Target Prescreening Based on 2D Gamma Kernels

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Abstract

This work develops and tests a new target prescreening algorithm based on 2D gamma kernels. The key feature of the new kernel set is the existence of a free parameter that determines the size of its region of support. We show that the scale affects the false alarm rate of the two parameter CFAR test. We also show that a linear discriminant function composed from the linear and quadratic terms of the intensity in the test cell neighborhood improves the false alarm rate when compared with the two parameter CFAR.

Keywords: gamma kernels, two parameter CFAR, automatic target detection.

Introduction

Conventional automatic target recognition systems utilize a two step approach to classify a target [Novak et al, 1993]. The first step is a detection stage that focuses the attention of the classifier to interesting image areas. Only these areas need to be further analyzed by subsequent algorithms. The advantage of this approach is fundamentally one of implementation. The algorithms for focus of attention require fewer computational resources than high performance pattern recognition methods. So, the focus of attention decreases the overall computational bandwidth requirement of the automatic target recognition (ATR) system. Alternatively, the focus of attention block can be thought of as a data reduction stage. If low power (eventually analog) VLSI implementations are found for the focus of attention, then low cost airborne systems may be deployed, and only the interesting image areas transmitted to ground stations for further processing. Hence the ATR processing will be physically divided into an airborne platform and a ground station. The requirement for focus of attention in these scenarios is one of eliminating as many false alarms as possible for 100% of correct target detection.

This paper introduces a novel target detector that makes maximal use of radial pixel intensity information around a test cell, in a manner similar to the two parameter CFAR (constant false alarm rate) detector [Novak et al, 1993]. We found that the neighborhood used to perform the CFAR test affects performance heavily. We propose a family of functions based on the gamma kernel (which is the integrand of the gamma function from statistics) to implement the new focus of attention block which we called the gamma CFAR (γCFAR). The advantage of this kernel is that it has a free parameter that defines the scale of the neighborhood to compute the estimates of the local intensity and its standard deviation required by the CFAR test. This parameter can be set through adaptation (although at this stage we are scanning for the best value). The quadratic gamma detector (QGD) implements a linear discriminant function of the four quantities (8 parameters) extracted by the gamma kernels, enhancing also the performance of the detection test. The paper presents preliminary comparison results of the algorithm with the two parameter CFAR performed at MIT/Lincoln Labs.

The Gamma Kernel

The gamma kernel was originally developed for time series analysis (Figure 1). The goal was to create a signal processing structure that would have a variable memory depth for a fixed number of stages (taps), unlike the tap delay line [Principe et al, 1993]. These systems are called generalized feedforward structures [Principe et al, 1992]. One such structure can be constructed by cascading first order leaky integrators, all with the same time constant μ. The impulse response from the input to tap k of such a structure is the integrand of the gamma function,

$$g_k(n) = \binom{n-1}{k-1} \mu^k (1-\mu)^{n-k} u(n-k) \qquad (1)$$

so we called this structure the gamma kernel. The gamma kernel may replace the delay kernel in the linear combiner, giving rise to the gamma filter. One of the interesting characteristics of the gamma filter is that the time scale of the tap signals $g_k(t)$ is normalized by the parameter μ, i.e. the time scale of the representations can be controlled by the selection of the parameter μ.

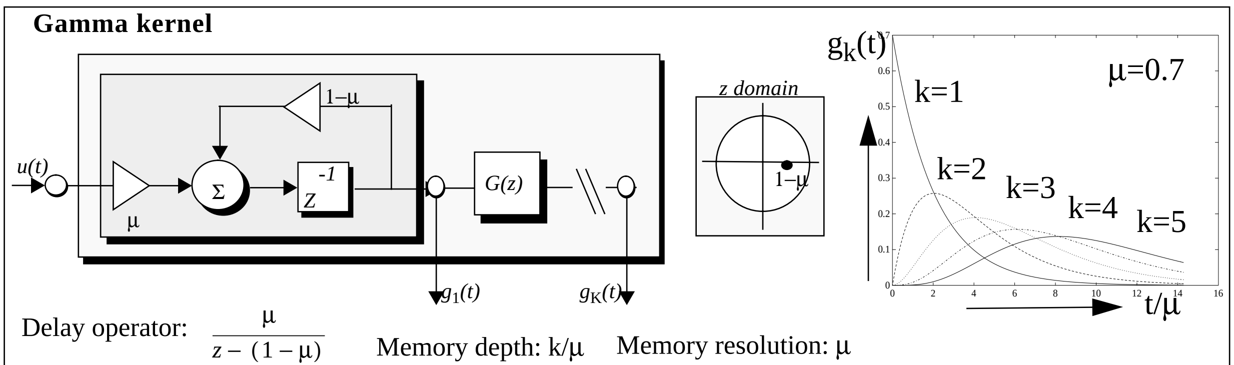

Figure 1. The block diagram, pole plot and impulse response forthe gamma kernel.

The advantage of the gamma filter is that it is IIR (infinite impulse response) but the stability is very easy to control since the feedback is local ($0<\mu<2$). Moreover, the adaptation of the filter parameters follows very closely the adaptation of the adaptive linear combiner as proposed by Wiener [Wiener, 1949]. The time constant of the leaky integrator is an extra parameter that can also be adapted for optimal performance (the optimization becomes a parametric least square [Celebi and Principe, 1995]). In our tests we found that the gamma filter outperformed the linear combiner with the same number of taps. The reason being that the recursive parameter is able to adaptively find in time the local region more relevant for the processing task (we tested this structure for echo cancellation [Palkar and Principe, 1994], time series prediction [Mozer, 1994], and system identification [Motter and Principe, 1994]).

Gamma Kernels for the CFAR test

For image processing the memory depth is equivalent to the spatial scale. So an extension of the gamma kernel to 2D would find the best spatial neighborhood to best meet the processing goals.

This is a very interesting property, mainly for object detection. In order to detect an object in a Synthetic Aperture Radar (SAR) image the known geometric properties of the object should be used only as an indication of the size, because SAR imagery is very different from optical images.

The size of the object is relevant in the construction of the two parameter CFAR detector [Novak et al, 1993] (Figure 2a), because it determines the size of the guardband. Little attention has been given to the width of the neighborhood used to estimate the clutter intensity and power. This is a difficult problem because the width should be as large as possible for statistical significance, but since the image field is nonstationary, if the width is too broad the statistics will be contaminated by irrelevant information for the local test. The gamma kernel can adaptively set both the guardband and the width of the neighborhood as we will explain next.

The analyzing functions to estimate the local mean and variance are 2D radially symmetric functions (the integrand of the gamma function), given by

$$g_{n,\mu}(k,l) = C\left(\sqrt{k^2+l^2}\right)^{n-1} e^{-\mu\sqrt{(k^2+l^2)}}$$
$$\Omega = \{(k,l); -N \le k, l \le N\} \qquad (2)$$

which are a direct extension of the 1D gamma filter [Principe et al, 1993]. Ω is the region of support of the kernel, n the kernel order, and μ the parameter that controls the shape (scale) of the kernel. A kernel of order n will have a peak at the sample n/μ away from the pivot point (0,0). The shape of the 2D gamma kernel is obtained by rotating the curves depicted in Figure 1 around the point (0,0).

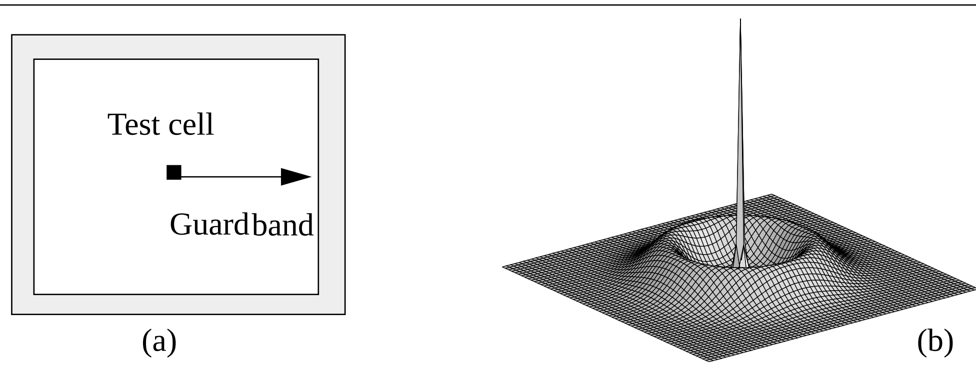

Figure 2. Two parameter CFAR detector stencil (left) and combined gamma kernel

Figure 2b shows the combination of g_1 and g_{15} in 2D. The similarity of this composite stencil to the CFAR stencil is intentional. Note that only two gamma kernels are used. The g_1 kernel will provide measurements of intensity of (and around) the test cell, and g_{15} will measure the intensity in a local neighborhood of the pixel under analysis. The choice of the 15^{th} order kernel was rather arbitrary at this stage of research. Probably better values exist. The CFAR test can be written as

$$x^2_0 - 2x_0\bar{x} + \bar{x}^2 - T^2_{CFAR}\overline{x^2} + T^2_{CFAR}\bar{x}^2 > 0 \qquad (3)$$

where x_0 is the test cell, T_{CFAR} is the threshold for the CFAR test, and $\bar{x}$, $\overline{x^2}$, $\bar{x}^2$ are the estimates for the mean value and power and mean value square measured on the local neighborhood given by the stencil. When we use the gamma kernels, the intensity and the power of the pixel in eqn. 3 get substituted by the output of the g_1 kernel operating on the image and the image squared. Likewise, the values for the $\bar{x}$, $\bar{x^2}$, $\bar{x}^2$ get substituted by the output of the g_{15} kernel operating on the image intensity and intensity squared, as in equation 4

$$(g_1 \bullet x)^2 - 2(g_1 \bullet x)(g_{15} \bullet x) + (g_{15} \bullet x)^2 - T_{CFAR}^2 (g_{15} \bullet x^2) + T_{CFAR}^2 (g_{15} \bullet x)^2 > 0 \quad (4)$$

where • represents the convolution operation. We call the system that implements this test the gamma CFAR detector or γCFAR. Notice that the basic difference between the two parameter CFAR and the γCFAR is in the shape of the stencil used to estimate the local statistics. Note also that the single parameter μ controls the shape of the g_1 and g_{15} stencils.

Effectively the CFAR test is combining partial information of 4 basic quantities computed from the image plane, the intensities $g_1 \bullet x$, $g_{15} \bullet x$ and powers $g_1 \bullet x^2$ and $g_{15} \bullet x^2$. We can utilize all the linear terms and the combined quadratic terms of these measurements (7 terms) plus a bias

$$f_\mu(x) = \begin{bmatrix} g_{1,\mu}x & g_{15,\mu}x & g_{1,\mu}x^2 & g_{15,\mu}x^2 & (g_{1,\mu}x)^2 & (g_{15,\mu}x)^2 & (g_{1,\mu}x)(g_{15,\mu}x) & 1 \end{bmatrix}^T \quad (5)$$

as the elements for a linear discriminant function, i.e.

$$y = w^T \cdot f_\mu(x) \quad \begin{matrix} \geq T & (target) \\ < T & (clutter) \end{matrix} \quad (6)$$

We call this detector the quadratic gamma detector, and it is shown in Figure 3 [Principe et al, 1995]. The QGD differs from the γCFAR detector in that it has more free parameters (8), but the kernels to estimate the local statistics are the same. More parameters normally mean greater discriminant power, but we acknowledge the fact that the constant false alarm rate of the γCFAR is lost in the QGD.

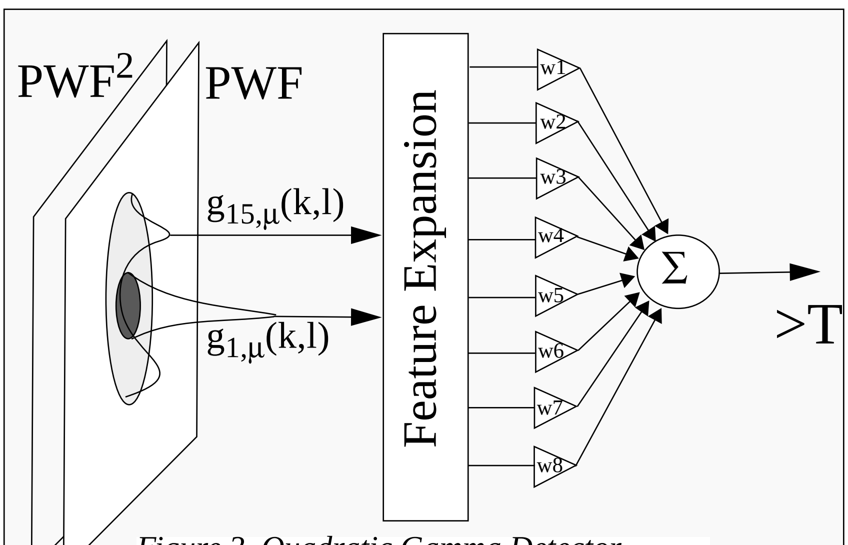

Figure 3. Quadratic Gamma Detector

The importance of the scale parameter μ

Once the order of the gamma kernels is set, the γCFAR detector is dependent only upon the scale parameters μ_1 and μ_{15} for g_1 and for g_{15}. We investigated the importance of the scale parameter in the performance of the γCFAR by scanning in 34 steps the range of possible μ vales for stable kernels (0 to 2) in a SAR data set containing targets and clutter. We used MIT/LL mission 90 full polarimetric 1 foot resolution data, and we embedded targets from TABILS 24 ISAR data. These data sets were taken at similar depression angles and have the same resolution. The embedding was done with the full polarimetric data, and the targets are added coherently. The PWF (polarimetric whitening filter) transformation is applied to the combined data. Although not perfect, this embedding methodology is acceptable to test focus of attention algorithms. We used 100 targets chips and 207 clutter chips, both from natural and cultural clutter (a parking lot in mission 90 data).

We plotted the number of false alarms created by the γCFAR as a function of μ_1 and μ_{15} for 100% detection, by scanning the μ_1 and μ_{15} in 34 steps (indices 1-34). For each value of μ_1 and μ_{15} the target chips provided the minimum threshold T to detect all the targets. With that value the γCFAR was applied to the clutter chips and the number of false alarms counted. Figure 4 shows the results.

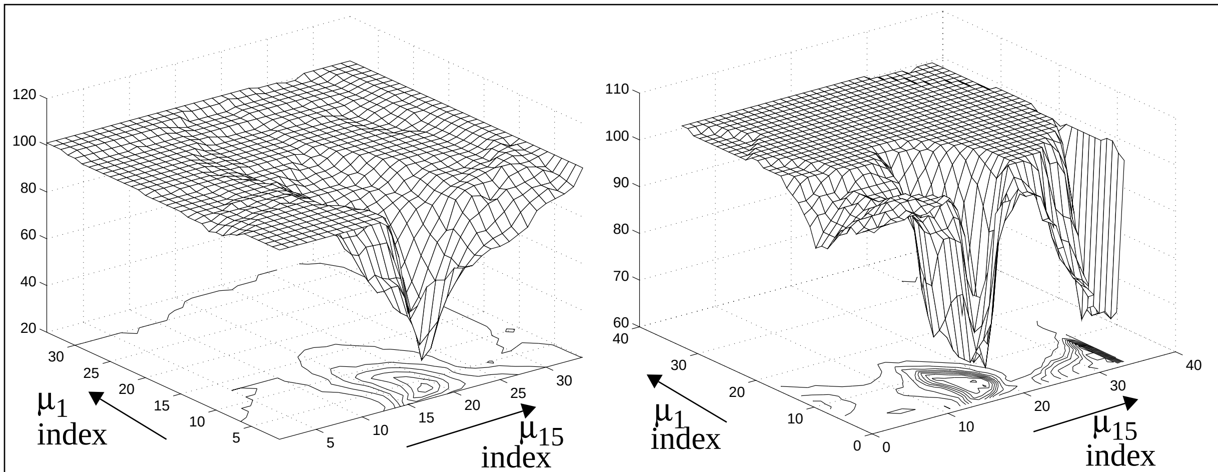

Figure 4. False alarms in natural clutter (left) and cultural clutter (right) as a function of μ_1 and μ_{15}.

What is important to note in this figure is the dramatic dependence of false alarm rate on the shape of the kernels. A small difference in the shape of the kernels makes a big difference in false alarm performance (100 false alarms to 30 in natural clutter). Hence we conclude that a productive way to set the scale parameters μ_1 and μ_{15} is to use adaptation algorithms from adaptive filter theory. Deciding on the shape of the stencil by the geometric characteristics of the vehicles, as done in the two parameter CFAR, will probably give sub optimal performance. This result also shows the advantage of the gamma kernel. Since the 2D kernels are circularly symmetric, a single parameter of the kernel controls the shape. More versatile shapes may perform better, but we have to be prepared for the explosion in the degrees of freedom and the inherent difficulty of setting more parameters.

Another interesting result from Figure 4 is the difference in the shape of the false alarms for natural and cultural clutter. There are more false alarms in cultural clutter than in natural clutter as can be expected, but notice also that for cultural clutter the place in the μ_1 and μ_{15} plane where the minimum occurs differs slightly from the natural clutter. The shape of the false alarm surface is not unimodal for cultural clutter. A second dip appears for large values of μ_1 index that must be further investigated. These results indicate that a different set of parameters may perform optimally for natural and cultural clutter, but further research must be done in this problem.

Adaptation of the QGD parameters

We utilized the least squares method to optimally compute the coefficients of the quadratic gamma detector in a training set [Principe et al, 1995]. Basically we will find the coefficients such that the power of the difference between the system output and a desired response is minimized (L2 norm). The parameter vector for the QGD is given in eqn. 4, and the decision function in eqn. 5. The problem then is one of computing the free parameters w1,...w8 and μ_1 and μ_{15}. The discrimination between the two input classes (targets and clutter) is done by a single threshold T. The weights are computed by solving a least square optimization from N images belonging to the clutter and target classes

$$
\begin{aligned}
F_\mu(X) &= \{f_\mu(x_0),\ldots f_\mu(x_{N-1})\} \\
& \quad w \\
w_{o,\mu} &= (F_\mu^T F_\mu)^{-1} F_\mu^T d
\end{aligned}
\tag{8}
$$

where d is the desired response (0 for clutter or 1 for target). Notice that this is a parametric least square problem, since the solution depends on the parameter μ. At this point in the research, we first selected the best values of μ_1 and μ_{15} by scanning the acceptable range as explained in the previous session. With those values of μ we solved the LS problem, which is over determined for N>8.

Results

A preliminary study of this quadratic gamma detector algorithm was conducted at MIT Lincoln Laboratory under an ARPA contract. The data for this test case consisted of high resolution (1ft x 1ft) fully polarimetric SAR imagery preprocessed using the PWF. The quadratic gamma detector algorithm was trained on two target types using spotlight target data and also man-made discretes from stripmap clutter data. A total of 135 target images (chips) were chosen for training; these were 5 degrees apart in aspect angle (i.e., 5, 10, 15 degrees, etc.). The clutter data used for training consisted of 100 typical man-made discretes. Evaluation of this test case was performed using spotlight target and stripmap clutter data. As in the training stage, spotlight data of two targets that were 5 degrees apart in aspect angle (i.e., 3, 8, 13, 18 degrees, etc.) were used for testing. The test clutter data consisted of 4727 stripmap clutter chips extracted from a total of 56 square Km in area. Thus, the test data set for this experiment was composed of 139 target chips and 4727 clutter chips.

The gamma detector was evaluated by running the data through the CFAR algorithm first (i.e. only over the chips that triggered the CFAR). Then, the ROC curves were obtained by computing the cumulative number of false alarms out of each algorithm. At a probability of detection of 1.0

(Pd = 1.0), the CFAR algorithm detected 139 targets and had 2499 false alarms, whereas the gamma detection algorithm, while also detecting 139 targets, reduced the above-mentioned false alarm number to 483 (see Figure 5).

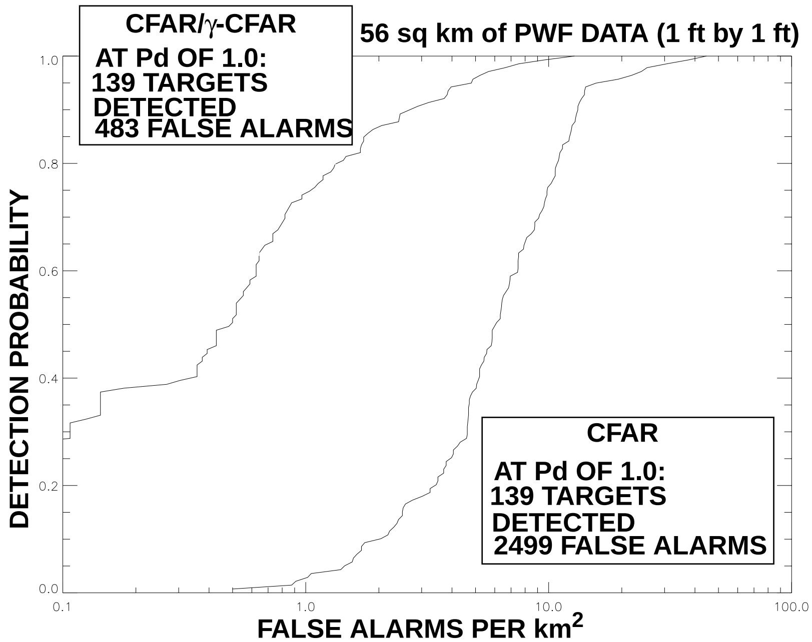

Figure 5. Discriminant performance of the Gamma Detector versus CFAR

These results show that the QGD has improved selectivity over the two parameter CFAR algorithm, i.e. it is able to decrease the false alarm rate of the two parameter CFAR. It will be interesting to find how it performs without the information of the two parameter CFAR (i.e. does it trigger in areas that the two parameter CFAR rejected). Another interesting study will be to substitute the two parameter CFAR by the γCFAR, since the two use the same features. The experience at the Computational NeuroEngineering Laboratory, University of Florida shows that the γCFAR outperforms the two parameter CFAR, but that the QGD is better than the γCFAR, primarily at 100% detection. However, we do not have enough test data to verify categorically these indications.

Some general comments are in order at this point. One of the issues always raised in the application of adaptive algorithms is how well they generalize. An adaptive algorithm uses the information in the training set to compute optimally a set of parameters, but what matters is the performance in test cases. As long as the number of the free parameters in the algorithm is kept small, and the training set is representative of the conditions found in the field, the performance degradation between training and testing can be shown to be small. As we can expect from these considerations, the generalization capability of the QGD algorithm (8 free parameters) is very good. Consequently, in practice the gamma detector can be trained for robust performance. What we gain in an adaptive algorithm is the ability to automatically set parameters tuned to local neighborhoods. As we discussed, it would be impractical to tune by hand the shape of the two parameter CFAR stencil, or the parameters of the QGD for optimal performance. Statistical approaches compute parameters based on global data characteristics that tend to fail in nonstationary environments as SAR image object discrimination/recognition.

An interesting question is what makes the QGD superior to the two parameter CFAR, e.g. the existence of more parameters or the shape of the kernels. Probably both aspects affect the performance, but for a minimal system, one would like to know which impacts more the decrease in false positives. Combined testing of the γCFAR and of the QGD will answer this question.

Presently we are extending the QGD with nonlinear processing units to create effectively a gamma neural network for image data, as extension of the gamma neural model originally developed for time signals [deVries and Principe, 1992]. This was the original idea, but instead of rushing to the final implementation, we carefully studied the different steps of the implementation. The big advantage is that we understand now much better each one of the pieces of the topology, and we have created intermediate benchmarks, that will allow us to quantify the possible improvements brought in by the nonlinearity.

Acknowledgments

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