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Bayesian defeat of camouflage

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BAYESIAN DEFEAT OF CAMOUFLAGE

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ABSTRACT

A new technique is shown for refining and reducing incoming camouflage data based upon the Bayesian paradigm. Innovation is displayed in use of a statistical conditioning sequence that avoids the need to form target features from the data. The result is a simplified and more accurate probabilistic indication of actual target presence. This probabilistic indication can then be incorporated into a variety of target detection scenarios or, alternately, to form the basis of a theoretically optimal Bayesian target detector.

Numeric simulation is presented to show the effectiveness of the technique against simulated camouflage.

1.0 INTRODUCTION

Camouflage of targets abound both in natural and militarily significant situations yet is seldom addressed within the automatic target detection arena. This is largely because conventional automatic target recognition techniques such as edge detection and region growing are not robust with respect to the breakup of target detail caused by camouflage. Further compounding the problem is the fact that there is less target information available to permit good recognition capability. An ideal solution would be a robust technique that makes best use of all available information and produces the highest rate of recognition possible. Fortunately, it is already well known that the Bayesian decision process satisfies this ideal.[1-3] The Bayesian process is seldom considered in practice; however, due to the perceived difficulty of obtaining the necessary probabilities. Although a demanding process, the probabilities can be developed on a problem by problem case allowing a truly robust and highest performance response to conditions of camouflage.

2.0 THEORY

The Bayesian recognizer can be given[1] as

$$\text{If} \quad \Lambda > \eta \quad \text{then recognize } H_1 \quad \text{else recognize } H_0 \tag{1}$$

where Λ, the likelihood function, is

$$\Lambda = \frac{p_{\boldsymbol{R}|H_1}(R|H_1)}{p_{\boldsymbol{R}|H_0}(R|H_0)} \tag{2}$$

η, a decision threshold independent of the data, R, is

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$$\eta = \frac{(c_{10} - c_{00}) P(H_0)}{(c_{01} - c_{11}) P(H_1)} \tag{3}$$

and the c's are the relative costs of correct and erroneous recognitions of H_1 and H_0.

Letting H_1 and H_0 be the cases where there is or is not a target in an image, R, the Bayesian recognizer of Eq. (1) can be suited to the problem of detecting the presence or absence of a camouflaged target. This is accomplished by properly evaluating Λ.

To evaluate Λ, one needs the probability density functions of $p_{\boldsymbol{R}|H_1}(R|H_1)$ and $p_{\boldsymbol{R}|H_0}(R|H_0)$. These are further developed in Subsections 2.1 and 2.2.

2.1 The Conditional Probability of the Image Given Target Presence

An indexing variable[4] is a target attribute such as position, orientation, articulation, size, etc. where every value is mutually exclusive. A target index, I_i, is an element of the Cartesian product of any such number of target indexing variables. The use of indexing is in simplification of the calculation of $p_{\boldsymbol{R}|H_1}(R|H_1)$.

As a result of target indexing

$$p_{\boldsymbol{R}|H_1}(R|H_1) = \sum_i p_{\boldsymbol{R}|I_i, H_1}(R|I_i, H_1) p_{\boldsymbol{I}_i|H_1}(I_i|H_1) \tag{4}$$

Generally, the scene can be partitioned into various regions, r_j, with independent stochastic behaviors, thus permitting Eq. (4) to be expanded further

$$p_{\boldsymbol{R}|H_1}(R|H_1) = \sum_i \prod_j p_{\boldsymbol{r}_j|I_i, H_1}(r_j|I_i, H_1) p_{\boldsymbol{I}_i|H_1}(I_i|H_1) \tag{5}$$

Finally, there can exist various states, C_i, of target camouflage, giving

$$p_{\boldsymbol{R}|H_1}(R|H_1) = \sum_i \prod_j \sum_k p_{\boldsymbol{r}_j|C_k, I_i, H_1}(r_j|C_k, I_i, H_1) p_{\boldsymbol{C}_k|I_i, H_1}(C_k|I_i, H_1) p_{\boldsymbol{I}_i|H_1}(I_i|H_1) \tag{6}$$

2.2 The Conditional Probability of the Image Given The Absence of the Target

If no target is present, the image, R, portrays only scene background with the specific probability $p_{\boldsymbol{R}|H_0}(R|H_0)$.

Again partitioning the scene into regions, r_j, with independent stochastic behaviors gives

$$p_{\boldsymbol{R}|H_0}(R|H_0) = \prod_j p_{\boldsymbol{r}_j|H_0}(r_j|H_0) \tag{7}$$

2.3 Continued Development Of The Likelihood Function

Substituting Eq.'s (6) and (7) into Eq. (2) gives for the likelihood

$$\Lambda = \sum_i p_{\boldsymbol{I}_i|H_1}(I_i|H_1) \prod_j \sum_k \frac{p_{\boldsymbol{r}_j|C_k, I_i, H_1}(r_j|C_k, I_i, H_1)}{p_{\boldsymbol{r}_j|H_0}(r_j|H_0)} p_{\boldsymbol{C}_k|I_i, H_1}(C_k|I_i, H_1) \tag{8}$$

Now for any regions, r_1, not affected by target presence

$$p_{r_l|C_k, I_i, H_1}(r_l|C_k, I_i, H_1) = p_{r_l|H_0}(r_l|H_0) \tag{9}$$

and so

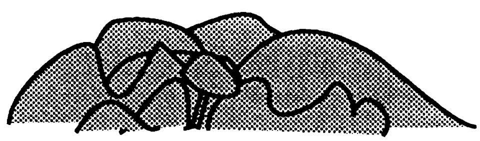
$$\sum_k \frac{p_{r_l|C_k, I_i, H_1}(r_l|C_k, I_i, H_1)}{p_{r_l|H_0}(r_l|H_0)} p_{C_k|I_i, H_1}(C_k|I_i, H_1) = 1 \tag{10}$$

Thus by the theorem of irrelevance[6], all regions, r_l, not affected by target presence need not enter into the $\prod$ calculation of Eq. (8). This allows greatly improved computational efficiency and retention of precision during the likelihood calculation.

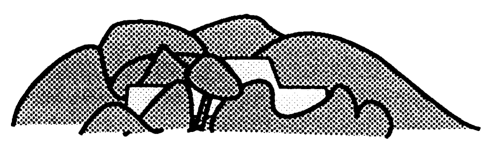
3.0 AN EXAMPLE

3.1 Problem Setup

The above concepts can best be illustrated by a simplified example where the problem is to recognize whether or not a target is camouflaged behind scene foliage of Fig. 1 When the target is present, it can further be assumed that the target is operating



(a) Target not present



(b) Target present

Figure 1. An Example Recognition Problem

under conditions of stealth, e.g. moonless night and a E-O image sensor, homogeneous temperature conditions and an IR image sensor, or low scene reflectivity and a LADAR image sensor.

Now if a target region is not camouflaged by the foliage, then it is in clear view. It is then possible to calculated the average gray level value, μ_j, of each pixel, j, of the uncamouflaged target region at the sensor's output based on the target's CAD model, the sensor model, and assumed target index, I_i. Consequently, we can rewrite Eq. (8) as

$$\Lambda = \sum_i p_{I_i|H_1}(I_i|H_1) \prod_j \sum_k \frac{p_{r_j|\mu_j, C_k, I_i, H_1}(r_j|\mu_j, C_k, I_i, H_1) p_{\mu_j|C_k, I_i, H_1}(\mu_j|C_k, I_i, H_1)}{p_{r_j|H_0}(r_j|H_0)} \bullet$$

$$p_{C_k|I_i, H_1}(C_k|I_i, H_1) \tag{11}$$

or yet more simply as

$$\Lambda = \sum_i p_{I_i|H_1}(I_i|H_1) \prod_j \sum_k \frac{p_{r_j|\mu_j, C_k, I_i, H_1}(r_j|\mu_j, C_k, I_i, H_1)}{p_{r_j|H_0}(r_j|H_0)} p_{C_k|I_i, H_1}(C_k|I_i, H_1) \tag{12}$$

since

$$p_{\mu_j|C_k,I_i,H_1}(\mu_j|C_k,I_i,H_1) = 1 \tag{13}$$

A change detection type of scenario is reasonable for this example. As a result, we can assume that the image sensor has been periodically viewing the scene and has developed and holds the average background gray level value, ψ_j, for each background pixel, j. Consequently, we can rewrite Eq. (12) as

$$\Lambda = \sum_i p_{I_i|H_1}(I_i|H_1)\prod_j\sum_k \frac{p_{r_j|\mu_j,C_k,I_i,H_1}(r_j|\mu_j,C_k,I_i,H_1)\,p_{\mu_j|C_k,I_i,H_1}(\mu_j|C_k,I_i,H_1)}{p_{r_j|\Psi_j,H_0}(r_j|\Psi_j,H_0)\,p_{\Psi_j|H_o}(\psi_j|H_0)} \bullet$$
$$p_{C_k|I_i,H_1}(C_k|I_i,H_1) \tag{14}$$

or yet more simply

$$\Lambda = \sum_i p_{I_i|H_1}(I_i|H_1)\prod_j\sum_k \frac{p_{r_j|\mu_j,C_k,I_i,H_1}(r_j|\mu_j,C_k,I_i,H_1)}{p_{r_j|\Psi_j,H_0}(r_j|\Psi_j,H_0)} p_{C_k|I_i,H_1}(C_k|I_i,H_1) \tag{15}$$

since

$$p_{\Psi_j|H_o}(\psi_j|H_0) = 1 \tag{16}$$

Finally, in our example other a-priori knowledge can be developed. The probability, $p(C)$, of any target pixel being camouflaged is independent of any other. Camouflage, if present, is total. The sensor noise, $p(S)$, is chosen to be zero-mean Normal with a standard deviation of σ and independent from pixel to pixel. This final choice will permit interesting comparisons with the matched filter detection processes of the next subsection.

3.2 Accuracy versus Computational Efficiency

We know from theory that the Bayesian decision rule of Eq. (1) produces the optimal recognition results of all decision rules; however, at the expense of computational efficiency. To achieve speedup, one must normally sacrifice optimal recognition accuracy. Unfortunately, there is no unifying theory for best trade-off of recognition accuracy and computational efficiency. One must therefore proceed on a case by case basis.

If there were no camouflage in our example, then the matched filter is both optimal and very efficient. Even when not optimal, the matched filter is often a favorite since it is easy to implement, especially via optical processing. Consequently Section 3.5 will show results both for Bayesian and matched filter recognition of camouflaged targets.

3.3 Local versus Global Recognition

It is common practice to conduct target recognition locally at every potential location in the image. If a target is locally recognized one or more times then the image as a whole is said to contain a target. On the other hand, theory underlying Eq. (1) indicates one should make only a single global recognition decision. Thus local recognition is suboptimal. In order to determine the exact recognition loss in our example, results are derived in Section 3.5 for both locally and globally optimal recognition of camouflaged targets.

3.4 Simulation Methodology

The receiver operating curve is the traditional method[1] of determining the performance of recognition systems although it is usually impossible to obtain the curve by analytic methods. As a result, example scenes were simulated and the recognition performances of the Bayesian and alternate recognizers of Subsections 3.2 and 3.3 were empirically determined. 10^4 images per run were used with a target size of 10 pixels to simulate resolution limited imaging. The target was randomly placed within in the image with probability of 0.5 while the horizontal position of the target within the image was made uniformly random over the area of interest. The probability of target pixel camouflage was set at 0.5. To insure good statistical results, a high quality pseudo-random number generator[7] was used throughout the simulation.

3.5 Results

To provide a degree of generalization to the results, the average background and target gray levels are normalized to 0 and 1 respectively. In all results below, the probability of recognizing a target when none is present is denoted P_e and the probability of recognizing a target when it actually is present is given as P_r. Any irregularity within the curves result from the finiteness of the runs.

Fig. 2 quantifies the loss of recognizability caused by the camouflage. In both cases, the recognition is optimal, i.e. Bayesian. Note that when camouflage is not present the Bayesian recognizer is the matched filter. Also as expected given camouflage, recognition is more difficult.

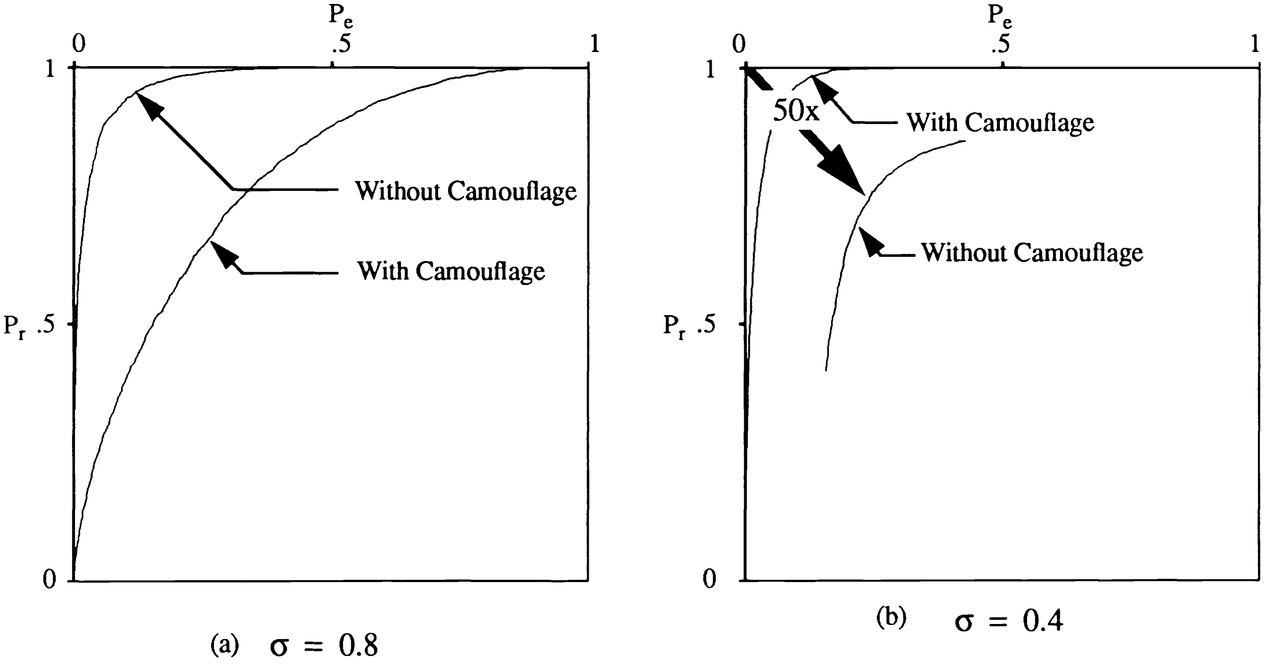
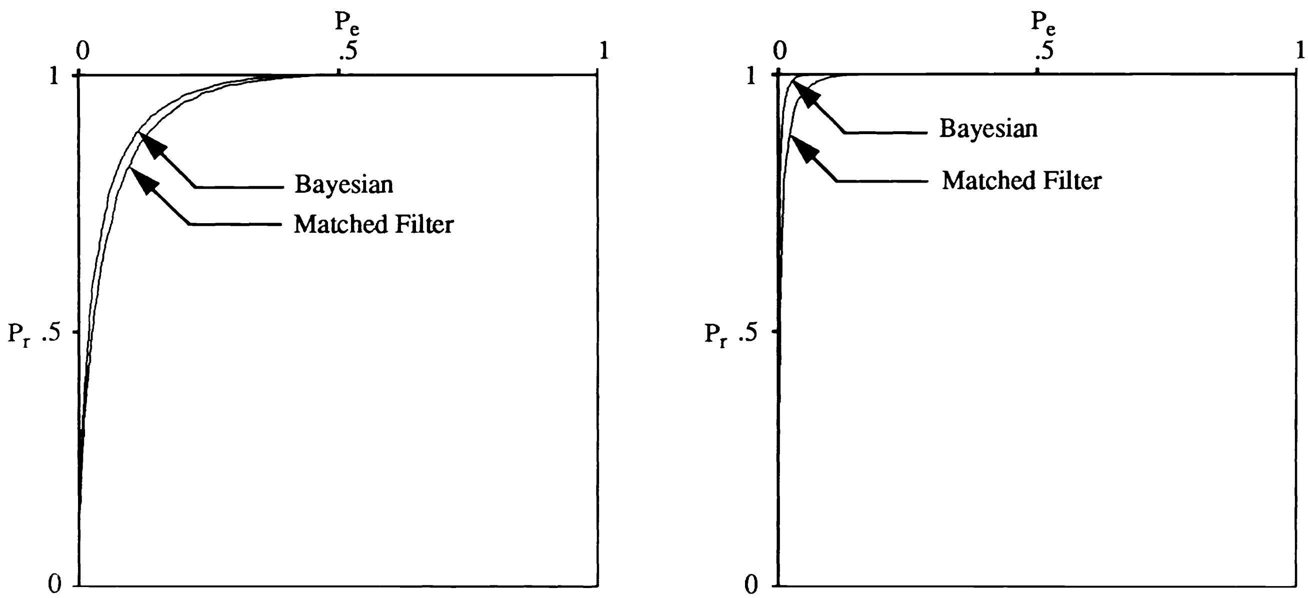


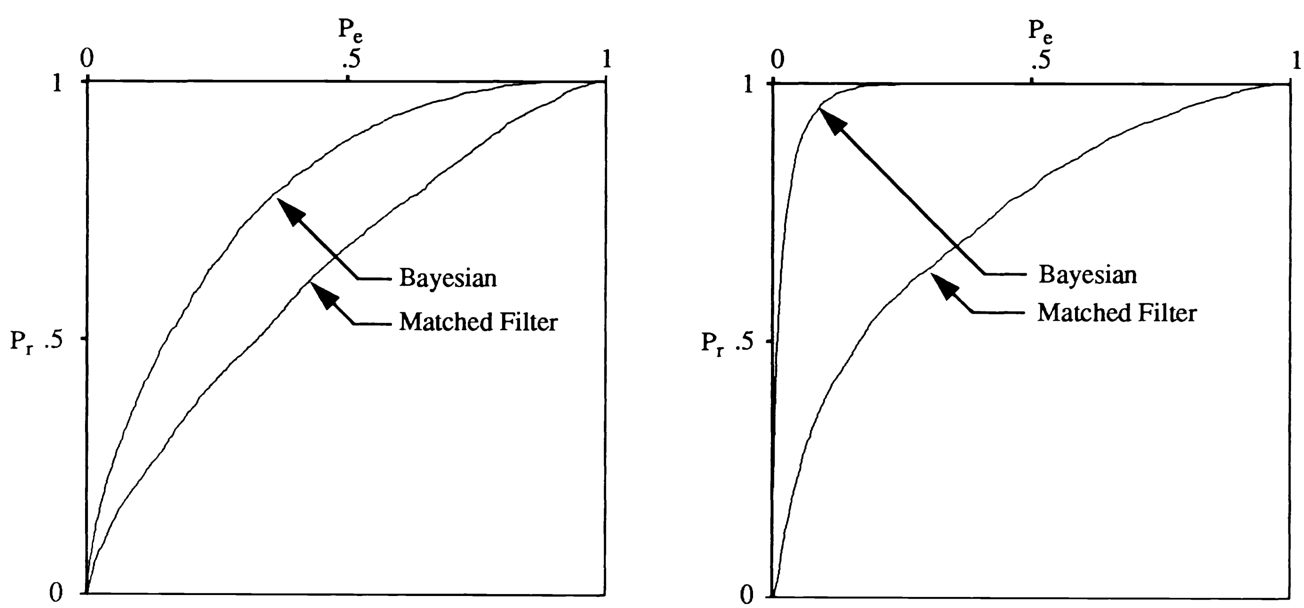
Figure 2. Optimal Recognition With and Without Camouflage

Assuming that the target position is perfectly known, e.g. the recognizer is provided perfect target location information from a target position cuer, then Figure 3. shows representative recognition results. Here the matched filter is no longer quite optimal. On the other hand, it does turns in a respectable performance that approaches optimality. Consequently, its use could be highly attractive as it has a considerable computational advantage over the Bayesian recognizer. Conditions change; however, as the uncertainty of the target position increases, Fig. 4 and 5.



(a) $\sigma = 0.8$ (b) $\sigma = 0.4$

Figure 3. Perfect Target Position Cueing Under Conditions of Camouflage



(a) $\sigma = 0.8$ (b) $\sigma = 0.4$

Figure 4. Target Position to Target Length Uncertainty of 10 Under Conditions of Camouflage

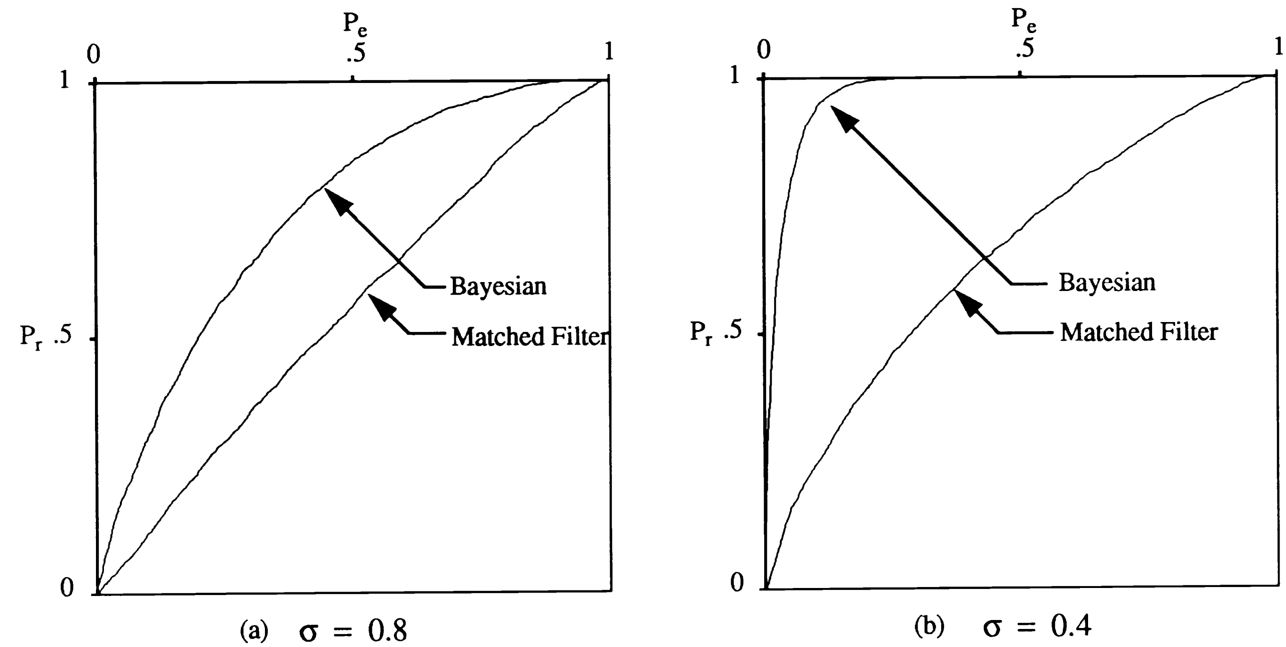


Figure 5. Target Position to Target Length Uncertainty of 20 Under Conditions of Camouflage

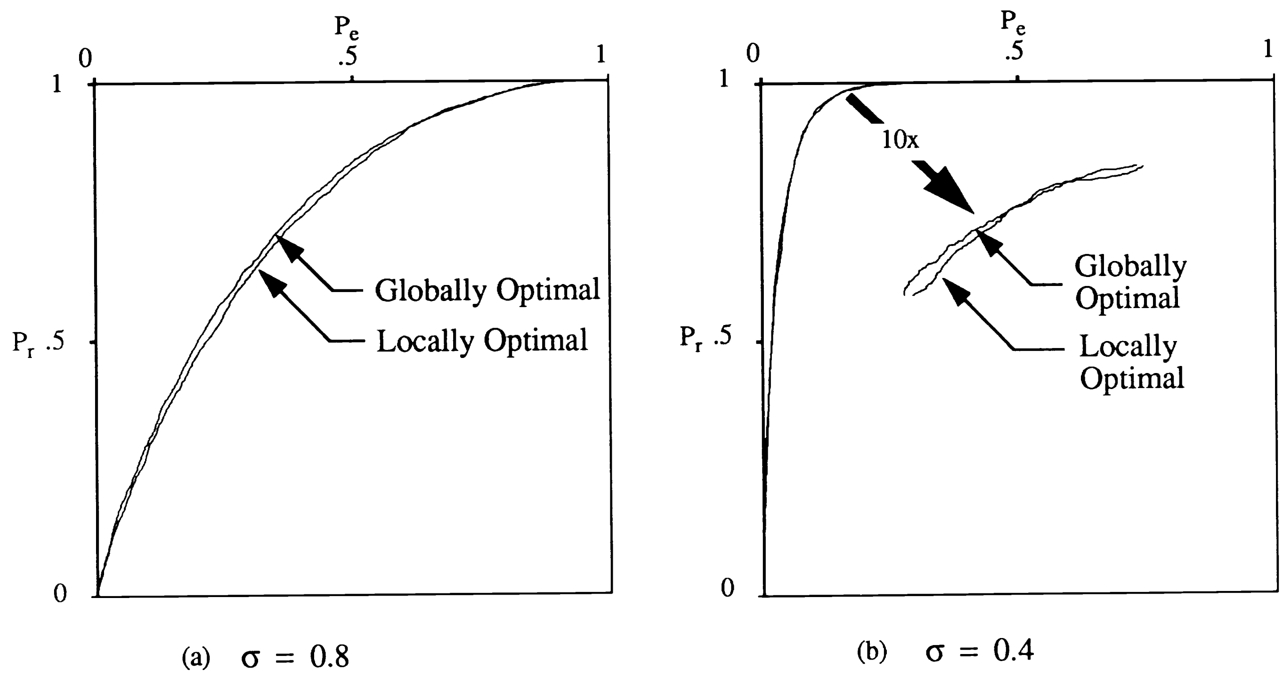


Figure 6. Local Versus Global Optimal Recognition for A Camouflaged Target Position Uncertainty to Length Ratio of 10

Now the matched filter rapidly looses accuracy, becoming little better than chance for the larger target position uncertainties.

Fig. 6 shows the relative behavior of the globally optimal Bayesian recognizer of Section 1.0 versus the locally optimal Bayesian recognizer of Section 3.3. The results provide limited support for the common practice of local target recognition at every potential position within the image. Given the uniform a-priori target position uncertainty of the example, little performance margin is lost compared to advantages gained: determination of target position and ability to recognize multiple targets without incurring increased complexity. Local target recognition techniques should be approached with caution nevertheless as there is little computational advantage. One simply substitutes IFs for ADDs. Further, if the a-priori target position uncertainty strays from uniform, the locally optimal recognition performance will rapidly degrade.

4.0 CONCLUSIONS

Recognition of a camouflaged target is a particularly daunting problem given conventional techniques such as edge detection and feature extraction but becomes practical via proper application of Bayesian techniques.

Results here show that the Bayesian approach becomes virtually mandatory when the position of the camouflaged target is not well known; however, when position is known the simpler matched filter functions almost as well. Locally optimal Bayesian recognition functions essentially as well as globally optimal Bayesian recognition for the case of uniformly target position uncertainty but can not be expected to function well as the target position uncertainty becomes non-uniform.

5.0 REFERENCES

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