A New Blind Ultra Wideband Impulse Radar Detector

S. M. Ali Tayaranian Hosseini
Amirkabir University of Technology
Tehran, Iran
ali_th@aut.ac.ir,

Hamidreza Amindavar
Amirkabir University of Technology
Tehran, Iran
hamidami@aut.ac.ir

Abstract— In this paper, we model the received signals in UWB radars as a Fourier series expansion with time varying coefficients to introduce a new MMSE estimator based on the unconditional orthonormal signal representation, moreover, a new method for detection of these signals in presence of (non)-Gaussian additive noise in stationary and moving target scenario is provided. We utilize the discrete prolate spheroidal sequences (DPSS) as unconditional orthonormal signals. Conventional UWB radar detectors use maximum likelihood detection which relies on correlating pair of adjacent segments. Simulations for CFAR detectors are presented to compare the introduced method with conventional UWB radar detectors called interleaved periodic correlation processing (IPCP).

Keywords- MMSE; UWB radar; discrete prolate spheroidal sequesce; IPCP.

I. INTRODUCTION

The application of UWB in radar systems has been introduced in the past several decades. The bandwidth of narrowband signals used in traditional radars is much less than the carrier frequency. Because of the narrowband pulses, they provide low resolution detection, but in today's applications, high resolution radars are required for fine and sensitive surveillance of the environment. The development of application of UWB radars has been surveyed in [1]. On the contrary to a narrowband signal, an ultra-short pulse has no pure sinusoidal waveform, but it is composed of sum sinusoids with different frequencies, hence backscattered signal from a target upon impingement of a real UWB signal has a complex shape in time. The UWB signal parameters, such as duration, number of sinusoids, location, and amplitude of scattered signal are strongly dependent upon the target. Because the signal from target exhibits is stochastic time series, its parameters are unknown. Therefore, blind detection has absorbed the attention of advanced UWB radar designers. A blind detector based on correlation of the received signal in two adjacent periods has been introduced [2] as the IPCP detector. IPCP requires an invariable channel in at least two adjacent periods which occurs in stationary or low speed moving target. Since it is not an easy task to perform matched filtering for high speed moving target models, UWB detectors become more complex in moving target scenario [3, 4]. In synchronized IPCP detector, the integration period in the correlation processing is determined by the observation interval or the scattered signal duration which depends on the target size, hence, the detection threshold depends on the target size. There are some limitations to produce short time pulses ([3], chapter10). Since the Fourier series method for waveform generation overcomes these limitations, UWB radar signals are generated using Fourier series-based waveform paradigm [3]. DPSS sequences are powerful tools to expand low pass signals in terms of orthonormal; their prominent feature is the independency of orthonormal bases from the signal. For example, non-coherent time-varying channel estimation as a recent work is made thanks to use DPSS sequences. This article is based on Fourier series signal generation, it shows that the UWB received signal is an almost periodic signal which can be represented as a Fourier series expansion with time-varying coefficients. Cyclostationary characteristics which appear in this type of waveform are exploited to determine an MSEE to estimate these time-varying coefficients and to provide a blind detector under two hypotheses; in presence of (non)-Gaussian background noise in stationary and moving target. We introduce a new detector that utilizes the unconditional orthonormal basis functions as the matched filters which are based on Discrete Prolate Spheroidal Sequences (DPSS) and are independent of the target and transmitted signal. Since time-varying channel estimation appears in moving target scenario, the proposed detector not only increases performance in stationary target, but also it results in a simpler detector in moving target scenario. On the other hand, there is no distribution constraint in the MSE estimator, therefore, with some reasonable assumptions, detecting signal of interest in presence of non-Gaussian noise and clutter is possible. In this paper non-Gaussian noise is modeled as the Middleton class A noise.

II. SYSTEM MODEL AND PROBLEM FORMULATION

The transmitted signal s1(t) is produced by a summation of finite number of Fourier series components. The required number of transmitting sources to generate a train of short pulses is a function of the pulse duration and the pulse repetition. In this case, the pulse train s1(t) can be represented by a summation of N Fourier components as [3]

$$s_1(t) = \sum_{n=-N/2}^{N/2} c_n e^{j\omega_n t} \tag{1}$$

Where ωn= 2πnf0 and f0 is pulse repetition frequency (PRF). cn are the complex harmonic coefficients, respectively. We assume s1(t) is transmitted as an UWB signal by the array antenna with P radiators which is shown in Fig.1 in a form of current pulse. For this signal, pulse duration in space is cτ (c is the velocity of light, τ is the pulse duration in time domain). If this pulse duration is much less than the linear size of the radiator L, then the pulse undergoes some modification while being transmitted, because the aperture of an array antenna is not simultaneously excited by the travelling current pulse while it moves along the radiator. In this case, a radiator of the antenna which has a length L>>cτ will radiate several pulses of an electromagnetic wave serially. As a result, a single

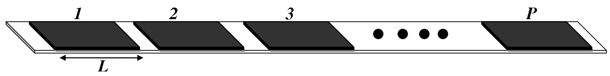

Figure 1. Array antenna with P radiators

pulse transforms into a sequence of K pulses where the time intervals between their radiations are τ_k. Another change occurs due to delay of signal radiated by P radiators of the antenna, in space. For adjacent radiators, this delay is $(d\ /\ c)\ \sin\ (\varphi)$, where d is the spacing between the radiators on the observation angle φ. However, due to anomalies in the propagation path the pulse train $s_2(t)$ which hits the target will be:

$$s_2(t) = \sum_{p=1}^{P}\sum_{k=1}^{K} \frac{ds_1\left(t+\tau_k+\frac{d_p}{c}\sin\phi\right)}{dt} \tag{2}$$

Next, we discuss what target model the transmitted signal is expected to meet.

III. MODEL OF TARGET IN UWB RADAR

We assume that $s_2(t)$ is scattering by the target which consists of M local scattering elements (bright points) located along the line L_t that $c\tau << L_t$ in UWB signal. Such signal reflects from discrete target elements and forms pulse sequence. Number of pulses, time delay τ_m, and intensity of signal depend on target shape and target element impulse response h_m. UWB signal possesses a large bandwidth that causes the radar cross section (RCS) to change significantly. So, in practical applications RCS of the target becomes frequency-depended [6]. The frequency-depended RCS causes that h_m instead of a single path (an attenuation and delay) to act as an FIR filter with complex coefficients with Rayleigh distribution in magnitude and uniform distribution in phase, however, the filter length can be modeled as a discrete Poisson random variable with a given mean. In this scenario, target RCS becomes time-depended magnitude, too, thus, h_m changes during the time [7]. However, assumption of an almost identical h_m for finite number of time pulse repetition intervals will be reasonable, if $2TV_R << c\tau$ (almost stationary target), where V_R is the radial velocity of target. But in moving target (especially in high altitude detection or high speed moving target) $h_m(t)$ will not be almost periodic. The whole signal which is affected by all M bright points presents the time distribution of scattered energy. It is formed during time interval $t_0 = 2L_t\ /\ c$; and so $s_3(t)$ which will be received by receiver antenna is:

$$s_3(t) = \sum_{m=1}^{M}\sum_{p=1}^{P}\sum_{k=1}^{K}\int\left[\frac{ds_1\left(t-\lambda+\tau_k+\frac{d_p}{c}\sin\varphi-\tau_m\right)}{dt} h_m(\lambda-\tau_m)\right]d\lambda \tag{3}$$

As mentioned before if a summation of N Fourier components is transmitted as a UWB signal, the received signal will be a wideband signal which is composed of a sum of non-stationary signals that each signal behaves like a sine wave with particular frequency f_0 or one of its harmonics multiplied by a "smoothly varying" amplitude function. The suitable model for this signal is the summation of N Fourier-series components with time-dependent coefficients.

$$s_3(t) = \sum_{n=-N/2}^{N/2} a_n(t)e^{j\omega_n t} \tag{4}$$

Where the coefficients $a_n(t)$ are band limited signals.

IV. UWB DETECTOR

By sampling the noisy received waveform $r(t) = s_3(t) + \upsilon(t)$ we obtain L samples. Then by f_0 the only known a priori information, we introduce a MMSE estimator to estimate the finite bandwidth signals $a_n(i)$ and then we develop our estimator to detect the presence of a UWB signal. The optimal window which is an index-limited sequence with maximum energy concentration in a finite frequency interval is related to the zeroth discrete prolate spheroidal sequence (DPSS) [8]. Modeling band limited signals as a linear combination of these orthonormal windows is well surveyed in [9]. Since $a_n(i)$ appears as a band limited process in this paper, we use DPSS sequences as the appropriate model for them.

$$a_n(i) = \sum_{m=1}^{\mathrm{M}} c_{mn}\phi_m(i) = \Phi(i)^T\mathbf{C}_n, \quad i{=}0,...,L\text{-}1 \tag{5}$$

$$\Phi(i) = [\phi_1(i)\phi_2(i)...\phi_{\mathrm{M}}(i)]^T$$

$$\mathbf{C}_n = [c_{1n}c_{2n}...c_{\mathrm{M}\,n}]^T$$

where $\{\ \phi_m(i)\ \}_{m=1}^{\mathrm{M}}$ are DPSS orthogonal sequences and C_n are the coefficient vector. The number of expansion functions M ($\mathrm{M} < L$) is frequency dependent and indicates the degree to which $a_n(i)$ varies with time. For small values of M, $a_n(i)$ is slowly varying (low pass process), and for large values of M, it is rapidly varying. Now, we model the received signal

$$r_{\omega_n}(i) \overset{\Delta}{=} a_n(i)e^{j2\pi nf_0 i} \tag{6}$$

Based on the above assumptions for the time-varying amplitude $a_n(i)$ or equation (5), the signal $r_{\omega_n}(i)$ can be expressed in the following vector form

$$\mathbf{r}_{\omega_n} = \mathbf{F}_n\mathbf{C}_n \tag{7}$$

where F_n is a $L\times\mathrm{M}$ matrix with entries

$$f_n(i,m)=\left\{\phi_m(i)e^{j2\pi nf_0 i}\right\},\begin{cases}0\le i\le L-1\\ 1\le m\le \mathrm{M}\end{cases}\tag{8}$$

and

$$\mathbf{r}_{\omega_k}=[r_{\omega_n}(0)\ \ r_{\omega_n}(1)\ \ \cdots\ \ r_{\omega_n}(L-1)]^T$$

and so:

$$\mathbf{r}=\sum_{n=-N/2}^{N/2}\mathbf{r}_{\omega_n}+\upsilon\tag{9}$$

Based on this model, we propose a MMSE estimator of the time varying amplitude $a_n(i)$: Let's consider the following linear estimator for $a_n(i)$:

$$\hat{a}_n(i)=\sum_{l=0}^{L-1}w_n^*(i,l)r(l)=\mathbf{w}_n(i)^H\mathbf{r}\tag{10}$$

where $\mathbf{w}_n(i)$ is a $L\times 1$ vector with weights which have to be determined. By substituting (9) into (10), we write the estimator as:

$$\begin{aligned}\hat{a}_n(i)&=\mathbf{w}_n(i)^H\sum_{n'=-N/2}^{N/2}\mathbf{F}_{n'}\mathbf{C}_{n'}+\mathbf{w}_n(i)^H\upsilon\\ &=\mathbf{w}_n(i)^H\mathbf{F}_n\mathbf{C}_n+\sum_{n'=-N/2,n'\neq n}^{N/2}\mathbf{w}_n(i)^H\mathbf{F}_{n'}\mathbf{C}_{n'}+\mathbf{w}_n(i)^H\upsilon\end{aligned}\tag{11}$$

The equation above shows that each estimate is formed of two components, the first depends on the time-varying amplitude at the frequency of interest nf_0; and the second is an error term which depends on all the other components of $r(i)$ at frequencies different from nf_0 and noise. The optimal estimator must produce the correct time-varying amplitude from the first component and minimize the contribution of the error term. In other words, we need to impose the restrictions that

$$\mathbf{w}_n(i)^H\mathbf{F}_n=\Phi(i)^H\tag{12}$$

Also we minimize the mean-squared error (MSE)

$$\mathrm{MSE}=E\left\{\left|a_n(i)-\hat{a}_n(i)\right|^2\right\}\tag{13}$$

We minimize this error subject to the constraints in (12) using the method of Lagrange multipliers, i.e. we minimize the cost function

$$\begin{aligned}J(i)=&\ \mathbf{w}_n(i)^H\Theta\mathbf{w}_n(i)+\sigma_\upsilon^2\mathbf{w}_n(i)^H\mathbf{w}_n(i)\\ &-\left[\mathbf{w}_n(i)^H\mathbf{F}_n-\Phi(i)^H\right]\lambda\end{aligned}\tag{14}$$

where

$$\Theta=\sum_{n'=-N/2,n'\neq n}^{N/2}\mathbf{F}_{n'}E\left\{\mathbf{C}_{n'}\mathbf{C}_{n'}^H\right\}\mathbf{F}_{n'}^H,\quad \sigma_\upsilon^2\mathbf{I}=E\left\{\upsilon\upsilon^H\right\}\tag{15}$$

and ¸ is a $\mathrm{M}\times 1$ vector of Lagrange multipliers. By setting the derivative of the cost function to zero, we obtain the following minimization conditions

$$\left(2\Theta+2\sigma_\upsilon^2\mathbf{I}\right)\mathbf{w}_n(i)=\lambda\mathbf{F}_n\tag{16}$$

By using the orthonormality of the DPSS functions and the conditions in (12) to solve the equation above for the vector ¸ we have

$$\mathbf{w}_n^{opt}(i)=\mathbf{F}_n\Phi(i)\tag{17}$$

Let's assume Θ = I: Despite the fact this assumption is not realistic, it is actually the most general that one could make about the modeling error in absence of any a priori information about it, by this assumption

$$\mathrm{MMSE}(i)=\left(1+\sigma_\upsilon^2\right)\Phi(i)^T\Phi(i)\tag{18}$$

Which can be shown to simply to $\left(1+\sigma_\upsilon^2\right)\sum_{m=1}^{\mathrm{M}}\left|\phi_m(i)\right|^2$. Although, MMSE seems time dependent in (18), but it is almost constant in practice. Also, MMSE depends on the set of DPSS functions selected can be exploited to obtain M and the number of required samples L: The suitable choice on M can be determined by minimizing MMSE as a function of M in a feedback procedure, in desired times. In Fig.2 MMSE is shown as a function of time for M = 20 and L = 1000. The optimal weights do not depend on the observed data. Therefore, (17) provides a suitable non-

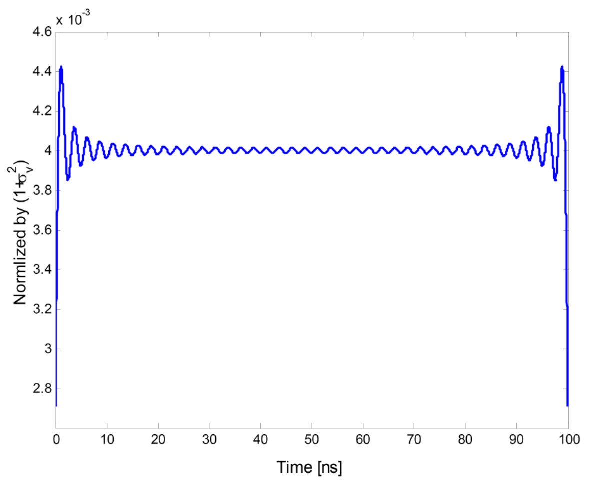

Figure 2. Time-dependent minimum mean-squared error.

coherent estimator in both stationary and moving target scenarios. This estimation approach is not limited by any restrictive assumption on noise and signal distribution, hence, noise suppression seems possible for both Gaussian and non-Gaussian noise.

In this article, the new detector is designed based on a simple scenario which is considered in [10]. According to this scenario under both hypotheses, by assuming that $r(i)$ are independent, identically distributed zero-mean Gaussian random variables, i.e. the worst assumption, the sufficient statistic is

$$l(\mathbf{r})=\sum_{i=0}^{L-1}r^2(i)\tag{19}$$

Based on Parseval's theorem, under H_1, sufficient statistic is equal to:

$$l(\mathbf{a})=\frac{T}{NL}\sum_{n=-N/2}^{N/2}\sum_{i=0}^{L-1}\left|a_n(i)\right|^2\tag{20}$$

If we change sufficient statistic from (19) to (20) we will consider noise suppressed signal under H1, so vast increasing performance appears in detection.

To define a threshold for a given probability of false alarm (P_{fa}), we need to determine an analytical expression for distribution function of $l(\mathbf{a})$ under H_0. Under non-Gaussian noise background and under H_0, $|a_n(i)|^2$ will be correlated random variables with different variances in both n and i, so it is impossible to get an analytical expression which describes distribution function for $l(\mathbf{a})$, even under Gaussian noise, it is rather difficult to define this analytical expression. Although, $|a_n(i)|^2$ are correlated, because of large number of elements in $l(\mathbf{a})$, as Central Limit theorem assumption Gaussian distribution is possible for $l(\mathbf{a})$. $l(\mathbf{a})$ satisfies Kolmogorov-Smirnov test which as a Gaussianity test for 100 normalized sample experiments in Gaussian noise and Middleton Class A noise as a non-Gaussian noise. Fig.3 shows Cumulative distribution function of $l(\mathbf{a})$ in both Gaussian and non-Gaussian noise to compare with a standard normal distribution.

V. Simulation And Result

Computer simulations of Detection characteristics of IPCP for a signal scattered by a stationary target is performed for two strategies 1) when delay and target size are known and 2) when target size is unknown and delay is

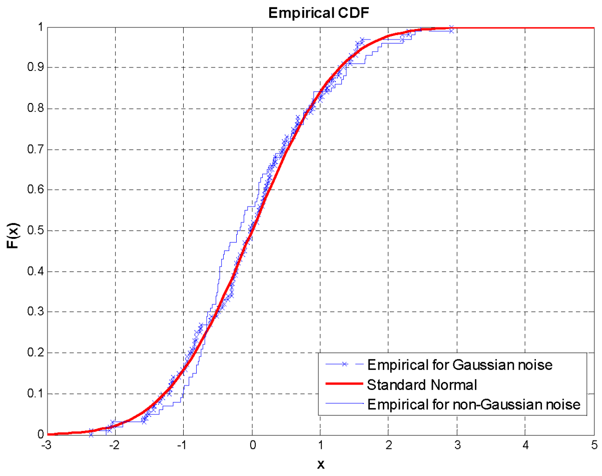

Figure3. Cumulative distribution function for l(a)

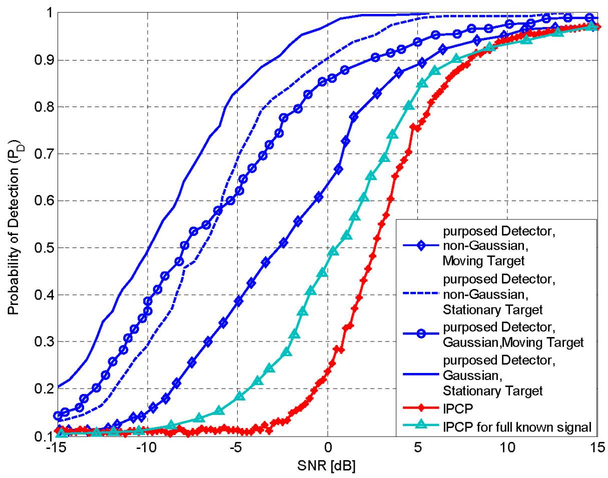

Figure 4. Detection Characteristic

estimated. These strategies are compared with proposed detector for value of false alarm rate 10^{-2} in Fig.4. In this simulation Baseband Barker code of length 11 introduced in [3] is used as transmitted signal and integration period for IPCP is assumed 20τ (τ is pulse length). One can see the effectiveness and the superiority of proposed detector over IPCP even in moving target and non-Gaussian noise. This is expected because of the fact that proposed detector makes a noise-suppression in its non-coherent estimation. Another simulation is proposed to determine the receiver operating characteristic (ROC) curves for the detector for stationary and moving target in both Gaussian and non-Gaussian noise. In both simulations we use just a time interval stationary and M =20 in moving target. The result shown in Fig.5 demonstrates the capability of detector to detect signal of interest (SOI) in moving target and non-Gaussian target detection in low SNR (0dB). Also, we use log scale for the abscissa in Fig.5 to make the curves more readable.

VI. Conclusion

In this paper, Time-dependent FIR filter is introduced as a more realistic assumption for target characteristic for UWB signals in radar. It is shown that an UWB received signal can be represented as a composed of band-limited

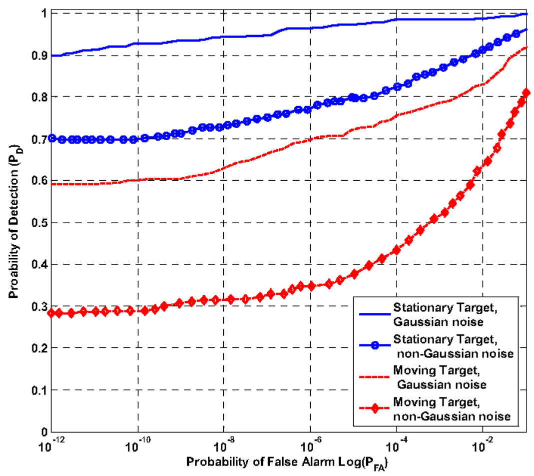

Figure 5. Receiver Operation Characteristic (ROC) in SNR=0dB

signals which DPSS can span perfectly. A non-coherent detector is proposed which exploits DPSS as unconditional orthonormal signals usefully to detect SOI in stationary and moving target. Since there is no assumption in detector for noise and signal distribution, detector appears much versatility in non-Gaussian noise.

References

[1] R. J. Fontana, "Recent advances in ultra wideband radar and ranging systems," IEEE International Conference on Ultra- Wideband (ICUWB), 2007.

[2] I. I. Immoreev, "Detection of UWB signals reflected from complex targets," IEEE Conference on UltraWideband Systems and Technologies, 2002.

[3] J. D. Taylor, "Ultra-wideband radar technology," CRC Press, Boca Raton, FL, 2001.

[4] Wei Guohua, Zhou Yuxiang and Wu Siliang, "Detection and localization of high speed moving targets using a short-range UWB impulse radar," IEEE Radar Conference, 2008.

[5] T. Zemen, C. F. Mecklenbr auker, “Time-variant channel estimation using discrete prolate spheroidal sequences,” *IEEE Tran. On Signal Processing,* vol. 53, Sept. 2005.

[6] I. I. Immoreev, “Ultra wideband radars: Futures and capabilities,” *J. of Communication Technologies and Electronics,* vol. 54, pp. 126, 2009.

[7] Shi-Wei Dong, Wei Ma, Hong-Tai Zhang, Le-De Qiu, “Ultrawideband radar target modeling using triangular patch model,” IEEE Microwaves, Radar and Wireless Communications, 2008.

[8] D. Van De Ville, W. Philips, and I. Lemahieu, “On the n dimensional extension of the discrete prolate spheroidal window,” *IEEE Tran. on Signal Processing Letters,* 2002.

[9] D. Slepian, “Prolate spheroidal wave functions, Fourier analysis, and uncertaintyV: The discrete case,” Bell Syst. Tech. J., vol. 57, no. 5, pp. 13711430, May-Jun. 1978.

[10] H. L. Van Trees, “Detection, estimation, and modulation theory,” Part I, John Wiley and sons, 2001.