Rotation invariant detection in a noisy environment using wavelet based joint transform correlator

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ABSTRACT

Wavelet based Joint transform correlator (JTC) for rotation invariant automatic target detection is proposed in this paper. Wavelet features of a set of rotationally distorted training images are first extracted at different levels of resolution. A simple composite filter formulation is then employed to construct the reference image of the JTC. Simulation results are presented showing the improved rotation-invariant detection performance of the proposed technique.

Keywords: joint transform correlator, rotation invariant detection, wavelet feature, filter modulation, composite reference image

1 INTRODUCTION

Rotation invariant detection is addressed in literature primarily in two different ways. The first approach uses geometric invariance properties in the filter formulation.[1-3] In these works, circular harmonic filter expansion for rotation invariance has been used. The main difficulty with this method is the proper choice of the harmonic expansion center. In the second approach, a number of rotationally distorted images are trained to come up with a filter, which is expected to work well with any other rotated image. This is the widely accepted synthetic discriminant function (SDF) approach.[4,5] Minimum variance synthetic discriminant filter (MVSDF)[6] and minimum average correlation energy (MACE) filter[7] are two such composite filter formulations. While they have been used with significant success, but the sub-optimal interpolation capability and broader correlation peaks limit their performances.

Wavelet transform has been attracting increasing attention in optical pattern recognition community for its attractive multiresolution, denoising and feature extraction capabilities.[8-11] We, here, propose to use wavelet features, modulated by a filter formulation to come up with a composite reference image, which is to be used in a joint transform correlator (JTC)[12] setup. The classical JTC results in poor discrimination in a noisy environment. In addition, the rotation invariant detection is not possible in a classical JTC. We address these two problems

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here in an efficient way. Filter modulation technique for extracting better features for rotation invariance has successfully been investigated[13-15] recently. Our approach is different from these in two major ways. First, the filter formulation we are using is more optimal, flexible and adaptive in nature. Secondly, we use a simple superposition scheme for getting a composite reference image. Another advantage is that we do not need to fabricate a complex filter, because of the use of JTC.

2 WAVELET-FEATURE BASED ROTATION-INVARIANT JTC

Let R be the range of rotational distortion. This is divided into M different classes of distortions. For each of these classes, a composite reference image is found out. Suppose, $w_1, w_2, \cdots, w_n$ are the wavelet-feature of n rotationally distorted training images in the class i. Let $s_i^1, s_i^2 \cdots, s_i^n$ are the corresponding filter-feature training images obtained from the following transformation.

$$s_i^k = \mathcal{F}^{-1}\frac{De^{j\phi}}{\mid W_k \mid + a} \tag{1}$$

where $\mid W_k \mid e^{j\phi} = \mathcal{F}\{w_k\}$. We use $a = f(W_k)$, which is to be selected for getting more optimal features through this transformation. Note that the above formulation named as amplitude modulated phase-only filter was introduced for getting more discriminating corrrelation peak.[16] Here we use it as a feature descriptor. The composite reference image c_i for the class i is then found using the following superposition:

$$c_i = s_i^1 + s_i^2 + \cdots + s_i^n \tag{2}$$

Now, in the reference half of input joint image (IJI) of JTC, we have M such composite images for M classes. With the input wavelet-transformed image t, the IJI is thus given by

$$g(x,y) = \sum_{i=1}^{M} c_i(x - x_i, y - y_i) + t(x,y) \tag{3}$$

where $c_i(x - x_i, y - y_i)$ and $t(x,y)$ respectively, represent the composite reference image for class i and the input image. The joint Fourier transform of this input results in:

$$G(u,v) = \sum_{i=1}^{M} C_i(u,v)exp(+jux_i + jvy_i) + T(u,v)exp(-jv - ju) \tag{4}$$

The joint power spectrum (JPS) is given by

$$\begin{aligned} |G(u,v)|^2 \quad = \quad & \sum |C_i(u,v)|^2 + |T(u,v)|^2 \\ & + \sum C_i(u,v)T^*(u,v)exp(jux_i - jvy_i) \\ & + \sum C_i^*(u,v)T(u,v)exp(-jux_i + jvy_i) \\ & + \sum_{l=1}^{M} \sum_{k=1,k\neq l}^{M} C_l(u,v)C_k^*(u,v)exp[ju(x_l - x_k) + jv(y_l - y_k)] \end{aligned} \tag{5}$$

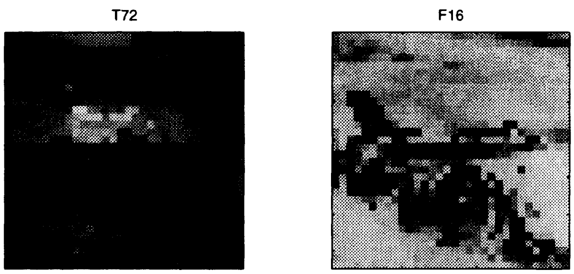

Figure 1: Test images: (a) T72 tank (target), (b) F16 aircraft (non-target)

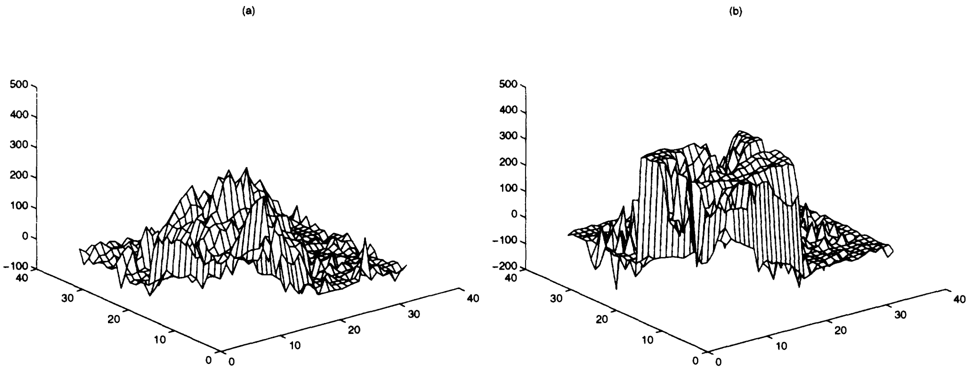

Figure 2: Wavelet features of (a) T72, (b) F16 using Haar wavelet transform at highest resolution

Note that because of the use of Eq. (1) the term $|C_i(u,v)|^2$ is very small compared to the term $|T(u,v)|^2$. In reality, with proper choice of the parameters D, a, and the wavelet filter parameters, we can find a desired minimum value for this term. With the same reasoning, also the fifth term, which is the cross correlation among the composite images, can be neglected from the JPS. Therefore, for all practical purposes, Eq. (5) can be approximated by

$$|G|^2 = |T|^2 + \sum_{i=1}^{M} (C_i T^* + T C_i^*)$$

The output correlation is found by subtracting the zero-order term contributed by the input image from the JPS and then taking the inverse Fourier transform.

Note that in this approach, we get M output correlation peaks, each corresponding to one class of rotations. Thus the correlation output also gives an estimate of the rotational distortion of the target. This is an interesting outcome of the current work.

3 SIMULATION RESULTS

To validate the performance of the proposed model, we consider the T72 tank image (target), and the F16 aircraft (non-target), as shown in Fig. 1. Each of the images is of 32×32 size, while the joint image is of the JTC is of size 256×256. The training images with different in-plane rotations are first selected. We consider an interval of 5 degrees in the distortion range of 0-90 degree. This is then divided into $M = 3$ classes of distortions of 0-30, 30-60, 60-90 degrees. The wavelet-feature descriptors of these training images are then found out. Figure 2 shows the corresponding features of undistorted T72 and F16. Here, we use Haar wavelet transform. The motivation to using Haar wavelet is to get more edge features. We are not interested in localization property of wavelet, wherein Haar transform is not very good at. It is a well-known fact that edge-enhanced images perform well in terms of correlation discrimination in a JTC. In other words, it is the dominance of low-frequency components in the features which is responsible for broader correlation peaks. Next, we modulate these features with the filter formulation in Eq. (1). The goal here is to obtain the sharper and more discriminating correlation performance of these filter formulations in the correlation operation. This new feature is then synthesized to form the reference image of JTC.

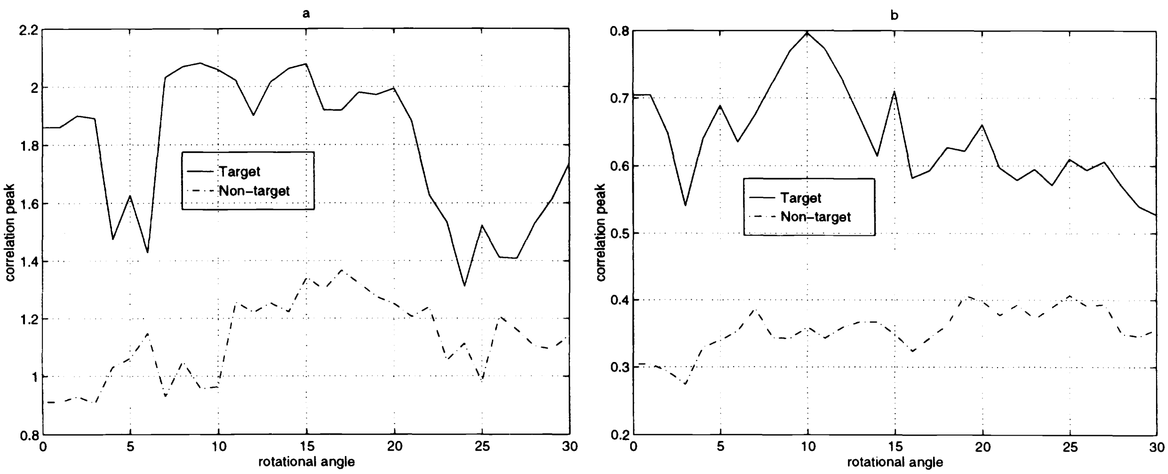

Figure 3: (a) Correlation performance with (a) low resolution wavelet feature (b) high resolution wavelet feature for 0-30 degree distortion

For testing the correlation performance we use distorted images at an interval of 1 degree. Figure 3 shows the correlation peak values from the JTC, for different distorted images in the range 0-30 degree. It shows that better discrimination between target and non-target is obtained with high resolution decomposition (Fig. 3(b)) than that with low resolution decomposition (Fig. 3(a)). The reason is the property of the wavelet transforms of having increasing decorrelation with increasing level of decomposition. But the price for high resolution is the decrease in the correlation peak values, as seen from the figure.

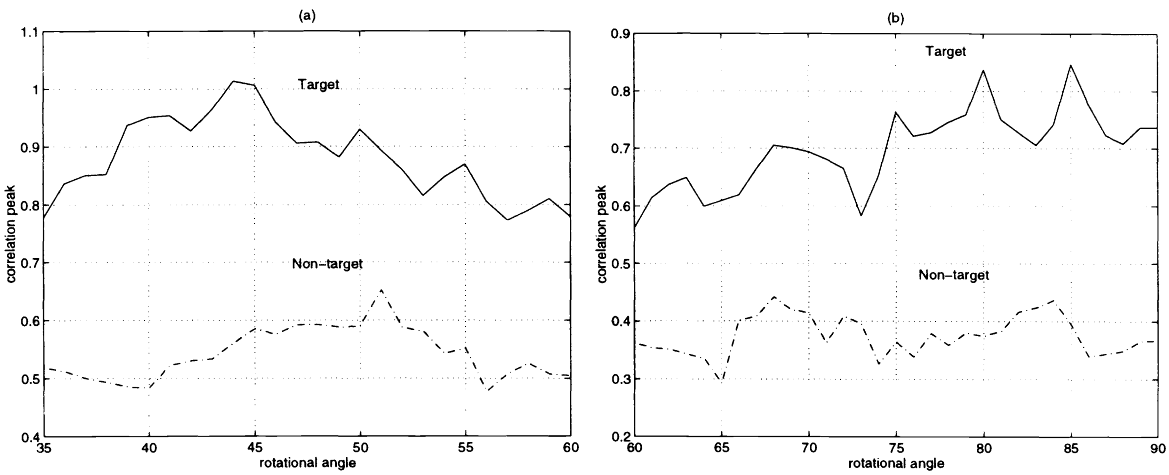

Figure 4: Correlation performance in the distortion range (a) 30-60 degree (b) 60-90 degree

For the remaining part of simulation we will be using the high-resolution features. Figure 4 illustrates the corresponding correlation performance in the distortion range of 30-60 and 60-90 degrees. Note that in these cases we can set a threshold value of correlation peak, above which the input can be treated as a target and below which it is a non-target. Next, we place the 3 composite reference images for the 3 classes of distortions in the input joint image. The input is now 91 distorted images of the target in the range 0-90 in step of 1 degree. We get 3 correlation peaks corresponding to the three classes of distortions. Figure 5(a) shows the interesting results. Note particularly, how class 1 (0-30) performs well in the distortion range 0-30, but its correlation performance is poor for the range 30-90 degrees. In the same way each class gives better performance in its domain of distortion. We then combine these better performances of each range. Figure 5(b) shows the resulting discrimination between target and non-target. Figure 6 gives the output correlation plot for a particular value of distortion of 90 degree. Note that the peak corresponding to class 3 (60-90), which is at the upper right hand corner of the correlation plane, is higher than the other two peaks. This tells that the input distorted image is in class 3, in addition to the result that it can be isolated from a non-target for the discrimination ability.

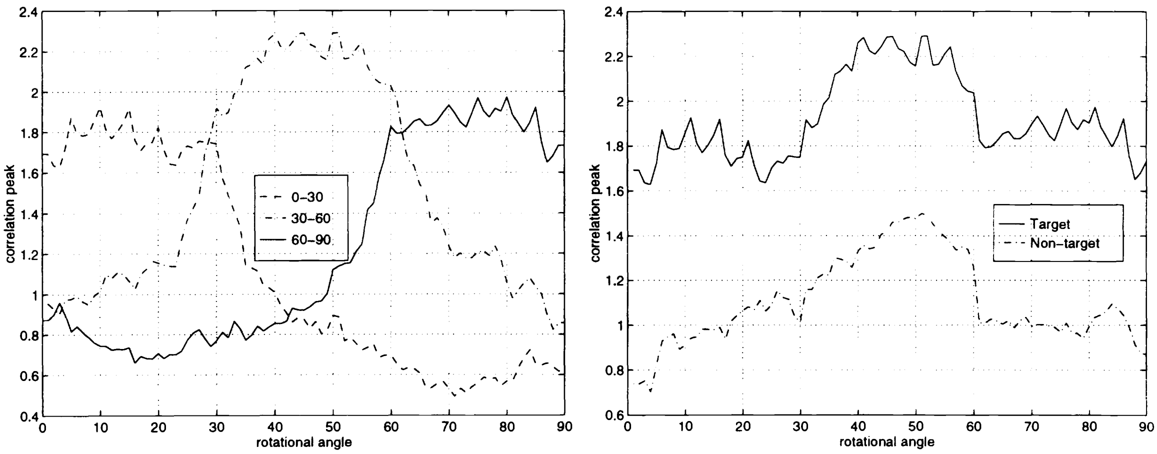

Figure 5: (a) Correlation performance of the composite JTC for the target (b) Correlation discrimination of target and non-target for the composite JTC

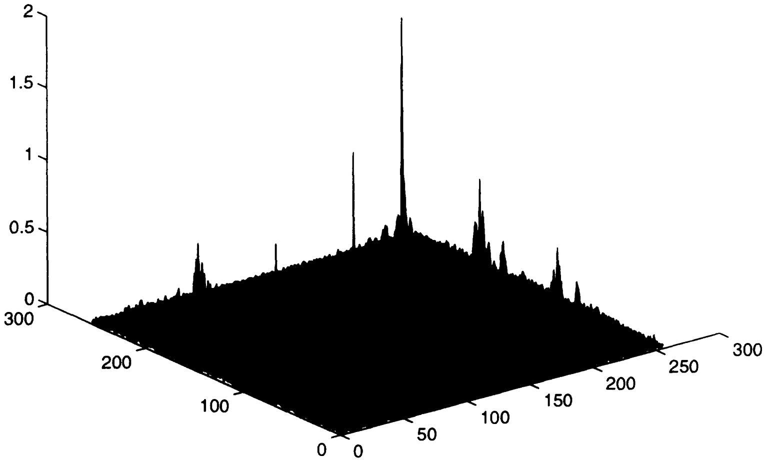

Figure 6: Correlation output for the target distorted at 90 degree

Finally, we performed the simulation with zero-mean, gaussian white noise of different variances. With 10 dB noise the discrimination is still good as seen from Fig. 7(a). Performance deteriorates as noise variance is increased as demonstrated by Fig. 7(b).

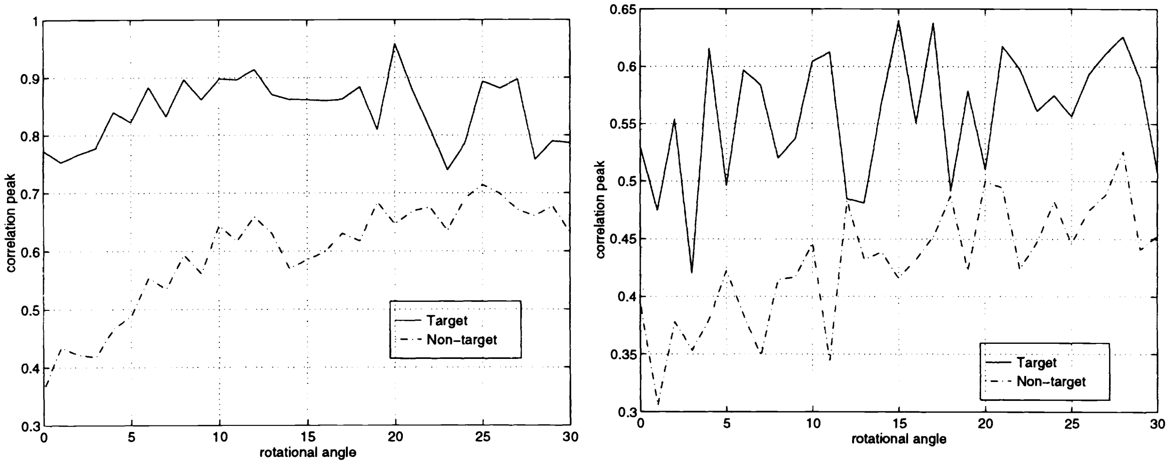

Figure 7: Correlation performance in noise (a) SNR=10 dB, (b) SNR=5 dB

4 CONCLUSION

An wavelet-based joint transform correlator for rotation-invariant optical target detection has been presented. The scheme used a simple technique for composite reference image formulation. With the choice of proper thresholding in the output correlation, the proposed technique is shown to result in highly robust and discriminating rotation-invariant detection.

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