Rotation-invariant target recognition using an amplitude-coupled minimum-average correlation-energy filter

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Abstract. An amplitude-coupled minimum-average correlation energy algorithm is implemented and tested for a rotation invariance feature. The algorithm is tested on synthetic aperture radar images for probability of correct classification.

Subject terms: algorithm; rotation invariance feature; synthetic aperture radar images.

Paper 09035 received Mar. 8, 1995; revised manuscript received Oct. 15, 1995; accepted for publication Oct. 18, 1995.

1 Introduction

The automatic target recognition (ATR) process using hybrid electro-optical correlators has always been an area of intense research. The possibility of achieving high speed and massive parallelism using reliable components and the apparent success of several different types of matched filters[1–5] offer good opportunities for suitable implementation of optical correlators. Among the matched filters, the amplitude-modulated phase-only filter (AMPOF)[5] is of particular interest here because of its sharp correlation peak and improved noise-related performances.[6–7] It offers a built-in noise tolerance which is essential for low-powered optical correlators. However, as with any other matched filters (such as a phase-only filter,[4] inverse filter (IF), and amplitude-compensated matched filter,[2]) AMPOF also performs poorly in distortion-related cases. Further, these matched filters are not suitable for multiclass ATR applications since they do not offer enough flexibility for adequate training using different classes of distorted images.

One of the important classes of filters, namely, minimum-average correlation-energy (MACE) filters,[8] incorporate all possible distorted images in their formulation. Thus, these filters can accommodate multiclass ATR via appropriate training. The MACE filters have also been shown to have a limited rotation-invariance property[9] since it is possible to train the correlator on all the rotated images using the MACE algorithm. The rotation-invariance property of a complex filter, in particular, is desirable in robotics, top-down reconnaissance, missile guidance, and similar applications.[9] Two different filters, namely, Mellin transform-based filters (MTF)[10] and circular harmonic filters (CHF),[11] are well known as in-plane rotation-invariant filters. The MTFs, however, are very computer intensive while CHFs do not offer good discrimination due to partial use of object information such as that contained in a single harmonic in one filter.

One of the drawbacks of MACE, however, is that it does not have sufficient noise tolerance.[12] Yet, it can be reasoned that when the limited in-plane rotation invariance of MACE is combined with AMPOF's built-in noise tolerance and sharp autocorrelation features, one may actually end up with much better ATR performance. The resulting combination referred to as the amplitude-coupled MACE is thus expected to offer minimum noise, sharper autocorrelation, minimum correlation energy, and improved in-plane rotation invariance for ATR applications using gray-scale images. Accordingly, in this paper, we investigate a rotation-invariance feature of an amplitude-coupled MACE and compare it with that obtained using a simple MACE algorithm. Further, we investigate the amplitude-coupled MACE filter in terms of the statistical probability of correct classification (P_c) between the in-class and out-of-class synthetic aperture radar (SAR) targets.

2 Background Review

The phase of a signal is a parameter vital to recovering the signal.[13] However, the amplitude content is also of considerable importance[14–15] since it provides an added dimension in the signal retrieval process. The AMPOF, which retains information pertaining to both phase and amplitude, has already been shown to outperform other types of matched filters [such as the phase-only filter (POF)] in discriminating in- and out-of-class targets in noisy environments.[6] Further, the different parameters involved in the AMPOF function formulation can be suitably tuned to provide better noise tolerance.[7] The generalized AMPOF function is[5]

$$H_{\text{ampof}}(u,v)=\{D/[|R(u,v)|+A]\}\exp[-j\varphi_R(u,v)], \qquad (1)$$

where $|R(u,v)|$ is the amplitude of the Fourier spectrum $R(u,v)$ of the reference function $r(x,y)$, $\varphi_R(u,v)$ is the phase factor of $R(u,v)$, and D and A are either constants or

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functions of u and v. The constraint $D \leqslant |R(u,v)|_{\min} + A$ ensures that the gain of an AMPOF-based correlator is less than or equal to unity for all frequency components. Further, when A is a function of u and v, $|R(u,v)| \geqslant A(u,v)$, and D is 1, the AMPOF is nothing but an inverse filter. Hence, a reasonably small $A(u,v)$ value in AMPOF may offer a sharp autocorrelation feature of an IF while at the same time it can be used to avoid the indeterminate condition otherwise associated with an IF. In fact, a prudent choice of $A(u,v)$ may actually offer bandpass characteristics to the AMPOF by attenuating unwanted noise frequencies in the filter magnitude plane. However, like any other matched filter, a particular shortcoming of AMPOF is that it does not incorporate multiple image information in its formulation. Hence, any rotation or distortion-related application necessitates the use of multiple filters, each corresponding to particular distorted or rotated images.

As noted earlier, a particular frequency domain filter, namely MACE, may include all possible distortion information in its formulation. A MACE filter is a linear combination of the preprocessed distorted (training) images.[9] It minimizes the average correlation plane energy while producing a prespecified correlation to a location of the training images. The basic MACE filter is given as[8]

$$\mathbf{H}_{\text{mace}} = \mathbf{D}^{-1}\mathbf{X}(\mathbf{X}^{+}\mathbf{D}^{-1}\mathbf{X})^{-1}\mathbf{c}, \tag{2}$$

where $\mathbf{D} = \Sigma \mathbf{D}_i$, $\mathbf{X} = \Sigma \mathbf{X}_i$ and $\mathbf{c} = \Sigma \mathbf{c}_i$, $\mathbf{H}_{\text{mace}}$ is the Fourier transform of the filter function, $\mathbf{X}_i$ is the i'th training set image (where the total number of in-plane rotated images is N), $\mathbf{D}_i$ is the diagonal matrix composed of the Fourier transform-square of the i'th training set image component and $\mathbf{c}_i$ is the predefined i'th correlation peak at the filter output plane. Note that the bold-faced parameters represent respective Fourier transformed versions and the superscripts -1 and $+$ denote inverse and transpose operations, respectively. The MACE filter minimizes the total correlation plane energy $E_T = \mathbf{H}_{\text{mace}}^{+}\mathbf{D}\mathbf{H}_{\text{mace}}$ subject to the constraint $\mathbf{H}_{\text{mace}}\mathbf{X}_i = \mathbf{c}_i$ for i number of training set images. The vector $\mathbf{c}$ is usually set to 1 for an in-class target recognition situation while it is considered to be 0 for an out-of-class case.

A practical issue associated with the synthesis of a MACE filter is the presence of a random bias term. A random bias term may be a constant noise term that is added uniformly to the entire input image.[16] The necessary condition to ensure invariance to the constant noise signal (with random amplitudes) is[16]

$$\mathbf{H}_{\text{mace}}{}^{T}\mathbf{c} = 0, \tag{3}$$

where T denotes a transpose operation and $\mathbf{c} = [1,1,1...,1]$ is the constant image vector of unit amplitude. The condition of Eq. (3) is usually satisfied by including a constant image in the training set and setting the corresponding output to 0. Further, Eq. (3) also justifies the use of zero mean noise in MACE filter synthesis.

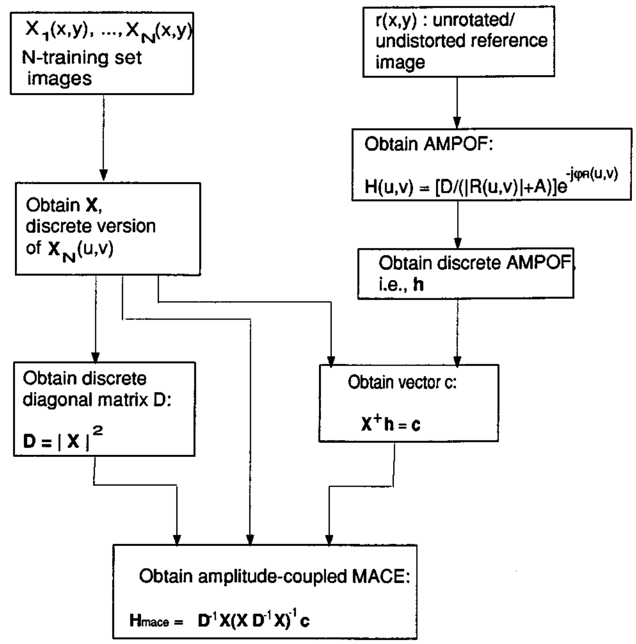

Fig. 1 Algorithm for amplitude-coupled MACE filter.

A bank of amplitude-coupled MACE filters may represent different distortion-related (such as rotation, and scale) cases. Alternatively, for the case of SAR application, each class of SAR target images may be used to generate a composite filter which can be then trained and tested. A broad aspect of this type of an ATR system is to operate in a wide-area search mode, maintain a very low false alarm density in case of different distortions such as rotation, and provide a high probability of correct classification. The ultimate purpose of the system is to provide a reliable baseline ATR process based on a pattern-matching classifier approach. A similar effort for the SAR target identification using matched spatial filters has been reported recently.[17]

3 Algorithm Development

For the case of amplitude-coupled MACE, we derive values for vector $\mathbf{c}$ from the AMPOF autocorrelation using unrotated reference images only. This autocorrelation value is then replicated for each element of vector $\mathbf{c}$ that corresponds to the in-class target class. The A and D parameters in the AMPOF function were both set to 1, for simplicity. Since AMPOF offers a very sharp and enhanced correlation value, the choice of this autocorrelation peak for vector $\mathbf{c}$ is expected to improve the target detection feature of the composite filter. Accordingly, this particular selection of $\mathbf{c}$ is also expected to offer better performance even in the presence of rotation-related distortion cases. This type of constraint is quite common in both theoretical[18] and experimental[19] research work. The algorithm for the amplitude-coupled MACE filter is summarized by the flowchart shown in Fig. 1. The rest of the elements of vector $\mathbf{c}$ are set to 0 for the out-of-class targets. An alternative

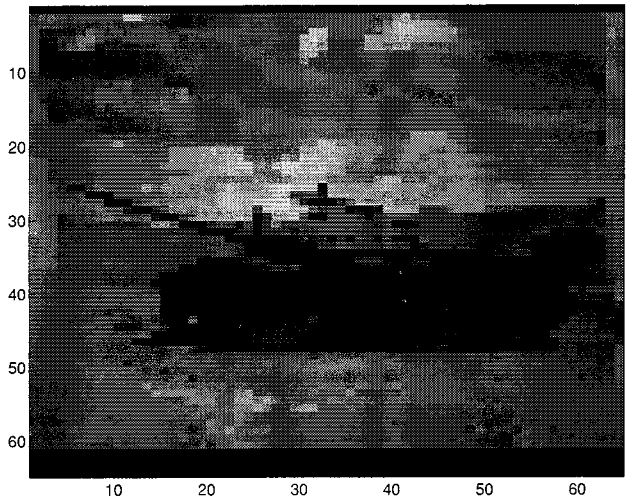

Fig. 2 Gray-scale image of a tank.

choice to implementing an amplitude-coupled MACE filter is to predefine **c** as 1 and 0 respectively for in-class and out-of-class targets.

In the algorithm of Fig. 1, the bold characters represent a discretized Fourier-transformed version of the corresponding vector and/or matrix. We start with N number of distorted training set images and obtain matrix **X** as described in Sec. 2. Next, we obtain the diagonal matrix **D** using matrix **X**. In order to obtain the useful features of an AMPOF, the AMPOF is further coupled with the MACE function. To accomplish this, each of the magnitude and phase components of the MACE filter is accessed and arranged according to Eq. (1). This offers an overall AMPOF nature to the composite MACE filter. Finally, the generalized MACE filter as represented by Eq. (2) is obtained.

For this rotation-invariance algorithm, the output correlation peak intensity is considered as a measure of ATR performance. As pointed out by Farn and Goodman,[18] the maximization of the correlation peak metric is a reasonable measure for the performance of any composite filter. Furthermore, we test the suitability of this algorithm in terms of probability of correct classification (P_c). More important, this P_c is obtained at an increased signal-to-noise ratio (SNR). Note that the P_c is defined by the number of occurrences (in a scale of 0 through 1) of maximum test correlation corresponding to the respective test-pattern filter.

4 Image Database

Two different databases of the images have been used in this study. The first group is a gray-scale 64×64-sized "Tank" image as shown in Fig. 2. The "Tank" image is reduced to a 32×32 size for the sake of memory constraint. Four different rotated (i.e., 0, 90, 180, and 270 deg) versions of this gray-scale image are also obtained. The second group of images are SAR images[20] as shown in Figs. 3(a) to 3(d) for "T72" tank, "M1" tank, fire "Truck" and a school "Bus" respectively. These latter images are simulated using Xpatch computer-aided design (CAD) software. In general, three types of CAD models such as that for the target itself, ground clutter, and tree clutter are common in practice. There are three variables (namely, frequency resolution, angles of interest, and polarizations) that need to be predefined to generate these models. The Xpatch offers coherent radar scattering data both unfocused and focused in nature. Some of the reasons for using Xpatch data for simulation include the high quality, diverseness, and control over parameter selection. The high quality of Xpatch data offers state-of-the-art scattering prediction, target/clutter interactions and validation with measurements. The diverseness of data include multiple frequencies (such as ultrahigh frequency, and L, X, and Ka bands for electromagnetic waves), fully polarimetric data, all azimuth and elevation angles, and different target articulations and obscuration. The control over parameter selection allows quantitative experiments.

The images generated using Xpatch are complex 64×64 image domain data for the above-mentioned four targets at 11 azimuth angles. The targets are located on rough ground plane. These SAR data are generated at a frequency of 10 GHz, an elevation angle of 40 deg, an azimuth range of 1, and a target azimuth angle in 5.2-ft (i.e., 3-deg places and 2 postdecimal degree places). Thus the data range from 2 to 7 deg in increments of 0.5 deg. The generated SAR images are for horizontal polarization only at a resolution of 1 ft×1 ft. However, the data may be modified to include other necessary polarizations and hence an exact model of the data may be obtained. The CAD models of SAR images in Figs. 3(a) through 3(d) are obtained at a 10 GHz frequency, a 40-deg elevation angle, an azimuth range of 1, and an angle of 2 deg.

5 Training and Results

As discussed in Section 3, we explore two baselining properties, namely, rotation invariance and the probability of correctness of the amplitude-coupled MACE filter. We implement both MACE and amplitude-coupled MACE filters. For proof-of-concept rotation invariance, we consider only one target class (e.g., the gray-scale "Tank"). In order to test the rotation-invariance feature, we test the four rotated images against the unrotated center image (which is included as reference image in the formulation). The correlation results are obtained as shown in Figs. 4(a) and 4(b) for MACE and amplitude-coupled MACE respectively. Since the rotated images are tested not simultaneously but sequentially, the peak locations in Fig. 4(a) do not necessarily represent true locations of the images in the input image plane. Further, since the usual response plot of an amplitude-coupled MACE filter shows localized frequency concentration at a certain region, the correlation peaks in Fig. 4(b) appear only at a certain frequency band (in this case at u=20). Figure 4(b) shows considerable improvement in the correlation peak. This maximum correlation-value technique described here has been successfully used for shift-invariant pattern-matching purposes.[17]

In order to demonstrate an overall rotation-invariance algorithm, we begin the training phase with a leave-one-out loop so that each time we read 10 SAR images out of a total of 11 and then construct a composite amplitude-coupled MACE filter with these images. We train each of the filters with the four in-plane rotated versions (i.e., 0, 90,

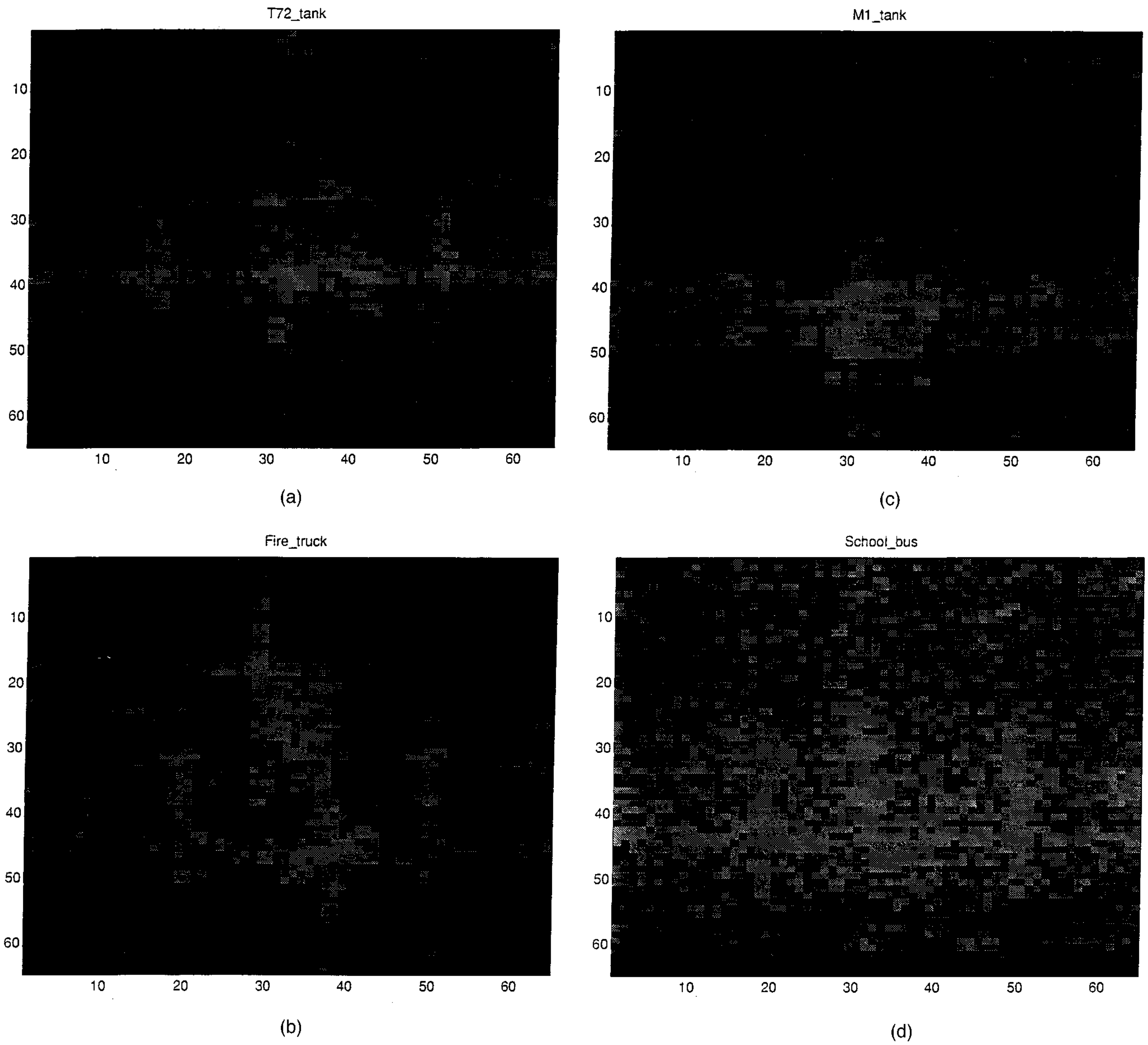

Fig. 3 SAR image of (a) T72 tank, (b) fire truck, (c) M1 tank, and (d) school bus.

180, and 270 deg) of the gray-scale "Tank" images. The testing is performed with the left-out image from the leave-one-out loop. Each one of the constructed filters with 24 in-plane rotated versions (i.e., 0, 15, 30, 45, 60 deg....., etc.) of the left-out image in each case is tested. The overall rotation invariance result is obtained as shown in Fig. 5. The dotted curve corresponds to amplitude-coupled MACE while the "+" points correspond to MACE filters respectively. As expected, the amplitude-coupled MACE performs better than the MACE. This improved correlation feature is desirable for the low-powered optical correlators. The four peaks in Fig. 5 for both the amplitude-compensated MACE and MACE filters correspond to the in-class match (at the four rotation angles) in the testing phase.

The simulation for another baseline feature, probability of correctness, is performed using all four classes of SAR targets comprising a total of 44 images. For the training phase, the leave-one-out loops for each of the target classes are initiated as before. Four different types of filters [corresponding to the four different classes of SAR targets of Figs. 3(a) through 3(d)] are generalized using 10 images from each class at a time. In order to make the overall computation statistically sound, noise of different variance is instantiated and added to each left-out image of each class. Next, each class of filters is tested against the noisy versions of the left-out image. The probability of correctness vector is increased each time when the maximum test correlation occurs corresponding to the respective test-pattern filter. Finally, the probability of correctness versus

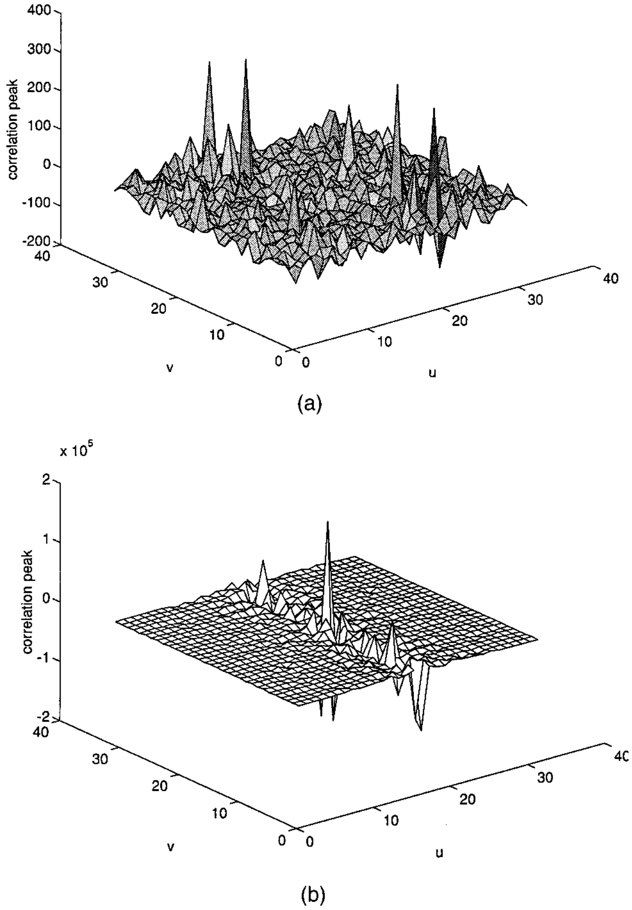

Fig. 4 Correlation using four rotated gray-scale tank images corresponding to (a) MACE and (b) amplitude-coupled MACE.

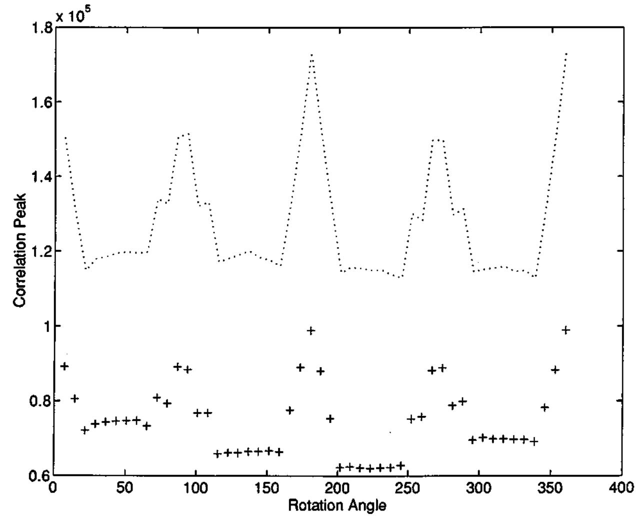

Fig. 5 Correlation peak versus rotation angle.

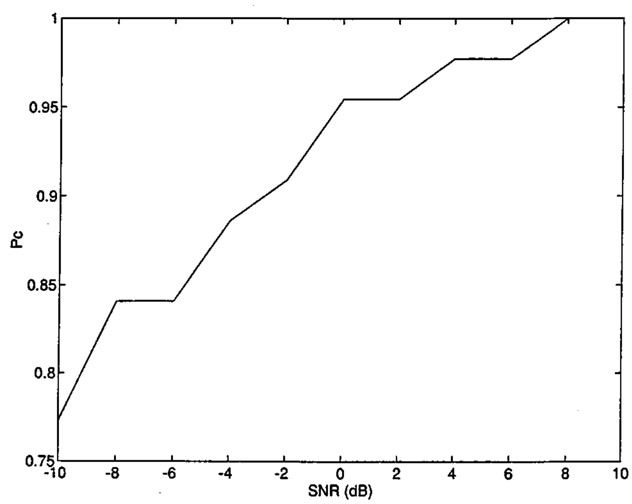

Fig. 6 Probability of correctness versus SNR.

the SNR plot is obtained as shown in Fig. 6. Here, the probability of correct classification for the amplitude-coupled MACE filter increases with increasing signal power. A 100% classification is obtained at about 8 dB of SNR. Note that this curve will turn out to be much smoother with smoother noise transitions.

6 Conclusion

One advantage of choosing the **c** vector from the AMPOF correlation is that it imitates the more realistic approach of implementing the amplitude-coupled filter using spatial light modulators (SLM). Since most of the electro-optics devices, including SLMs, necessitate control over phase and amplitude, the choice of an AMPOF-related **c** vector only imposes a more suitable constraint on the MACE filter. This is because the AMPOF-related **c** vector imposes specific phase and amplitude constraints on the type of SLMs required for optical implementation of the filter. This type of constraint is quite similar to other SLM-dependent constraints[18,19] that have been exploited before. As expected, the amplitude-coupled MACE algorithm offers a much better rotation invariance than a MACE algorithm. The rate of probability of correct classification is also quite impressive.

Acknowledgment

The authors were supported in this research in part by the Advanced Research Program Agency (administered by Ohio Aerospace Institute) Grant No. MDA972-93-1-0015.

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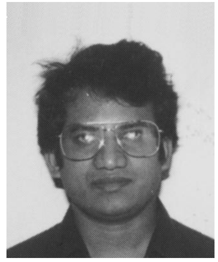

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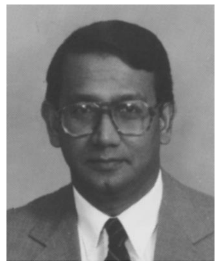

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