Estimating the Length of a Radar Shadow in Shadow-Feature-Enhanced Detection Using a Fuzzy System

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Abstract

Shadow-feature-enhanced radar detection algorithms potentially allow the probability of target detection to be substantially increased when a target casts a radar shadow across a region of clutter beyond it. However, when the length of the radar shadow is not correctly known, much of the potential performance gain may be lost. We demonstrate a method for estimating the length of the radar shadow using a simple fuzzy system. We apply the shadow length estimation to the shadow-feature-enhanced ML-CFAR detector, showing that its performance can be greatly improved when the shadow length is not known *a priori.*

I Introduction

Radar shadows are observed when an object that lies within the main beam of a radar transmitter screens a region of the detection space. Objects lying within the screened region, or *shadow*, reflect no energy back to the radar receiver. When a target screens a region of clutter, such as shown in Fig. 1, the probability of detecting the target may be increased by resolving the lower power returns of the radar shadow from the surrounding higher power clutter returns. Theory and applications of this general concept to enhancing radar detection performance have been discussed in a number of papers [1], [2], [3], [4], [5]: Orlando and Haykin have implemented a system for automatic detection of icebergs from their radar shadows using the Hough transform [1]; more recently, Lombardo et al. have devised a method for target detection in synthetic aperture radar images using shadow information [2]; Khomenko and Zatserklyany have presented a basic concept for detection of ships from their radar shadows [3]; Leung and Minett have developed a method for enhancing the detection performance of the Maximum-Likelihood Constant False Alarm Rate (ML-CFAR) detector [7] based on the shadow information called Shadow-Feature-Enhanced ML-CFAR (SF-ML-CFAR) detection [4], [5].

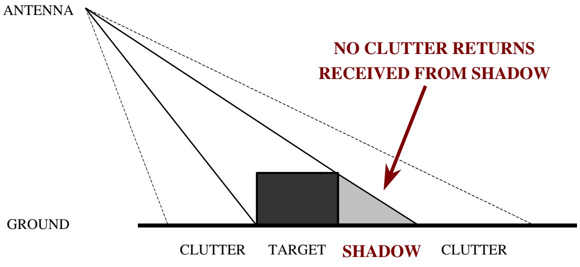

Fig. 1. Radar shadow cast by a target screening a region of clutter.

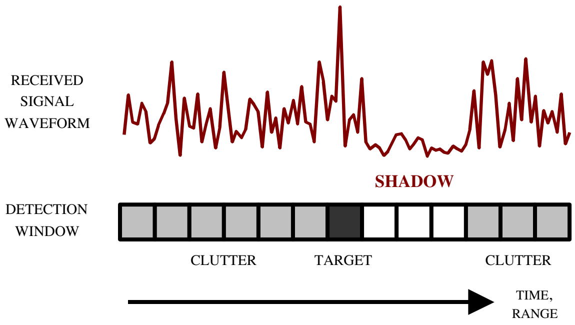

Fig. 2. Simulated signal received from a target and its shadow in homogeneous clutter.

Fig. 2 highlights the basic principal of one dimensional shadow-feature-enhanced detection. When a target casts a radar shadow (which ideally consists of noise only, but more generally also contains some clutter), the signal returns received from the shadow can be readily distinguished from the higher power clutter returns and the presence of the target deduced. The SF-ML-CFAR shadow feature algorithm [5] works on the basis that the expected length of the shadow is known in advance. In theory, the shadow length can be calculated accurately from factors such as the target range, the expected target size, the grazing angle of the antenna, the terrain profile, and by performing ground detection prior to target detection. In practice, however, the actual length of the radar shadow cannot always be determined precisely, leading to reduced detection enhancement, and may need to be estimated.

Section II of this paper summarizes the performance degradation of the SF-ML-CFAR detector under typical operating conditions when the estimated shadow length does not match the actual length of the radar shadow. The resultant reduction in performance motivates our search for an accurate method for shadow length estimation. Section III describes a simple fuzzy system for shadow length estimation. The rule base of the fuzzy system consists of a set of fuzzy rules, one for each possible shadow length, to distinguish the shadow from the neighboring clutter. In Section IV, we analyze the performance of the shadow-feature-enhanced SF-ML-CFAR detector when the radar shadow length is estimated using the fuzzy system presented in Section III. We

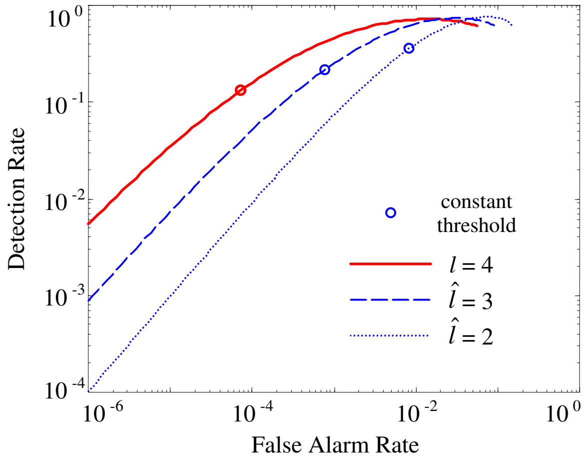

Fig. 3. Performance degradation due to estimated shadow length set too short, $\hat{l} < l = 4$.

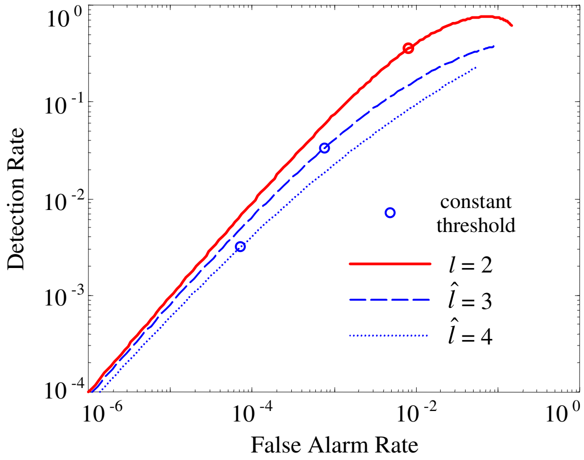

Fig. 4. Performance degradation due to estimated shadow length set too long, $\hat{l} > l = 2$.

go on to show that performance close to the ideal performance when the actual length of the radar shadow is known can be achieved for shadows of length two bins or longer.

II Performance of the SF-ML-CFAR Detector with Incorrect Setting of Shadow Length

In this section, we show how the detection performance of the SF-ML-CFAR detector under typical operating conditions decreases when the estimated shadow length does not match the actual length of the radar shadow. The SF-ML-CFAR detector performs target detection by seeking both high signal returns in the main test bin and low signal returns in each of the bins in which the shadow is expected, immediately beyond the main test bin. A target is detected only when the returns in the main test bin are greater than a certain test bin threshold **and** the returns in each of the shadow bins are lower than a certain shadow bin threshold. More details are given in [5][1].

Shadow feature enhancements are particularly useful at low grazing angles. For example, for flat terrain, a grazing angle of $\tan^{-1}\frac{1}{2}$ ($\approx 26.5^o$) would produce a shadow twice as long as the height of the object casting the shadow. When the cell size is matched to the expected target height, this results in a radar shadow of length 2 bins. Lower grazing angles produce longer shadows. In this paper, we assume that the grazing angle is low ($\leq 30^o$) and so ignore detected shadows of length 1 cell, which may be attributed to weak clutter returns rather than to the shadow feature.

The false alarm rate and detection rate of the SF-ML-CFAR detector for a Swerling 1 target in Rayleigh clutter when the shadow length, l, is known *a priori* are [5]

$$P^F = \left[1 + \frac{\alpha^2}{m}\right]^{-m} \left\{1 - \left[1 + \frac{(k\alpha)^2}{m}\right]^{-m}\right\}^l \tag{1}$$

and

$$\begin{aligned} P^D = {} & \left[1 + \frac{\alpha^2}{m\,(1 + SCNR)}\right]^{-m} \\ & \times \left\{1 - \left[1 + \frac{(k\alpha)^2\, CNR}{m}\right]^{-m}\right\}^l \end{aligned} \tag{2}$$

respectively, where α is the test bin threshold, $k\alpha$ is the shadow bin threshold, m is the number of samples used to estimate the clutter scale parameter, $SCNR$ is the signal-to-clutter-plus-noise ratio, and CNR is the clutter-plus-noise-to-noise ratio.

When the estimated shadow length, $\hat{l}$, is set too short, the only change required in expressions (1) and (2) is to replace the actual shadow length, l, by the estimated shadow length, $\hat{l}$ [6]. For example, Fig. 3 illustrates the effect on performance when an actual shadow length of 4 bins is modeled by an estimated shadow length of 2 or 3 bins ($m = 8$; $k = 1$; $SCNR = 0$dB; $CNR = 10$dB). In each case, the result is a net performance degradation, particularly severe at low false alarm rates. When the estimated shadow length is instead set too long, the expression for the false alarm rate is the same as that when the estimated shadow length is set too short, while the detection rate is instead given by [6]

$$\begin{aligned} P^D = {} & \left[1 + \frac{\alpha^2}{m\,(1 + SCNR)}\right]^{-m} \\ & \times \left\{1 - \left[1 + \frac{(k\alpha)^2\, CNR}{m}\right]^{-m}\right\}^l \\ & \times \left\{1 - \left[1 + \frac{(k\alpha)^2}{m}\right]^{-m}\right\}^{(\hat{l}-l)} \end{aligned} \tag{3}$$

Fig. 4 illustrates the effect on performance when an actual shadow length of 2 bins is modeled by an estimated shadow

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[1] A corrected version of [5] is available from the authors on request.

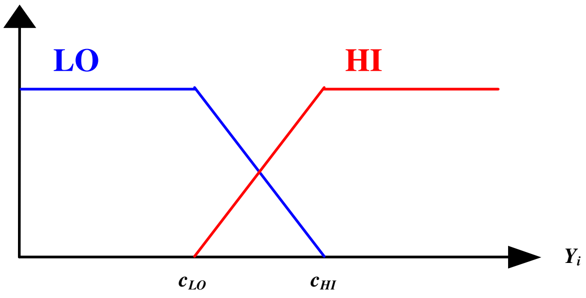

Fig. 5. Membership functions of the input fuzzy sets.

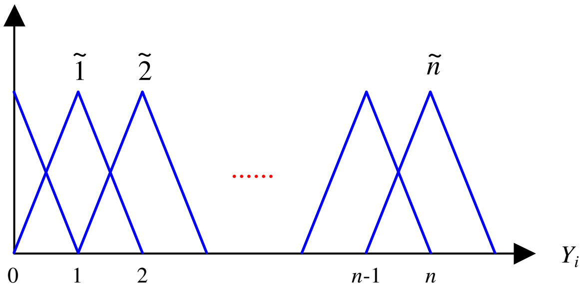

Fig. 6. Membership functions of the output fuzzy sets.

length of 3 or 4 bins. Again, the detection performance decreases, although not particularly so at low false alarm rates. These two sets of results suggest the need to accurately estimate the length of a radar shadow when using the SF-ML-CFAR detector.

III A Simple Fuzzy System for Estimating Radar Shadow Length

We now construct a simple fuzzy system to distinguish higher power clutter returns from lower power noise (shadow) returns, and thereby estimate the length of a radar shadow. We quantize the signal returns, Y_i, in the bins beyond the test bin to just two input states, LO and HI, whose membership functions are shown in Fig. 5. The constants C_{LO} and C_{HI} can be used to tune the fuzzy system based on the relative power of the noise and clutter; in our experiments, we set C_{LO} to zero and C_{HI} to the maximum-likelihood estimate of the clutter scale parameter (assuming Rayleigh clutter). We also quantize the estimated shadow length, $\hat{l}$, to $n+1$ output states $\tilde{j} = \tilde{0} \ldots \tilde{n}$, where $\tilde{j}$ is a fuzzy number, "roughly j", with membership function as shown in Fig. 6, and n is some application-specific maximum shadow length, e.g. $n = m$. We have chosen to model the shadow length using fuzzy numbers rather than crisp numbers because the length of an actual radar shadow may not correspond to an integral number of bins, making an integral representation of its length imprecise.

We define a rule base of fuzzy inference rules,

$$\begin{aligned}
\text{R0}: \ & \text{IF}\,(Y_1 = \text{HI}) \ \text{AND} \ (Y_2 = \text{HI}) \ldots \\
& \quad \text{AND} \ (Y_n = \text{HI}) \quad \text{THEN} \quad (\hat{l} = \tilde{0}), \\
\text{R1}: \ & \text{IF}\,(Y_1 = \text{LO}) \ \text{AND} \ (Y_2 = \text{HI}) \ldots \\
& \quad \text{AND} \ (Y_n = \text{HI}) \quad \text{THEN} \quad (\hat{l} = \tilde{1}), \\
& \quad \vdots \\
\text{R}n\text{:} \ & \text{IF}\,(Y_1 = \text{LO}) \ \text{AND} \ (Y_2 = \text{LO}) \ldots \\
& \quad \text{AND} \ (Y_n = \text{LO}) \quad \text{THEN} \quad (\hat{l} = \tilde{n}),
\end{aligned}$$

allowing us to recover an estimate for the shadow length using sup-min composition and centroid defuzzification.

We have found that another method for estimating the length of the radar shadow, using maximum-likelihood estimation, produces results barely distinguishable from those for the fuzzy system described here; we shall not discuss this alternative method further.

IV Application to Shadow-Feature-Enhanced Detection

We now apply the fuzzy system described above to estimate the shadow length for a Swerling 1 target in Rayleigh clutter with SF-ML-CFAR detection. The combined shadow length estimation/SF-ML-CFAR detection system has the structure shown in Fig. 7. The detection window receives data for a particular observation from the receiver. The shadow length estimation system begins by processing the clutter bin data to estimate the clutter scale parameter using maximum-likelihood estimation; we assume the clutter to be Rayleigh distributed. The input fuzzy sets of the fuzzy system are then tuned; we set C_{LO} to zero and C_{HI} to the estimate of the clutter scale parameter, although other settings may also be appropriate. The shadow bin data is then passed to the fuzzy system for estimation of the radar shadow length. Next, the test bin threshold, α, is recovered by specifying a nominal false alarm rate and solving (1) with l set to the estimated shadow length, $\hat{l}$. This threshold is then used to implement the decision rules in the main test bin and each of the shadow bins. Recall from Section II that a target is only detected when the returns in the main test bin are greater than the test bin threshold, α, and the returns in each of the shadow bins are lower than the shadow bin threshold, $k\alpha$.

In order to determine the detection performance of the combined estimation/detection system, we have run Monte-Carlo simulations at nominal false alarm rates 10^0, $10^{-1} \ldots 10^{-7}$, with up to four million iterations per point. Figs. 8 & 9 show the results of these simulations for actual shadow lengths $l = 4$ and $l = 2$, respectively, for parameter values $m = 8$, $k = 1$, $SCNR = 0$dB, and $CNR = 10$dB. Fig. 8 confirms that the performance of the SF-ML-CFAR detector with shadow length estimation is very close that of the basic SF-ML-CFAR detection performance with known shadow length ($l = 4$) and far exceeds that of the ML-CFAR detector. Just as importantly, by comparing Fig. 8 to Fig. 3, we observe that its performance exceeds that of the basic SF-ML-CFAR detector with shadow length incorrectly set too short. Comparing Figs. 9 & 4 indicates that its perfor-

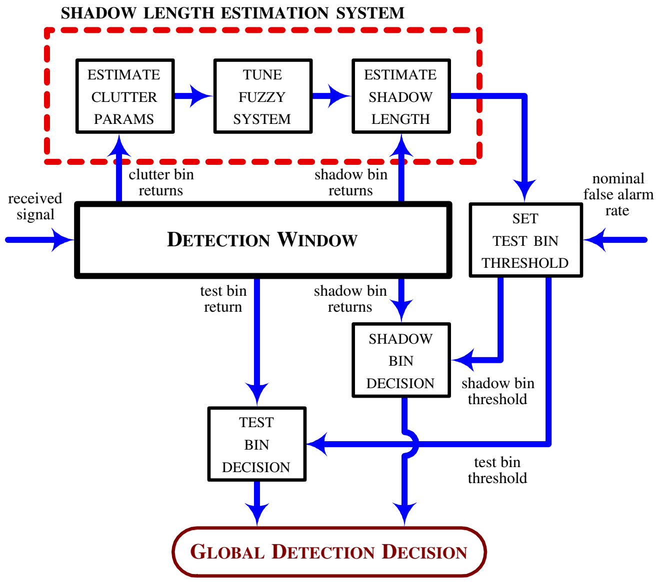

Fig. 7. Structure of the combined shadow length estimation/SF-ML-CFAR detection system.

mance also exceeds that of the basic SF-ML-CFAR detector when the shadow length is incorrectly set too long.

V Conclusion

In this paper, we have presented a fuzzy system for estimating the length of a radar shadow, having described how the performance of the basic shadow-feature-enhanced ML-CFAR detector degrades when the radar shadow length is not known. By combining shadow length estimation with SF-ML-CFAR detection, the detector can attain performance close to the optimal performance when the shadow length is known *a priori*. Furthermore, the shadow-length-estimation system is able to compensate for the lack of *a priori* knowledge of the shadow length to provide performance exceeding that of the basic SF-ML-CFAR detector when the shadow length is set incorrectly.

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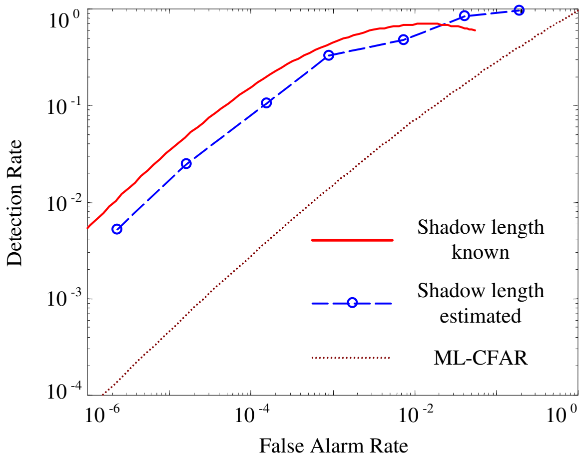

Fig. 8. Receiver operating characteristics of the SF-ML-CFAR detector with and without shadow length estimation, actual shadow length $l = 4$.

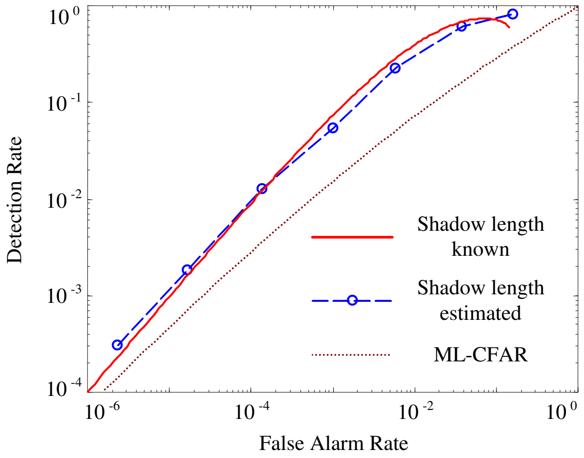

Fig. 9. Receiver operating characteristics of the SF-ML-CFAR detector with and without shadow length estimation, actual shadow length $l = 2$.

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