **A** and **B**, respectively. Whereas for the computation of the proposed OHS, $O(N_A + N_B)$ multiplications and additions are

(a) Crowd image

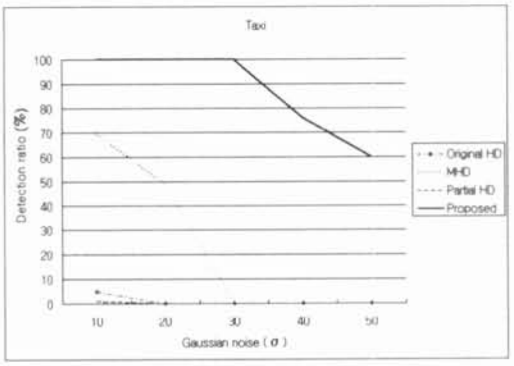


(b) Taxi image

Figure 4: Detection results for Gaussian noise cases ($\sigma = 20$)



(a) Crowd image



(b) Taxi image

Figure 5: Dectection ratios as a function of the Gaussian noise level σ

required.

4 Experimental Results

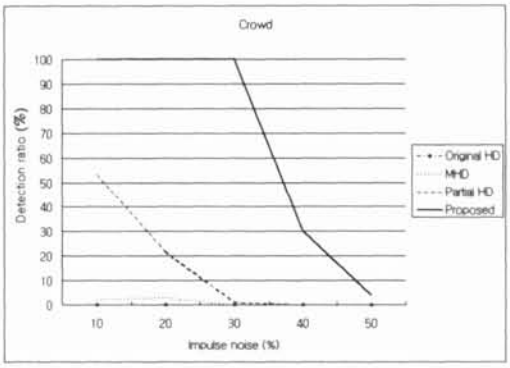
The effectiveness of the proposed OHS is shown by the matching experiments in which an object is detected in an input image. The matching point is detected by finding a point that yields a minimum translational Hausdorff measure $H(A \oplus t, B)$ for possible translation t, where $\oplus$ denotes the translation operation. The matching performance of the proposed algorithm is compared with that of the original HD, MHD, and partial HD, with various noise types and levels.

Figs. 3(a) and (b) show a test input (Crowd, 256×256) and its model (64×64) image, respectively. Figs. 3(c) and (d) also show a test input (Taxi, 256×230) and its model (64×64) image, respectively. Detection results by the proposed algorithm are shown in Fig. 4 for the two test images contaminated by Gaussian noise ($\sigma = 20$), where σ denotes the standard deviation of the Gaussian function. Even though the input image is severly distorted by the noise in the case of Fig. 4(a), the proposed algorithm yields a good matching result.

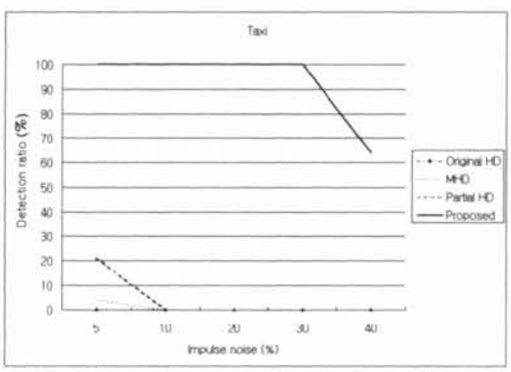
Fig. 5 shows the detection ratio of four methods as a function of the Gaussian noise level σ. The detection ratio is obtained by 100 experiments with different random seeds for each noise level. This result shows that the proposed algorithm yields the best matching results on the whole. The MHD algorithm yields the good results for Gaussian noise cases.

Fig. 6 illustrates the detection ratio of four methods as a function of the impulse noise level, where the impulse noise ratio is defined by the percentage of the number of flipped pixels to the total number of pixels. The detection ratio is obtained by 100 experiments with different random seeds for each noise level. The proposed algorithm yields the best matching results for severe distortion because it is based on robust statistics. The proposed algorithm employs the robust characteristics, thus it is robust against the large noise level.

To show the effectiveness of the proposed algorithm, the matching of an aerial image with a satellite image is performed. Figs. 7(a) and (b) show the aerial image (320×240) and the Indian remote



(a) Crowd image



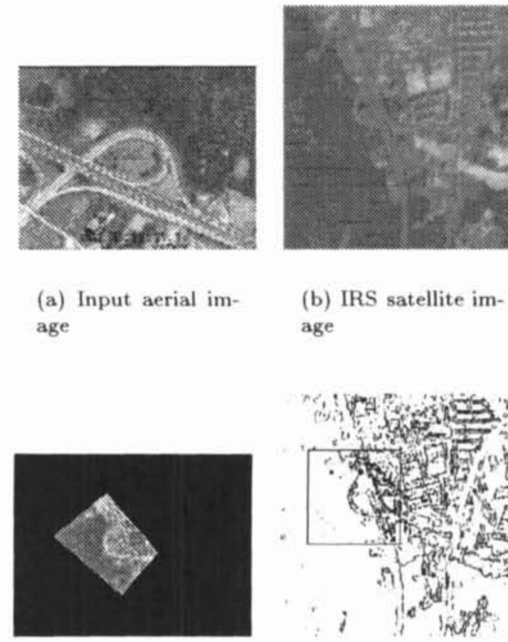
(b) Taxi image

Figure 6: Dectection ratios as a function of the impulse noise level

sensing (IRS) satellite image (256 $\times$ 256), respectively. This satellite image is quantized to six bits and shows $5m$ ground resolution. The input aerial image is compensated to match the IRS satellite image, and the compensated image is shown in Fig. 7(c). Fig. 7(d) shows a correct matching result by the proposed algorithm. In box the compensated aerial edge image is superimposed on the IRS satellite edge image. By adopting robust characteristics, the proposed algorithm yields good results for various real images with Gaussian and impulse noise.

5 Conclusions

In this paper, a new HD similarity measure is introduced based on robust statistics and its effectiveness is shown via various experiments. Further research will focus on the development of the fast algorithm and the investigation of its statistical characteristics against various types of noise.



(a) Input aerial image (b) IRS satellite image

(c) Compensated image (d) Matching result

Figure 7: Matching result with aerial and satellite images

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