The 9th IET Data Fusion and Target Tracking Conference

DF&TT 2012

16 – 17 May 2012 | CCT Venues – Smithfield, London, UK

Wednesday 16 May 2012

08:30		**Registration and refreshments**
09:15		**Chairman's welcome** **Simon Maskell,** Technical Manager, Intelligence, Surveillance and Reconnaissance, **QinetiQ**
09:30		**Keynote speaker** **Video analytics past, present, and future…** Dr Colin Lewis, Consultant Science Advisor
10:30	C1	**Commended paper**
		Gaussian mixture PHD filter for multi-target tracking using passive Doppler-only measurements M B Guldogan[1], U Orguner[1], F Gustafsson[1], *[1]Linköping University, Sweden*
11:00		**Refreshments and networking**
		Session 1 Multi-target tracking
11:30	1.1	**Box-particle intensity filter** M. Schikora[1], A. Gning[2], L. Mihaylova[2], D. Cremers[3], W. Koch[1], R. Streit[4], *[1]Fraunhofer FKIE, Germany, [2]Lancaster University, UK [3]Technical University of Munich, Germany, [4]Metron Inc., USA*
12:00	1.2	**A Bayesian look at the optimal track labelling problem** E H Aoki[1], Y Boers[2], L Svensson[3], P Mandal[1], A Bagchi[1], *[1]University of Twente, Netherlands, [2]Thales Nederland B.V., Netherlands, [3]Chalmers University of Technology, Sweden*
12:30		**Lunch**
		Session 2 Multi-sensor tracking
13:30	2.1	**Decentralised road-map assisted ground target tracking using a team of UAVs** H Oh[1], S Kim[1], A Tsourdos[1], B White[1], *[1]Cranfield University, UK*
14:00	2.2	**Track degradation as a consequence of distributed sensor fusion** P F Easthope[1], *[1]L-3 Communications ASA Ltd, UK*
14:30	2.3	**Performance of bearing-only ESM-radar track association** C R Offer[1], *[1]Thales UK, UK*
15:00		**Refreshments and networking**
		Session 3 Video applications
15:30	3.1	**Person tracking via audio and video fusion** E D'Arca[1], N M Robertson[1], J R Hopgood[2], *[1]Heriot Watt University, UK, [2]University of Edinburgh, UK*
16:00		**Close**

Thursday 17 May 2012

08:30		**Arrival refreshments**
09:00		**Keynote speaker** **Geolocation - maps, measurements and methods** Professor Fredrick Gustaffson, Linköping University, Sweden
10:00	C2	**Commended paper**
		Optimized instrumental density for particle filter in Track-Before-Detect A Lepoutre[1], O Rabaste[1], F Le Gland[2], *[1]ONERA, France, [2]INRIA Rennes, France*
10:30		**Refreshments and networking**
		Session 4 Non-linear filters
11:00	4.1	**Bayes optimal knowledge exploitation for target tracking with hard constraints** F Papi[1], M Podt[1], Y Boers[1], G Battistello[2], M Ulmke[2], *[1]ThalesNederland BV, Netherlands [2]Fraunhofer FKIE, Germany*
		Session 5 Learning
11:30	5.1	**Particle learning methods for state and parameter estimation** C J Nemeth[1], P Fearnhead[1], L Mihaylova[1], D Vorley[2], *[1]Lancaster University, UK, [2]MBDA, UK*
12:00	5.2	**An application of sequential Monte Carlo samplers: an alternative to particle filters for non-linear non-Gaussian sequential inference with zero process noise** S Maskell[1], *[1]QinetiQ, UK*
12:30	5.3	**Unsupervised learning of maritime traffic patterns for anomaly detection** M Vespe[1], K Bryan[1], P Braca[1], I Visentini[1], *[1]NATO Undersea Research Centre, Italy*
13:00		**Lunch**
		Session 6 Automotive applications
14:00	6.1	**Tracking and managing real world electric vehicle power usage and supply** G A Hill[1], P T Blythe[1], V Suresh[1], *[1]Newcastle University, UK*
14:30	6.2	**Noise power estimation for generalized detector employment in automotive detection and tracking systems** M S Shbat[1], V Tuzlukov[1], *[1]Kyungpook National University, South Korea*
15.00		**Discussion**
15:30		**Close**

NOISE POWER ESTIMATION UNDER GENERALIZED DETECTOR EMPLOYMENT IN AUTOMOTIVE DETECTION AND TRACKING SYSTEMS

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Keywords: Generalized detector (GD), adaptive detection threshold, noise power estimation, radar sensor, constant false alarm rate (CFAR).

Abstract

The noise power estimation process is a vital factor to adaptively define a threshold of target return signal in radar sensor systems and controller area networks (CAN) that are employed to design safety driving applications, collision avoidance systems, and target vehicle tracking systems. This research derives the required detection threshold under implementation of the generalized detector (GD) in frequency modulation continuous wave (FMCW) radar sensor systems for safety driving and tracking applications, for example, under closing vehicle detection. In this paper we propose an appropriate adaptive noise power estimation technique to define the GD threshold based on locally observed noise samples. The improvement in the detection performance reflects an effectiveness of the proposed solution.

1 Introduction

Employment of radar sensor in safety driving and tracking systems is confirmed to be successful and efficient for large area of applications [2], including an implementation of controller area networks (CANs). The advantages to use the 24 GHz frequency modulation continuous wave (FMCW) radar sensor for vehicle applications such as closing vehicle detection (CVD) and blind spot detection (BSD) are discussed in [1,8]. The generalized detector (GD) is designed based on the generalized approach to signal processing in noise [5]. Engineering interpretation is a combination of the Neyman-Pearson (NP) detector that is optimal under detection of signals with known parameters and the energy detector that is ideal under detection of signals with unknown parameters. Efficiency to use the GD for BSD and VCD systems is discussed in [3,4].

In this paper, the GD flowchart is explained in detail and a suitable threshold under target return signal detection is defined and set to be adaptively changed with on time and locally observed noise samples. An appropriate noise power estimation method is proposed to be used with the derived threshold under target return signal detection. This method depends on adaptive noise power estimation (ANPE) technique which is effective and compatible to be coupled with GD.

In order to evaluate a feasibility to use the GD with the proposed adaptive threshold and noise power estimation technique, the GD detection performance is compared with the cell averaging constant false alarm rate (CA-CFAR) detector one, which is widely used in practice and shows the best detection performance among whole CFAR detector family. Comparative results prove that the GD performance is higher than that of CA-CFAR detector under the same initial conditions. The rest of this paper is organized as follows. The GD flowchart and definition of the detection threshold are introduced in section 2. The noise power estimation technique is discussed in section 3.The simulation results using general analysis are presented in section 4. Some conclusions are presented in section 5.

2 GD flowchart and threshold

2.1 The GD flowchart

The GD flowchart is presented in Fig. 1 [6]. GD is considered as a combination of NP and energy detectors. The additional filter (AF) is the source of reference noise with resonance frequency detuned relatively to the preliminary filter (PF) one. The value of detuning between the AF and PF should be more than 4~5 times the signal bandwidth Δf_a in order to consider the processes at the filter outputs as independent and uncorrelated (the correlation coefficient is not more that 0.05). The model signal generator (MSG) generates the model signal $a^*(t)$ (local oscillator), which in practice is very important to permanently maintain the physical sense of the signal detection algorithm. The relationship between the target return signal $a(t)$ and the model signal can be presented in the following form:

$$a^*(t) = ka(t), \qquad (1)$$

where k is the coefficient of proportionality. The threshold apparatus (THRA) defines the GD threshold. Signal model generator switching apparatus (SGSA) is used to switch on the MSG with the purpose to define the unknown parameters of detected signal. The decision block (DB) with the decision function $\varphi(\alpha)$ defines the decision-making rule under signal detection. The switch K1 takes the position (1) to define the detection threshold, and takes the position (2) after threshold definition. The switch K2 works to put the THRA in and out of service.

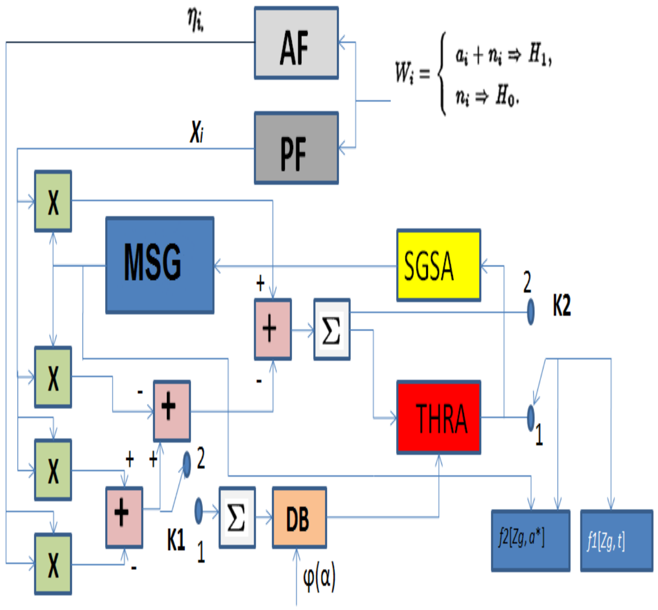

Figure 1: The GD functional diagram.

$X(t)$ is the input stochastic process observed within the limits of the time interval [0,T]. Based on the input stochastic samples ($X_1,...,X_N$) at the PF output, and the observed sample at the AF output ($\eta_1,....,\eta_N$), a general form of the generalized approach (GA) to signal processing in noise can be defined as follows

$$\sum_{i=1}^{N} 2X_i a_i^* - \sum_{i=1}^{N} X_i^2 + \sum_{i=1}^{N} \eta_i^2 \quad \begin{matrix} > K_g \Rightarrow H_1 \\ < K_g \Rightarrow H_0 \end{matrix} \tag{2}$$

In (2), the first term corresponds to the Neyman-Pearson detector twice the gain, and considers as a sufficient statistic for the mean. The second term corresponds to the energy detector connected with the PF, and is considered as a sufficient statistic for definition of variance. The third term corresponds to the energy detector connected with the AF, and K_g is the GD threshold. In the case of hypothesis H_1 when $X_i = a_i + \zeta_i$, the left side of (2) takes the form $\sum_{i=1}^{N} a_i^2 + \sum_{i=1}^{N} \eta_i^2 - \sum_{i=1}^{N} \zeta_i^2$. It is well known that $\sum_{i=1}^{N} a_i^2 = E_a$ is the signal energy, and $\sum_{i=1}^{N} \eta_i^2 - \sum_{i=1}^{N} \zeta_i^2$ is the background noise which is generated by two GD linear systems: AF and PF. The background noise is a difference between the energy characteristics of noise forming at PF and AF outputs. In the opposite case H_0 when $X_i = n_i$, the left side of (2) is the background noise only.

Thus, the received signal and noise can be appeared at the PF output and only the noise is appeared at the AF output. If the Gaussian noise comes in the AF and PF inputs, the noise forming at the AF and PF outputs is Gaussian too, because these two filters are linear systems.

2.2 The GD threshold

The probability of false alarm P_{FA} should be adjusted to provide an acceptable number of false alarms within a given period called the false alarm time T_{FA}. Thus, the P_{FA} can be defined under the hypothesis H_0 in the following simple form:

$$P_{FA} = P(V \geq K_g), \tag{3}$$

where $V = V(t)$ is the noise power defined at a specific time, and $P(V \geq K_g)$ is the probability that the noise power exceeds the GD threshold under the hypothesis H_0. According to the main functioning principles of GA to signal processing in noise, the target return signal must exceed the GD threshold by absolute value before a signal would be recognized. A fixed value of the GD threshold can be used if the noise power at the GD input is constant (the noise variance is constant). Thus, setting the GD threshold by absolute value to be reasonably higher than the background noise power at the GD output may result in the acceptable probability of detection with low false alarm rate. This condition cannot be guaranteed, especially, in the case of unexpected external sources for noise and interference in different radar sensor systems. The main parameters used to determine the GD threshold are the background noise variance (noise power) at the GD output and the P_{FA}.

The perfect knowledge of pdf parameters at the GD output under the hypotheses H_0 and H_1, $p(x;H_0)$ and $p(x;H_1)$, respectively, is required to carry out the likelihood ratio test (LRT), that means the expected target return signal is know under the various hypotheses, as well as the noise variance σ_n^2 (noise power). In practice, the previous assumptions are not true. Based on the degree of knowledge about the noise $n(t)$ where the pdfs that form the likelihood ratio may depend on one or more parameters *z* that are unknown, there are three major cases: 1) the first case when *z* is a random variable with a known pdf; 2) the second case when *z* is a random variable with an unknown pdf; 3) and the third case when *z* is a deterministic variable but unknown. The first case is of interest to define the GD threshold, because the noise pdf at the GD input is known, and the background noise pdf at the GD output can be determined or measured. Under the hypothesis H_0 (no signal), the pdf at the GD output $p(x;H_0)$ (the background noise pdf), when the noise at the GD input $n(t)$ is a narrow-band with Rayleigh amplitude envelope and uniform random phase within the limits of the interval $[0,2\pi]$ process, can be written as:

$$p\ (x;H_0)=\begin{cases}\dfrac{1}{4\sigma_n^2}\exp\left(-\dfrac{|x|}{2\sigma_n^2}\right) & , \quad x\geq 0\\ 0\ , & x<0\end{cases} \tag{4}$$

where σ_n^2 is the noise variance at the GR input. The probability of false alarm P_{FA} can be presented in the following form:

$$P_{FA}=\int_{K_g}^{+\infty}p(x;H_0)dx=\frac{1}{2}\exp\left(-\frac{K_g}{2\sigma_n^2}\right). \tag{5}$$

where K_g is the GR threshold determined as

$$K_g=-2\sigma_n^2\ln 2P_{FA}. \tag{6}$$

If the scaling factor is used, the modified GD threshold is given by:

$$K_g=\sigma_n^2 T, \tag{7}$$

where $T=-2\ln 2P_{FA}$ is the scaling factor or we can write:

$$P_{FA}=\frac{1}{2}\exp\left(-\frac{T}{2}\right). \tag{8}$$

The last equation allows us to determine the probability of false alarm P_{FA} for a given scaling factor T or, more likely, to determine the required value of T for the desired P_{FA}.

3 Adaptive noise power estimation technique

For the white Gaussian noise (WGN), the knowledge of the past samples does not give any information about the other coming samples, and also the power spectral density (PSD) is constant over the entire frequency band. After filtering the WGN (the output of the AF), the PSD will be no longer constant, so the filtered noise is called the colored noise. The average power of colored noise can be estimated by averaging the observed noise peaks. Assume that the noise is nearly white within the limits of the AF frequency band and the observed noise samples obey the Rayleigh distribution:

$$p(x)=\frac{x}{\sigma_n^2}\exp\left(-\frac{x^2}{2\sigma_n^2}\right). \qquad 0\leq x\leq\infty \tag{9}$$

The cumulative distribution function (CDF) is given by

$$F(x)=1-\exp\left(-\frac{x^2}{2\sigma_n^2}\right). \tag{10}$$

The *p*th order percentage, the value of a variable below which a certain percent of observations fall or may be found, can be presented in the following form:

$$x_p=F^{-1}(p)=\beta\sqrt{-2\log(1-p)}, \qquad 0<p<1 \tag{11}$$

where β corresponds to the Rayleigh distribution mode. Thus, $p(\beta)$ gives the pdf maximum. The variance of the Rayleigh random variable x can be defined in the following form:

$$Var(x)=\sigma_n^2=\frac{4-\pi}{2}\beta. \tag{12}$$

Under this noise power estimation technique, the noise samples at the AF output are analyzed within the limits of frequency domain (the discrete Fourier transform DFT is applied). Thus, for each frequency bin k, the noise distribution can be presented by the means of Rayleigh with mode $\beta(k)$ that can be used to define a reference noise level L_σ. The desired noise envelope L_n can be estimated by simple way using L_σ in (11):

$$L_n=L_\sigma\sqrt{-2\log(1-p)}. \tag{13}$$

There is a need to estimate the frequency dependent values of $\beta(k)$. The mean of Rayleigh random variable x is given by

$$E[x]=\beta\sqrt{\pi/2}. \tag{14}$$

Based on (14), it is possible to define the frequency dependent $\beta(k)$ using the noise mean:

$$\beta=\frac{E[x]}{\sqrt{\pi/2}}. \tag{15}$$

The noise mean definition requires sufficient observations for statistical evaluation. More details about this estimation technique (ANPE) can be found in [7].

4 Simulation results

In Fig. 2, the simulation results of the proposed noise power estimation technique (ANPE) are presented when the sampling frequency is 10 KHz and $p=0.8$ that means only 20% of the noise can be misclassified according to Rayleigh distribution.

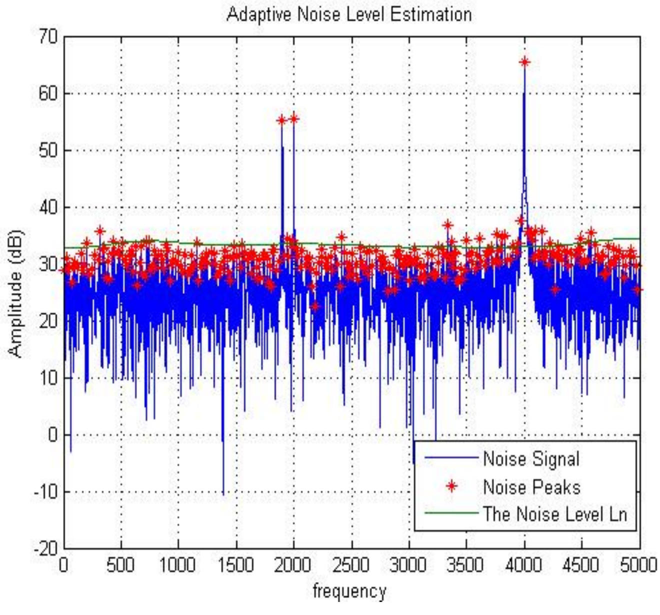

Figure 2: The noise power estimation technique.

As mentioned before, in order to evaluate an improvement in the detection performance, the GD performance is compared with the cell averaging constant false alarm rate (CA-CFAR) detector one under the same initial conditions. The probability of detection P_D is defined as the ratio between the number of observed components that exceed the threshold K_g and the total number of observations *M:*

$$P_D = \frac{K}{M}. \tag{16}$$

These two detectors are compared in the receiver of ultra wide band (UWB) linear FMCW (LFMCW) radar sensor system where the bandwidth $B = 600$ MHz, the operation frequency of the radar sensor $f = 24$ GHz (24 GHz LFMCW radar sensor is widely used for middle range and short range radar MRR/SRR applications), the modulation time is 0.0625 sec which means that the up-sweep time equals to 0.03125 sec. The probability of false alarm P_{FA} is set to be constant and equals to 10^{-3}, the number of reference cells for noise power estimation in CA-CFAR detector is set to be $N = 20$, and finally, the number of observations $M = 1000$. The result of this comparison is shown in Fig. 3, when $P_D = 0.1$ and less that is not acceptable for any kind of applications, or is considered as non operational region, the CA-CFAR detector performance is better, but for $P_D > 0.1$, the GD shows the better detection performance for wide range of SNR values (until $P_D = 0.95$ approximately). For example, at P_D equals to 0.8, the required SNR in the case of CA-CFAR detector is 15 dB, but in the case of GD, it is less than 12.5 dB. For high SNR, both detectors have almost the same detection performance.

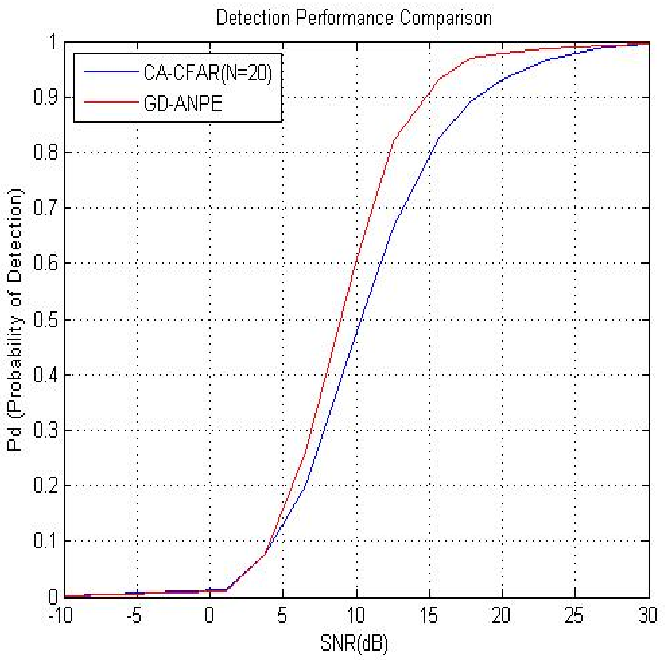

Figure 3: The detection performance comparison.

5 Conclusions

The signal detection techniques have a major problem against the noise power changes (the noise variance in not constant), especially, when the threshold should be adaptively adjusted with the locally and real time observations of the noise samples.

The employment of the proposed noise power level estimation method with the GD to determine the detection threshold demonstrates higher detection performance in terms of probability of detection improvement for the same SNR in comparison with the CA-CFAR detector under the same initial conditions. Further improvement in the detection performance can be achieved in the case of development of better noise estimation technique which leads to smaller estimation error (more accuracy), and helps the GD to increase the probability of detection for large scale of SNR values.

References

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