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DISTORTION INVARIANT CLASS-ASSOCIATIVE TARGET DETECTION USING PROJECTION-SLICE SYNTHETIC DISCRIMINANT FUNCTION

Md. Waliullah Khan Nomani, Tanwir Zubayer Islam, Sayed Mustafa Khelat Bari, Md. Rafiqul Haider and Mohammed Nazrul Islam

Department of Electrical and Electronic Engineering, Bangladesh University of Engineering and Technology, Dhaka 1000, Bangladesh, E-mail: nomani6@yahoo.com, nazrul@eee.buet.ac.bd

ABSTRACT

The projection-slice theorem is used to generate the synthetic discriminant function based matched filters that are capable of discerning rotation and scale distortions for applications to class-associative target detection. A composite image is synthesized from training images from each class employing the projection-slice algorithm. Then an optoelectronic fringe-adjusted joint transform correlator technique is used to correlate the test images with the composite images of each class. Simulation results are furnished to prove the effectiveness of the proposed system.

1. INTRODUCTION

In pattern recognition technique, proper detection and processing speed are the principal criteria, which can only be met in optical system [1]. Optical system performs pattern recognition based on the correlation, which is implemented by using the ability of a lens to perform a Fourier transform in parallel and in real time [2]. Matched spatial filter correlators and joint transform correlators (JTCs) are the two widely used techniques in optical pattern recognition [3-4]. The class-associative target detection is also based on the JTC technique, where a class of objects is defined as a group of similar or dissimilar images [5]. With the advent of the synthetic discriminant functions (SDFs), the algorithms for only correlation-based distortion-invariant recognition system for class of objects are turned myopic [6]. The entire two-dimensional (2-D) image is used in the design of the filter so that the filter response contains a composite image at any given point in space. This implies that the filter response does not match any of the training images and thus debilitate the performance of the SDF-based system. A new technique, named the projection-slice SDF (PSDF), has been developed to create the SDF-based matched filters that are capable of discerning rotation and scale distortions [7]. However, this technique has not yet been used for class-associative target detection.

The objective of the paper is to investigate the performance of SDF and PSDF techniques in case of rotation and scale variations for class-associative target detection. Through our theoretical development and simulations results, we can profess that the PSDF technique outwits the SDF technique in both the cases of rotation and scale variation.

2. THEORETICAL ANALYSIS

In the projection-slice theorem, a one-dimensional (1-D) Fourier transform along a projected line in an image corresponds to a slice in the 2-D Fourier transform of the image along the same line. By taking different slices from the training images, a composite image can be generated such that the frequency components from different images do not interfere with each other. The 1D projection of a function $f(x, y)$ along a line l and at an angle ϕ, is given by

$$g(\phi,s)=\int_l f(x,y)dl \tag{1}$$

All points on this line satisfy the following equation

$$x \sin \phi - y \cos \phi = s \tag{2}$$

where s is the distance from the origin. Now the projection function, $g(\phi, s)$, can be written as

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$$g(\phi, s) = \iint \begin{matrix} f(x, y) \times \\ \delta(x\sin(\phi) - y\cos(\phi) - s)dxdy \end{matrix} \quad (3)$$

The 1D Fourier transformation of equation (3) gives the following

$$G(\phi, \omega) = \int e^{-j\omega s} g(\phi, s) ds \quad (4)$$

Equation (4) represents the 1D Fourier slice of the 2D Fourier transform of the function, $f(x, y)$. Now combining all the Fourier slices, we can get back the original function. Substituting the value of $g(\phi, s)$ in equation (4) and using the shifting property of Dirac delta function, we get

$$G(\phi, \omega) = \iint f(x, y) e^{-j\omega(x\sin(\phi) - y\cos(\phi) - s)} dxdy \quad (5)$$

Then from equation (5), we can obtain $f(x, y)$ as follows

$$f(x, y) = \frac{1}{4\pi^2} \iint G(\phi, \omega) e^{j\omega(x\sin\phi - y\cos\phi)} |\omega| d\omega d\phi \quad (6)$$

where $|\omega|$ is the determinant of the Jacobian of the of the change of the variable from rectangular to polar coordinate.

Now if we take M equispaced projections of each of the N training images, the separation in angle of the mth slice of nth training image can be expressed as

$$\phi_{mn} = \frac{m\pi}{M} + \frac{n\pi}{MN}, \quad m = 0, 1, 2....M-1; \; n = 0, 1, 2....N-1 \quad (7)$$

The generalized PSDF-based filter transfer function can be defined by

$$R(u, v) = \sum_{n=0}^{N} \sum_{m=0}^{M} a_n G_n(\omega\cos\phi, \omega\sin\phi) \delta(\phi - \phi_{mn}) |\omega| \quad (8)$$

where G_n is the Fourier transform of the nth training image and a_n is a normalization factor similar to that used in the SDF-based filter design.

Finally, the inverse Fourier transform of equation (8) produces a composite image, which is used as the reference image to perform distortion-invariant pattern recognition.

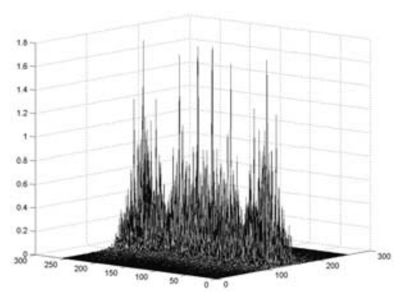
3. SIMULATION RESULTS

To investigate the performance of the proposed PSDF-based pattern recognition scheme, we have used binary images of English characters, "A", "P" and "Z", where "A" and "P" are the target images. Each character has a size of 32×32 pixels. The size of the joint image is 256×256 pixels. Simulations are performed on a computer using the MATLAB software package.

Figure 1(a) shows the joint image containing input images of the characters with different degree of rotation in the right half of the plane and the reference images generated by the SDF technique in left half of the plane. The corresponding correlation output is shown in figure 1(b). It can be observed that the targets are detected but not significantly.

Figure 2(a) shows the joint image of the reference image and input images with scale variation. The correlation results on this joint image are presented in figure 2(b).

(a)



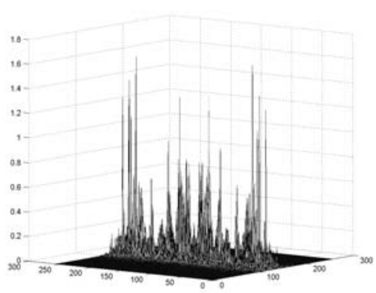
(b)

Fig. 1: SDF technique with rotated objects, (a) joint image containing the targets and the reference class images, (b) correlation output.

Now the performance of the PSDF-based pattern recognition scheme is evaluated. Figures 3(a) and 3(b) show the joint image and the correlation output, respectively, with scale variation included. By comparing with figure 1(b), it can be concluded that the PSDF technique performs better than the SDF technique. Similarly, better performance of the PSDF technique compared to that of the SDF technique is observed for the case of rotation in figures 4(a) and 4(b).

The comparative performance of the SDF and the PSDF techniques are listed in table 1. In this comparative analysis, all the parameters and variables are kept constant throughout the simulation process for both type of variation, i.e. scale and rotation variation. The comparison is made in terms of the ratio of the lowest peak to the highest peak of the target, and the ratio of the lowest peak of the target to the highest peak of the non-target. It can be observed that the ratio of the lowest peak of the target to the highest peak of the target is 0.88 for the SDF technique, whereas it is 0.92 for the PSDF technique, when the targets are rotated to various degrees. In case of scale variation also, the ratio improves from 0.73 in SDF technique to 0.88 in PSDF technique. In an ideal case, the ratio should be unity and thus the PSDF technique is seen to show better recognition performance compared to the SDF technique.

(a)



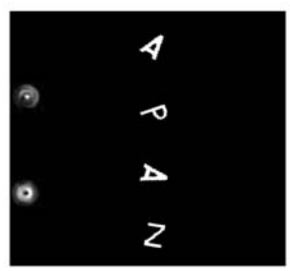
(b)

Fig. 2: SDF technique with scaled objects, (a) joint image containing the targets and the reference class images, (b) correlation output.

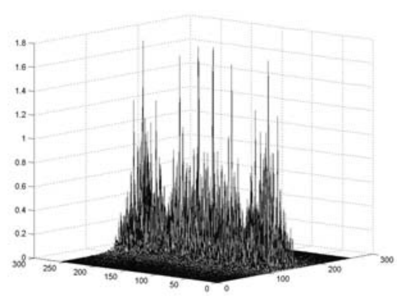
Next the ratio of the lowest peak of the target to the highest peak of the non-target should be as small as possible. For rotated input targets, this ratio is 0.70 and 0.75 for the PSDF and SDF techniques, respectively. For targets scaled to various extents, the ratio is 0.5 and 0.82 for the PSDF and SDF techniques, respectively. Therefore, it is obvious that the PSDF technique rejects non-target more efficiently as compared to the SDF technique in all the cases of distortion.

Table 1: Comparative performance of the SDF and PSDF techniques

Reference Class	Ratio between Lowest Peak of target and Highest Peak of target	Ratio between Lowest Peak of target and Highest Peak of Non-target
Rotation invariant SDF	0.88	0.75
Scale invariant SDF	0.73	0.82
Rotation invariant PSDF	0.92	0.70
Scale invariant PSDF	0.88	0.5



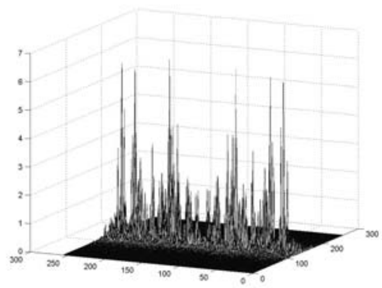
(a)



(b)

Fig. 3: PSDF technique with rotated objects, (a) joint image containing the targets and the reference class images, (b) correlation output.

(a)



(b)

Fig. 4: PSDF technique with scaled objects, (a) joint image containing the targets and the reference class images, (b) correlation output.

4. CONCLUSION

In this paper, an improved approach is proposed to overcome various distortions, such as rotation and scale variations, in case of class-associative target detection. Simulation results confirm that the proposed PSDF-based pattern recognition technique performs better as compared to the SDF-based technique in respect of correlation accuracy and efficiency in presence of distortions.

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