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A new synthetic HMT for distortion-invariant recognition

Yang-Hoi Doh*

왜곡불변 인식을 위한 새로운 합성 HMT

도 양 회*

ABSTRACT

A new synthetic hit-miss transform(SHMT) algorithm is proposed for distortion-invariant recognition of various objects in noisy and cluttered input images. The proposed SHMT algorithm uses synthetic structuring elements(SEs), which are synthesized based on SDF algorithm. The synthetic hit structuring element(SE) is composed of the linear combination of hit SEs, and the synthetic miss SE is composed of the linear combination of miss SEs. Based on various simulations, it is shown that the proposed algorithm can be applied to a HMT correlator to improve its ability to detect various objects with distortions in noisy and cluttered scenes.

Key Words : Synthetic HMT, Distortion-invariant recognition, SDF function

Ⅰ. Introduction

A hit-miss transform(HMT) is a basic tool that can be used to perform pattern recognition efficiently. The HMT has been optically implemented on a variety of optical processors including coherent[1-3] and incoherent[4,5] optical correlators. These methods for pattern recognition provides the shift-invariance required to allow the location of an object when its position is not known, or to allow multiple objects in different positions to be located and identified. However, standard algorithms for HMT can cause problems in detecting various true class objects[6].

The performance of HMT in object recognition is critically dependent on the shape and the size of the structuring element(SE). Thus, an optimal SE is necessary to improve the false alarm rate and the ability to detect objects of different shapes. To adapt to this condition, a synthetic HMT(SHMT) algorithm based on set theory was developed[7]. However, this algorithm also restricts effective applications in detecting distorted objects due to scale mismatch, in-plane rotation, out-of-plane

* 제주대학교 전기전자공학부, 첨단기술연구소
Department of Electrical and Electronic Eng., Cheju Nat'l Univ., Res. Inst. of Adv. Tech.

rotation, etc. The synthetic discriminant function (SDF) filter is one method, which achieves the distortion- invariance while still retaining the shift-invariant feature[8,9].

In this paper, a new SHMT algorithm is proposed to provide the distortion-invariant recognition of various objects in noisy and cluttered input images. The synthetic SEs are synthesized based on an SDF algorithm. The synthetic hit SE is composed of the linear combination of hit SEs, and the synthetic miss SE is composed of the linear combination of miss SEs. Based on various simulations, it is shown that the proposed algorithm can be applied to a HMT correlator to improve its ability to detect various objects with distortions in noisy and cluttered scenes.

II. Morphological Hit-Miss Transform

In morphology, the HMT is used to locate a specific shape in a noisy and cluttered image. If we denote a binary image by X, its complement by XC, a foreground(hit) SE by H, and a background(miss) SE by M, then the HMT is defined[1] as intersection of two erosions, i.e.,

$$X \otimes (H, M) = [(X \cdot H) \cap (X^C \cdot M)] = [(X * H)_{T_H} \cap (X^C * M)_{T_M}] \quad (1)$$

where ∘ denotes erosion operation, $*$ denotes correlation operation, TH is hit threshold and TM is miss threshold. The first erosion $X \circ H$, the hit transform, gives an output peak wherever the foreground object H is present in the binary image X. The second erosion $X^C \circ M$, the miss transform, gives an output peak whenever the background object M is present in the background image XC. These erosion operations can be implemented by optical correlation. The intersection (AND) of the two erosions creates an output only at the locations where the desired objects and the background regions are present in the image. To locate a particular object in a scene with HMT, one often chooses the miss SE, M, as the complement of the foreground SE, H(in this case we assume that H has a border region defined around it with pixel values of zero). The HMT is implemented optically by forming two correlations, thresholding each one, and then forming their intersection.

III. Synthetic Discriminant Function Filter

An attractive approach to distortion-invariant pattern recognition is the use of an SDF filter as a matched spatial filter(MSF) in a correlator. The SDF filter can be easily applied to distortion -invariant pattern recognition, while the use of the optical correlator provides shift invariance. The SDF filter function g(x,y) can be expressed as a linear combination of the set of reference images, fi(x,y), i.e., [8,9]

$$g(x, y) = \sum_{i=1}^{N_t} a_i f_i(x, y) \quad (2)$$

where ai is the weighting coefficient. In matrix-vector form, ai can be described as

$$\mathbf{a} = \mathbf{R}^{-1}\mathbf{u} \quad (3)$$

Here, R is a vector inner product(VIP) matrix and its elements Rii and Rij are

$$R_{ii} = \max(f_i * f_i)$$
$$R_{ij} = \max(f_i * f_j) \quad (4)$$

where Rii is the auto-correlation peak value of the i-th reference image fi(x,y), Rij is the cross-correlation peak value of the i-th reference image fi(x,y) and j-th reference image fj(x,y), and u is the constraint vector that decides the ratio of the correlation peak value of each reference image.

$$\boldsymbol{u} = [1\,1\,1 \cdots 1]^T \tag{5}$$

For both intraclass recognition and interclass discrimination, a mutual orthogonal function SDF (MOF-SDF) filter function is used. This can recognize true class objects with unit outputs and can also reject false class objects with zero outputs. For this purpose, the elements of u must be '1' for true class objects and must be '0' for false class objects, i.e.,

$$\boldsymbol{u} = [1\,1 \cdots 1\,0\,0 \cdots 0]^T \tag{6}$$

IV. Proposed Hit-Miss Transform Algorithm

A new synthetic HMT algorithm is proposed for distortion-invariant recognition of various objects in noisy and cluttered input images. The proposed SHMT algorithm uses the impulse function of the SDF filter to synthesize the optimal synthetic SEs. The proposed synthetic SEs enable a HMT correlator to improve its ability to detect objects of different shape and size in noisy and cluttered scene.

We determine the synthetic hit SE, HSDF, as the linear combination of k hit SE's, Hi, and the synthetic miss SE, MSDF, as the linear combination of k miss SE's, Mi, respectively. These filter functions are defined as follows;

$$H_{\mathrm{SDF}} = \sum_{i=1}^{k} a_i H_i \tag{7}$$

$$M_{\mathrm{SDF}} = \sum_{i=1}^{k} b_i M_i \tag{8}$$

where ai and bi are the weighting coefficients for the synthetic hit SE and synthetic miss SE, respectively. In matrix-vector form, ai and bi can be described as

$$\mathbf{a} = \mathbf{R}_{\mathbf{hit}}^{-1}\mathbf{u} \tag{9}$$

$$\mathbf{a} = \mathbf{R}_{\mathbf{miss}}^{-1}\mathbf{u} \tag{10}$$

where Rhit and Rmiss are VIP matrices of the hit SEs and the miss SEs, respectively. Also u is the constraint vector of the desired correlation values. Here, an ECP SDF can be used for intraclass pattern recognition and an MOF SDF can be used for both intraclass recognition and interclass discrimination.

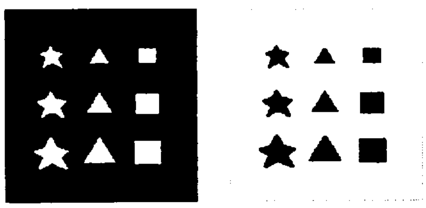
The proposed SHMT is implemented by using a synthetic hit SE and a synthetic miss SE, i.e.,

$$\begin{aligned} X &\otimes (H_{\mathrm{SDF}}, M_{\mathrm{SDF}}) \\ &= (X \cdot \sum_{i=1}^{k} a_i H_i) \cap (X^C \cdot \sum_{i=1}^{k} b_i M_i) \\ &= (X * \sum_{i=1}^{k} a_i H_i)_{T_H} \cap (X^C * \sum_{i=1}^{k} b_i M_i)_{T_M} \end{aligned} \tag{11}$$

The hit transform output detects objects larger than or equal in size to the synthetic hit SE. The miss transform output detects objects smaller than or equal in size to the inner region of the synthetic miss SE. The final SHMT output detects objects from the smallest to the largest specified by the size of the synthetic hit SE and the synthetic miss SE. The proposed SHMT also uses with rank-order erosion operations and this achieves efficient distortion invariant object recognition in a cluttered input image.

V. Simulation Results

The proposed SHMT algorithm involves correlating a binary input image with a synthetic hit SE, correlating the complement of the input image with a synthetic miss SE, thresholding each correlation output and intersecting each thresholded result. Fig. 1 is a simple test input image and its complement image used to show usefulness of the proposed SHMT detection algorithm. Each column of input image consists of three stars, three triangles and three squares of different size.



(a) (b)

Fig. 1. (a) Input images, and (b) complement images of input for SHMT detection example.

Fig. 2 shows an example of scale invariant detection by using the ECP-SDF algorithm. We want to recognize three triangles of different size in the input image of Fig. 1. To do so, we use only the smallest size triangle and the largest size triangle as reference images. The synthetic hit SE [Fig. 2(a)] and synthetic miss SE[Fig. 2(b)] are determined by ECP-SDF algorithm. Here, the elements of the constraint vector that corresponds to the smallest triangle and the largest triangle are 1.

The hit correlation output shown in Fig. 2(c) and the miss correlation output shown in Fig. 2(d) depicts correlation peaks at the location of each object and background. To obtain the hit transform [Fig. 2(e)] and the miss transform [Fig. 2(f)], we threshold the hit correlation output and miss correlation output, respectively. The threshold is determined by acceptance level for distorted objects. If we raise the threshold, the rejection rate for distorted objects increases. If we lower the threshold, it increases. Because there is no distortion in the input image, we determined the threshold value of hit correlation as 95% of autocorrelation peak value of the synthetic hit SE [Fig. 2(a)] and the threshold value of miss correlation as 95% of autocorrelation peak value of the synthetic miss SE [Fig. 2(b)].

The result of hit transform shows that it can detect objects larger than or equal to the size of

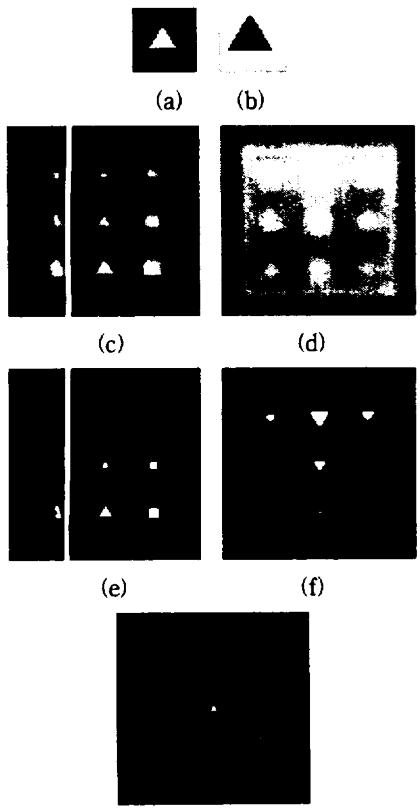


Fig. 2. Example of scale-invariant SHMT detection : (a) synthetic hit SE, (b) synthetic miss SE, (c) hit correlation output, (d) miss correlation output, (e) hit transform result, (f) miss transform result, and (g) final SHMT result.

the synthetic hit SE. It shows three correct peaks at the second column and four false peaks at other positions. The result of miss transform shows that it can detect objects smaller than or equal to the size of inner region of the synthetic miss SE. It shows three correct peaks at the second column and two false peaks at other positions. The final SHMT output shown in Fig. 2(g) is an intersection of the results of hit transform of Fig. 2(e) and the result of miss transform of Fig. 2(f). It shows peaks at the location of the two reference images(the smallest and the largest triangle) and also a peak at the location of the intermediate image(the non-training medium-size triangle) of the two training images. This means scale-invariant detection can be achieved by using ECP-SDF algorithm in the proposed SHMT.

Fig. 3 shows an example of detecting and rejecting particular objects. To reject an object, we use MOF-SDF algorithm in synthesizing SE. In the input image of Fig. 1, we want to recognize the smallest and the largest triangle, but we want to reject the medium-size triangle. In this case, all three triangles are used as the reference images of the MOF-SDF algorithm to synthesize synthetic SEs[Fig.3(a) and 3(b)]. Here, the elements of the constraint vector that correspond to the smallest and the largest triangle are 1 and correspond to the medium-size triangle is 0.

The hit correlation output shown in Fig. 3(c) and the miss correlation output shown in Fig. 3(d) also depicts correlation peaks at the location of each object and background. We can also obtain results of the hit transform [Fig. 3(e)] and the miss transform [Fig. 3(f)] by thresholding the hit correlation output and the miss correlation output, respectively. In absence of distortion in the input image, the threshold value of hit correlation is 95% of the autocorrelation peak value of the synthetic hit SE [Fig. 3(a)] and the threshold value of miss correlation is 95% of autocorrelation peak value of the synthetic miss SE [Fig. 3(b)], respectively.

The result of hit transform shows two correct peaks at the second column. The result of miss transform shows two correct peaks at the second column and some false peaks at other positions. The final SHMT output [Fig. 3(g)] shows peaks at the location of the two true class reference images (the small and the large triangle) and no peak at the location of the false class reference image (the medium-size triangle). This result shows the rejection of a particular object can be achieved by

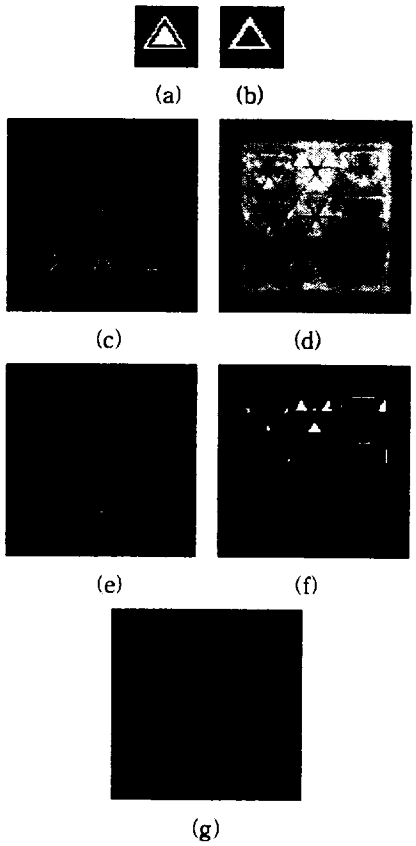


Fig. 3. Example of SHMT detecting and rejecting particular objects: (a) synthetic hit SE, (b) synthetic miss SE, (c) hit correlation output, (d) miss correlation output, (e) hit transform result, (f) miss transform result, and (g) final SHMT result.

using MOF-SDF algorithm in the proposed SHMT.

Fig. 4 shows an example of detecting various objects of similar size. In the input image of Fig. 1, we want to recognize the three medium-size objects (the second row) and to reject the smallest and the largest objects (the first and the third row). In this case, the three medium-size objects are used as the reference images of the ECP-SDF algorithm to synthesize synthetic SEs [Fig. 4(a) and 4(b)]. Here, the elements of the constraint vector that corresponds to the three medium-size objects are '1'.

The hit correlation output shown in Fig. 4(c) and the miss correlation output shown in Fig. 4(d) also depicts correlation peaks at the location of each object and back-ground. We can also obtain results of the hit transform [Fig. 4(e)] and the miss transform [Fig. 4(f)] by thresholding the hit correlation output and miss correlation output, respectively. In absence of distortion in the input image, the threshold value of hit correlation is 95% of the autocorrelation peak value of the synthetic hit SE [Fig. 4(a)] and the threshold value of miss correlation is 95% of autocorrelation peak value of the synthetic miss SE [Fig. 4(b)], respectively.

The result of hit transform shows three correct peaks at the second row and three false peaks at the location of larger objects than the medium-size objects(the third row). The result of miss transform shows three correct peaks at the second row and three false peaks at the location of smaller objects than the medium-size objects(the first row). The final SHMT output [Fig. 4(g)] shows peaks at the location of the three true class reference images(the three medium size objects). Thus, detection of various object of similar size also can be achieved by using ECP-SDF algorithm in the proposed SHMT.

Based on the results of Fig. 1, Fig. 2, Fig. 3, and Fig. 4, it has been shown that the proposed SHMT algorithm can be used to obtain distortion-invariance for multiple object recognition. And the algorithm can be adapted to various applications by selection of proper reference images.

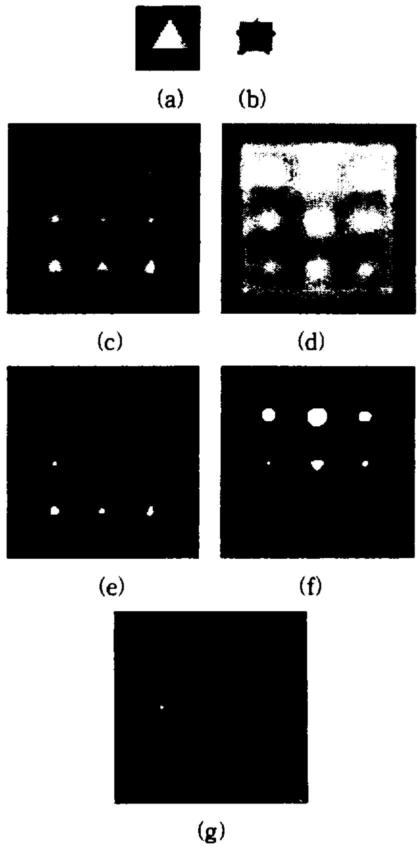


Fig. 4. Example of SHMT detecting various objects: (a) synthetic hit SE, (b) synthetic miss SE, (c) hit correlation output, (d) miss correlation output, (e) hit transform result, (f) miss transform result, and (g) final SHMT result.

VI. Conclusion

A new morphological HMT detection algorithm has been proposed for the efficient recognition of various objects. The proposed algorithm uses synthetic SEs to achieve distortion-invariant recognition, and the algorithm can be adapted to various applications by selection of proper reference images. The synthetic SEs are synthesized based on SDF algorithm. The synthetic SE uses the impulse function of the SDF filter as SE. The synthetic hit and the miss SEs are determined by the linear combination of the hit and miss SE's, respectively. The simulation results show that the proposed SHMT algorithm is an attractive nonlinear image processing method that can be applied to the HMT correlator to improve its false alarm rate and its detection capability of multiple distorted objects.

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