Novel System Architecture and Waveform Design for Cognitive Radar Radio Networks

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Abstract

A novel approach for encapsulating communication and radar functionalities in a single waveform design for cognitive radar radio (CRR) networks is proposed. This approach aims at extracting the target parameters from the radar scene, as well as facilitating high data rate communications between CRR nodes by adopting a single waveform optimization solution. Each CRR node encapsulates its communication data into the radar signal such that the radio and radar information is always separable and can be shared over the entire network. Such CRR networks are aimed at addressing the communication and radar detection problems in mission-critical and military applications, where there is a need of integrating the knowledge about the target scene gained from distinct radar entities functioning in tandem with each other. The high spatial resolution capability and immunity to multipath fading make ultra-wideband (UWB) signals an appropriate choice for this CRR application. The proposed solution is achieved by applying the mutual information (MI) based strategy to design the sequence of UWB transmission pulses and embed into them the communication data with the pulse position modulation (PPM) scheme. Simulation results demonstrate a significant improvement in parameter extraction from the radar scene such as the target position and impulse response, while still maintaining high throughput communication links with low bit error probability between the CRR nodes.

Index Terms

Cognitive radar radio (CRR) network, joint communication-radar waveform design, ultra-wideband (UWB), mutual information (MI), target signature extraction

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I. INTRODUCTION

A. Background on Cognitive Radar Waveform Design

Cognitive radar is an innovative paradigm to describe radar systems that constantly employ information gathering mechanisms to adapt their operational modes and facilitate intelligent illumination of the target scene. Subsequently, this updated target scene information can be utilized to allocate crucial resources like transmission power and spectrum in a more efficient manner [1], [2].

In a cognitive radar, the information of the target scene parameters is relayed to the transmitter by the receiver through a continuous feedback loop, which allows the development of waveform design techniques that offer better target resolution capabilities [3]. Excitation pulses can be optimized by application of information theory to radar signal processing. Bell [4] studied the design of waveforms in the context of illumination of extended targets for target detection and information extraction. Yang and Blum [5] extended the work of Bell [4] by using mutual information (MI) as a waveform optimization criterion subject to the limited transmission power in the multiple-input multiple-output (MIMO) radar configuration.

The work in [5] in particular focuses upon the problem of radar waveform design for target classification and identification, where the conditional MI between the random target impulse response and the reflected signals is maximized given the knowledge of the transmitted signals. Another problem that [6] addresses is the design of waveforms based on minimization of mean square error (MMSE) in estimating the target response. Analysis in [6] indicates that the above mentioned two problems lead to the same waveform solution. The work in [3] focuses upon designing ultra-wideband (UWB) transmission waveforms with an aim of minimizing the MI between the received radar pulses at successive instants of time. This is achieved by designing the probing signals that will result in independent responses from the target scene in a bid to gain more knowledge about the changing target parameters at each instant of time.

In this work, we try to develop a novel cognitive architecture for the joint communication-radar waveform design. Before we describe the actual architecture, we provide a general background on the existing proposal of joint communication-radar networks in the next subsection.
B. Background on Joint Communication-Radar Networks

Wireless communications and radar have always been independent research entities in the past. Wireless communications focus upon achieving the best possible information capacity across a noisy wireless channel under power and complexity constraints. On the other hand, radar systems attempt to achieve better target resolution and parameter estimation in the presence of surrounding clutter and noise. In recent years, research into integrating communication and radar systems under a common platform has gained significant momentum [7]–[9]. Such a joint radar and communication system would constitute a unique cost-efficient solution for future intelligent surveillance applications, for which both environmental sensing and establishment of ad hoc communication links is essential. This type of systems can be used in mission-critical and military operations to address the surveillance and communication issues simultaneously [7]. It is thus envisaged that future personal communication devices will have comprehensive radar-like functions such as spectrum sensing and localization, in addition to multi-mode and multi-band communication capability.

Recent works such as [7] and [8] in particular focus upon the development of devices that have multiple radio functions and combine communication and radar in a small portable form with ultra low power consumption. These works have adopted the orthogonal frequency division multiplexing (OFDM) techniques fused with UWB technologies to realize the communication-radar integration. However, these innovative radar radio systems create other implementation issues, such as excessive demand of signal processing power, high speed analog-to-digital circuitry, agile radio frequency front-end for multi-mode operation, etc. Systems, which use UWB-OFDM for localization [7]–[9], utilize the same waveform family for designing joint communication-radar signals. These methods share a common drawback due to the fact that the auto-correlation (related to the range resolution of the radar) of the UWB-OFDM signal depends both on the location of the notch as well as the OFDM signal bandwidth. Hence, it can be seen that although the radar target range estimation is unaffected by the presence of the OFDM signal, its range resolution depends on the notch bandwidth into which the OFDM signal is embedded.

C. Joint Communication-Radar Waveform Design from a Cognitive Radar Radio (CRR) Perspective

The current work aims at jointly addressing the communication and radar problems and makes use of a cognitive waveform selection approach in order to enhance the performance of the CRR nodes.
through more efficient extraction of the target parameters from the radar scene. To achieve this goal, we integrate the above mentioned ideas on cognitive waveform selection presented in [3] and the UWB pulse position modulation (PPM) technique to obtain a unified waveform design solution, which offers a superior radar performance and high data rate communication capability between the CRR nodes. In our method, the radio and radar signals can both mutually coexist by sharing the same frequency band. Hence, the range resolution of the radar is not affected by the communication signal design parameters. This makes the proposed UWB-PPM method superior to the existing methods employing UWB-OFDM solutions. The CRR waveforms obtained would not only benefit from an information-theoretic approach for efficient target parameter extraction but also utilize the same signal for establishing ad hoc communication links by adopting the UWB-PPM transmission strategy.

From a radar perspective, we adopt a multi-path channel model as mentioned in [10] for the proposed CRR waveform design under IEEE 802.15.4 MAC layer as shown in [11]. We assume the target Radar Cross Section (RCS) scintillations along with Additive White Gaussian Noise (AWGN) conditions. The CRR nodes are assumed to be mono-static radar units where the transmitter and receiver subsystems are co-located and hence can access information about the target scene parameters within themselves. We also assume perfect synchronization between CRR nodes in order to address the multi-user interference between different CRR nodes. We have chosen UWB-PPM waveform design solution against the continuous waveforms for the following reasons

- The operational environment is relatively harsh to radio-communications and is subject to scenario and location dependent propagation properties, such as densely cluttered environments. UWB provides a waveform design which is immune to multi-path channel fading.
- UWB-PPM waveform design is robust to hostile environments providing Low Probability of Interception (LPI) waveforms and can avoid jamming interference.
- UWB-PPM provides for rapid low transmission power ad hoc networks which can be configured “on the fly” without reserving or contending of spectrum assignment.

The above benefits offered by UWB-PPM make it suitable for the proposed waveform design problem. The key contributions of this work are as follows:

- Developing a cognitive radar model based on the concept of MI minimization between successive backscattered radar pulses for extraction of target parameters like relative distance from a CRR node, target impulse response and velocity;
• UWB-PPM based joint communication-radar waveform design; and
• Performance analysis of the CRR network in terms of the target parameter extraction and communication bit error rate (BER) between CRR nodes.

The rest of the paper is organized as follows. In Section II, we present the system architecture for the radar scene and the radio network under consideration. In Section III, we analyze the performance of the communication link achieved through the CRR waveform. In Section IV, we describe the MI based cognitive waveform selection approach. In Section V, we present simulation results for target impulse response extraction, MI based waveform optimization results, and BER performance achieved by the proposed scheme compared to other works in this area. Finally, some concluding remarks are drawn in Section VI. Throughout this paper, we use \(| \cdot |\) to represent the determinant of a matrix, \((\cdot)^T\) to indicate the Hermitian transpose, and \(E(\cdot)\) to represent the expectation operator.

II. System Architecture

As discussed extensively in the existing literature, modern radar systems make use of pulse compression techniques such as linear frequency modulation or phase-coded waveforms employing Barker codes or Costas codes in order to improve the target delay-Doppler resolution [12]. In this work, we adopt the idea of utilizing phase-coded waveforms for generation of orthogonal sequences required for transmission over various transmitting antennas. We will consider UWB probing signals [2], though the general methodology is also applicable to any other type of excitation. The waveform comprises a sequence of UWB Gaussian pulses in which the phase of each pulse is modulated in accordance with the orthogonal sequences corresponding to the column vectors of a Walsh-Hadamard matrix [12]. Each normalized Gaussian pulse takes the following form

\[
u(t) = \frac{1}{\sqrt{2\pi T}} \exp \left(-\frac{t^2}{T^2}\right)
\]  

where \(T\) determines the pulse width and is assumed to be 0.2 ns, which is a typical value commonly used in UWB ranging applications [12].

A. CRR Network Setup

Fig. 1(a) exemplifies a typical CRR network comprising distinct CRR nodes capable of maintaining communication links between themselves, gathering data on the radar scene from sensors (suppose that the targets also induce a certain event observable at the sensors), and maintaining active probing of the
target scene through the backscattered radar signals. The communication and radar functionalities occur simultaneously, where the CRR signal is used for communications between CRR nodes as well as range and target impulse response estimation. The individual radar nodes are required to intelligently select effective surveillance mechanisms while maintaining the ability to communicate critical information via an ad hoc network between themselves to share radar scene information. The CRR units can also gather intelligence on a specific phenomenon-of-interest like radioactivity or biohazard induced by the targets, through communicating to remote sensors. Fig. 1(a) represents such a setup in which this joint communication-radar operations could be realized.

B. CRR Node Transmitter Subsystem

Fig. 1(b) presents the internal architecture of a single CRR node. We initially construct an ensemble of orthogonal sequences of UWB Gaussian pulses based upon the Walsh-Hadamard codes. Each sequence corresponds to a particular column vector of a Walsh-Hadamard matrix as illustrated in Fig. 2(a). All the column vectors of the ensemble matrix undergo PPM in accordance with the communication data to be sent over the CRR link as shown in Fig. 2(a). The PPM does not affect the orthogonality of the distinct waveforms as demonstrated in [13], which will also be discussed in further detail in Section III and verified in the subsequent simulation results. The data link could be established between two CRR nodes or between a CRR node and a remote sensor monitoring the phenomenon-of-interest. In order to facilitate identification, the unique addresses of the source and the destination are embedded in the preamble of the data to be sent. An UWB-PPM signal is selected by the waveform selection module from the ensemble based on the MI minimization algorithm as to be described in Section IV. This integrated signal is then sent by the transmitter to probe the radar radio environment. The received signal comprises both the target return and the communication data from other CRR nodes and the sensors. Eventually, the former can be used to estimate the target parameters like range, velocity, and impulse response.

C. Target Channel Model

We now consider a CRR node with the same antenna used for both transmission and reception purposes. Let $x$ represent a particular sequence of orthogonal waveforms to be used for transmission. Let $n$ represent the colored noise. By colored noise we mean the combination of additive white Gaussian noise (AWGN), backscattering from non-target scattering centers, and also the interference...
caused by the simultaneous operation of multiple CRR nodes. It is assumed that the length of the UWB radar pulse sequence is greater than or equal to the frame length of data to be transmitted. As shown in [13] and verified by our simulation results to be discussed later, PPM does not affect the orthogonality between various CRR waveforms. Thus we can safely design and optimize radar excitations with or without PPM.

We can express the received signal for the antenna element as

$$y = Hx + n$$

(2)

The variable $x \in \mathbb{C}^{K \times 1}$ denotes the transmitted signal vector with $K$ being the length of the UWB radar sequence, $y \in \mathbb{C}^{K \times 1}$ denotes the received signal vector, $H \in \mathbb{C}^{K \times K}$ denotes the target channel impulse response comprising the combined response of the transmitter-to-target, target itself, and target-to-receiver channels, and $n \in \mathbb{C}^{K \times 1}$ denotes the noise vector. $\mathbb{C}$ represents the complex number domain. We further define $E(H^TH) = R_H$ to be the target channel covariance matrix and $E(n^Tn) = R_n$ to be the noise variance. The channel response matrix $H$ is comprised of target and clutter sources and does not include the other CRR nodes. We have assumed that the scatterer RCS fluctuates and produces uncorrelated back-scattered signal from scan to scan under the Swerling III assumption. This assumption captures the dynamic variations in the channel response $H$ for a mobile target.

RCS scintillation of the target can vary slowly or rapidly depending on the target size, shape, dynamics, and its relative motion with respect to the radar. Thus, due to the wide variety of RCS scintillation sources, changes in the RCS are modeled statistically as random processes. We consider the target as a dominant scatterer amidst several clutter sources. Depending upon the motion and clutter characteristics, the radar targets have been classified into Swerling models as found in [14]. In Swerling III, the RCS samples measured by the radar are correlated throughout an entire scan but are uncorrelated from scan to scan (slow fluctuation), and the radar scene is dominated by a single powerful scatterer and many weak scatterers in its vicinity. This model will be considered in the current work. The entries of $H$ in (2) associated with the target response contain the RCS of the desired target and are approximated by the Swerling III variations (see also [15] and [14]):

$$f(\xi) = \frac{1}{\xi_{av}} \exp\left(-\frac{\xi}{\xi_{av}}\right)$$

(3)

where $\xi > 0$ represents the random RCS fluctuation with $\xi_{av}$ being the average RCS. All the other
entries of $H$ denote the RCS of clutter sources and are assumed to be stationary. Hence, for a Swerling III model, we would expect the target echoes due to successive scans to be uncorrelated. Towards this end, we seek to use excitation sequences that will produce uncorrelated returns at two consecutive time instants.

D. CRR Node Receiver Subsystem

The reflected signal is gathered by the receive antenna and passed on to a matched filter bank as illustrated in Fig. 1(b), which matches the received signal to each individual transmission waveform stored in the receiver. At this stage, the radio signal that exists in the form of the UWB-PPM data is extracted by removing the excess delays between UWB pulses through demodulation. Once the radio signal is removed, the remaining waveform is treated purely as the radar backscatter. The target impulse response and parameter estimation module then attempts to discriminate the target from the surrounding clutter.

The estimated channel response and received signal characteristics such as noise variance are forwarded to the MI minimization module. In the light of the updated radar scene, the MI minimization module selects a suitable sequence for the transmitting antenna in order to acquire the best knowledge about the target in the next time instant. This operation facilitates adaptive illumination of the radar environment and essentially leads to a cognitive dynamic system featuring the following two properties described in [1]: (i) intelligent signal processing, which builds on real-time learning through continuous interaction of the radar with the surroundings; and (ii) feedback from the receiver to the transmitter, which is a facilitator of intelligence.

In summary, the CRR waveform design approach involves the following two steps:

- Step I: Designing of the UWB-PPM waveforms in accordance with the communication data to be sent with an appropriate selection of the PPM delay (Section III); and
- Step II: Waveform selection based on the MI minimization approach to facilitate more effective target signature extraction (Section IV).

III. Step I: UWB-PPM Waveform Design

In this section, we focus upon constructing the CRR waveforms by introducing PPM to the column vectors of the Walsh-Hadamard matrix, which is in accordance with the data to be transmitted, thus forming an ensemble $S$. As to be seen from the simulation results, this introduction of excess delays
into the radar pulses contained in \( S \) does not affect the orthogonality between various CRR waveforms. The communication source and destination identities are embedded in the preamble of the data frame. It is assumed that the data frame length is less than or equal to the length of the probing signal (i.e., length of the column vector of the Walsh-Hadamard matrix).

Fig. 2(a) demonstrates the proposed UWB-PPM scheme for a 16-bit data frame, where the polarity and the delay of the UWB pulses are determined by the column vector of the Walsh-Hadamard code and the PPM data, respectively. Fig. 2(b) represents the auto- and cross-correlation between CRR signals. The former exhibits a sharp peak at the zero delay, whereas the latter gives rise to much smaller values throughout the entire range of delay samples. This observation verifies the orthogonality between distinct CRR signals even after the PPM operation. In this way, different CRR nodes can share the same spectral resources simultaneously as long as they use different column vectors to design their waveforms. Fig. 2(c) indicates the spectrum of an arbitrarily selected CRR signal \( y_t \) received at a reference distance of 20 m from the transmitting node operating at 4 GHz. The transmission power complies with the regulations set by the FCC mask for UWB wireless devices transmitting in outdoors and indoors, which is at \(-41.3 \, \text{dBm/MHz}\) in the frequency range 3.6 – 10.1 GHz [16]. The width of each pulse in the CRR signal is assumed to be 0.2 ns.

A. PPM Delay Selection in CRR Waveforms

Performance of UWB-PPM communications in terms of the BER and the throughput has been well investigated in the literature. Some of the recent works include [17]–[19]. In these works, the time hopping scheme for UWB-PPM has been analyzed. UWB communications offer high data rates for communications and good immunity from multipath fading over short ranges.

In this paper, we use a simple UWB-PPM scheme, where we design the PPM delay used for sending ‘1’ or ‘0’ such that the BER on the communication link is significantly reduced. As mentioned in [20] and [21], if the transmitted pulse is Gaussian UWB signal, then the Euclidean distance defined for the separation between two radar pulses for transmitting ‘1’ and ‘0’ is given by

\[
d(\zeta) = \sqrt{1 - \left\{ 1 - 4\pi \left( \frac{\zeta}{T} \right)^2 + \frac{4\pi^2}{3} \left( \frac{\zeta}{T} \right)^4 \right\} \exp \left[ -\pi \left( \frac{\zeta}{T} \right)^2 \right]}
\]

(4)

where \( \zeta \) is the PPM delay to be designed and \( d(\zeta) \) represents the Euclidean distance between the PPM symbols. As shown in [20], the best signal design is the one that maximizes the squared Euclidean
distance. For a given choice of pulse width $T$, we choose the PPM delay $\zeta$ that maximizes square of the Euclidean distance, $d^2(\zeta)$. At the same time, we also ensure that the orthogonality between radar signals is maintained after choosing a particular $\zeta$. In other words, we seek a value for $\zeta$, which keeps the cross-correlation between the designed waveforms below a predetermined level such that the orthogonality between them is maintained.

The BER for such an UWB-PPM scheme is given as [20]

$$P_e(\zeta) = Q\left(\sqrt{\frac{\lambda d^2(\zeta)}{2}}\right)$$

where $P_e$ is the probability of error at a signal-to-noise ratio (SNR) of $\lambda$ and $Q(\cdot)$ stands for the Marcum-$Q$ function. Since we ensure that the orthogonality between CRR waveforms is not distorted, we can adopt an iterative design algorithm that maximizes the target scene information and at the same time is capable of maintaining active communication links between CRR nodes with an acceptable BER performance. The selection of PPM delay $\zeta$ is based upon minimization of $P_e$, viz.,

$$\hat{\zeta} = \arg\min_{\zeta} P_e(\zeta) = \arg\min_{\zeta} Q\left(\sqrt{\frac{\lambda d^2(\zeta)}{2}}\right)$$

under the constraint of keeping the cross-correlation between designed waveforms below a pre-specified threshold. Once the communication data have been embedded into the orthogonal codes, we then proceed to selecting from these waveforms the best possible signal to be transmitted in the next time instant based on minimization of MI.

IV. STEP II: MI BASED WAVEFORM SELECTION

The basic idea behind the MI minimization approach is that, we intend to identify the best possible radar waveform for the next time instant based upon the current received backscattered signal. As the radar channel is dynamic due to the fluctuations in RCS of the target and other factors such as Doppler shift caused by relative motion of the target and the surrounding clutter, there is a need for a dynamic waveform design and selection approach in order to constantly gain information from the target scene.

A. Target Impulse Response and Parameter Estimation

The radar receiver has a complete knowledge of the transmitted waveform at all instants of time. Hence, we can use this information to extract parameters like target impulse response, target channel
covariance matrix $R_H$, and noise variance $R_n$. Let $y_t$ and $y_{t-1}$ be the received signal vectors at two successive time instants. Using (2) we have,

$$E(y_T^T y_t) = x_t^T R_H x_t + R_n = \sigma_t^2$$

(7)

$$E(y_{T-1}^T y_{t-1}) = x_{t-1}^T R_H x_{t-1} + R_n = \sigma_{t-1}^2$$

(8)

where $\sigma_t^2$ and $\sigma_{t-1}^2$ represent the variances of the received signals at respective time instants.

Solving (7) and (8) simultaneously we can estimate the values for $R_H$ and $R_n$. These values will be used to generate the estimate for $y_{t+1}$ for all values of $x_{t+1} \in S$ using (2), where $S$ is the ensemble of the transmitted waveforms. We will choose $x_{t+1} \in S$ based on the proposed MI minimization approach.

This process of estimation of the target channel covariance matrix and the noise variance will be performed at every instance of reception of $y_t$, and their values will be thus updated and used to generate new estimates for $y_{t+1}$.

B. MI Minimization Between Successive Target Echoes

MI between two random vectors $y_i$ and $y_j$, denoted as $MI(y_i, y_j)$, is a measure of the information that $y_i$ conveys about $y_j$, or equivalently, the information that $y_j$ conveys about $y_i$. If the two random vectors are statistically dependent, then the MI between them is high. Similarly, if $y_{t-1}$ and $y_t$ represent two received backscattered signals at successive time intervals and they are statistically dependent (i.e., high MI), then we cannot expect any gain in information about the radar scene. We therefore, desire to obtain uncorrelated and independent target images from the radar scene in order to acquire more target scene information from scan to scan. Subsequently, we select only those waveforms for transmission that would produce less statistically dependent backscattered signals from the same radar scene. In other words, we intend to find the best transmission waveform $x_t$ by selecting from the ensemble $S$ a waveform that would minimize the MI between the current received target echo and the estimated echo in the next time instant.

Let $y_t = \{y_{t,1}, y_{t,2}, \ldots, y_{t,K}\} \sim \mathcal{N}(\mu_t, \sigma_t^2)$ be the received signal vector, which is normally distributed over $K$ samples with mean $\mu_t$ and variance $\sigma_t^2$. Then we can express the MI between the successive received signal vectors in subsequent time instants as

$$MI(y_{t-1}, y_t) = H(y_{t-1} | x_{t-1}) + H(y_t | x_t) - H(y_{t-1}, y_t | x_{t-1}, x_t)$$

(9)
where the first term $H(y_{t-1}|x_{t-1})$ represents the average information or entropy. By classical definition of entropy it is the measure of uncertainty in the received signal at the time instant $t-1$ given the knowledge of the transmitted signal $x_{t-1}$. The knowledge of the transmitted waveform is assumed to be present at all time instants. The other two terms in (9) are similarly defined.

Let $y$ represent the sequence of the $k^{th}$ ($k = 1, 2, \ldots, K$) sample of $N$ successive received signal vectors. Therefore, $y = \{y_{t,k}, y_{t-1,k}, \ldots, y_{t-N+1,k}\}$ follows a multivariate normal distribution with mean vector $\mu$ and covariance matrix $\Sigma$. The joint probability density function of $y$ is

$$f_y(y) = \frac{1}{(\sqrt{2\pi})^N |\Sigma|^\frac{1}{2}} \exp \left[ -\frac{(y - \mu)^T \Sigma^{-1} (y - \mu)}{2} \right]$$

(10)

Subsequently, the joint entropy can be expressed as

$$H(y|x) = \frac{1}{2} \ln \left[ (2\pi e)^N |\Sigma| \right] \text{ nats}$$

(11)

The detailed proof of (11) is shown in Appendix A. Following this, we can derive the joint entropy $H(y_t, y_{t-1}|x_t, x_{t-1})$ by substituting $N = 2$ in (11):

$$H(y_t, y_{t-1}|x_t, x_{t-1}) = H(y_{t,k}, y_{t-1,k}|x_{t,k}, x_{t-1,k}) = \frac{1}{2} \ln \left[ (2\pi e)^2 |\Sigma| \right] \text{ nats}$$

(12)

Let the covariance matrix $\Sigma$ be represented as (see also [22])

$$\Sigma = \begin{bmatrix} \sigma_t^2 & \rho \sigma_t \sigma_{t-1} \\ \rho \sigma_t \sigma_{t-1} & \sigma_{t-1}^2 \end{bmatrix}$$

(13)

where $\rho$ is the correlation coefficient. Thus,

$$|\Sigma| = \sigma_t^2 \sigma_{t-1}^2 - (\rho \sigma_t \sigma_{t-1})^2$$

$$= \sigma_t^2 \sigma_{t-1}^2 (1 - \rho^2)$$

(14)

Let the univariate probability density function of the received signal vector $y_t$ be represented as

$$\Psi(y) = \frac{1}{\sqrt{2\pi \sigma_t^2}} \exp \left[ -\frac{(y - \mu_t)^2}{2\sigma_t^2} \right]$$

(15)
By definition of entropy,

\[
H(y_t|x_t) = -\int \Psi(y) \ln[\Psi(y)] dy
\]

\[
= -\int \Psi(y) \left[-\frac{(y - \mu_t)^2}{2\sigma_t^2} - \ln \left(\sqrt{2\pi\sigma_t^2}\right)\right] dy
\]

\[
= \frac{E[(y - \mu_t)^2]}{2\sigma_t^2} + \frac{1}{2} \ln (2\pi\sigma_t^2)
\]

\[
= \frac{1}{2} + \frac{1}{2} \ln (2\pi\sigma_t^2)
\]

\[
= \frac{1}{2} \ln (2\pi e\sigma_t^2) \quad \text{nats}
\]

(16)

Similarly we can write

\[
H(y_{t-1}|x_{t-1}) = \frac{1}{2} \ln (2\pi e\sigma_{t-1}^2) \quad \text{nats}
\]

(17)

Thus using (9), (12), (14), (16) and (17) we obtain

\[
\text{MI}(y_{t-1}, y_t) = H(y_{t-1}|x_{t-1}) + H(y_t|x_t) - H(y_{t-1}, y_t|x_{t-1}, x_t)
\]

\[
= \frac{1}{2} \ln (2\pi e\sigma_{t-1}^2) + \frac{1}{2} \ln (2\pi e\sigma_t^2) - \frac{1}{2} \ln [(2\pi e)^2|\Sigma]]
\]

\[
= \frac{1}{2} \ln (2\pi e\sigma_{t-1}^2) + \frac{1}{2} \ln (2\pi e\sigma_t^2) - \frac{1}{2} \ln [(2\pi e)^2\sigma_t^2\sigma_{t-1}^2(1 - \rho^2)]
\]

\[
= -\frac{1}{2} \ln(1 - \rho^2)
\]

(18)

We can estimate the correlation coefficient \( \rho = \frac{E[y_t^Ty_{t-1}]}{\sqrt{\sigma_t^2\sigma_{t-1}^2}} \). As mentioned in Section IV-A, we can estimate the values for \( y_{t+1} \) over all possible values of \( x_{t+1} \in S \) using (2). Thus we can also form an estimate of all values of the corresponding \( \rho = \frac{E[y_{t+1}^Ty_{t+1}]}{\sqrt{\sigma_{t+1}^2\sigma_t^2}} \) and choose the value for \( x_{t+1} \) that minimizes (18).

The MI minimization approach can be expressed as:

\[
\text{MI}^* = \min_{x_{t+1} \in S} -\frac{1}{2} \ln(1 - \rho^2)
\]

subject to the power constraint \( E(x_{t+1}^Tx_{t+1}) \leq P_0 \), where \( P_0 \) is the power available at the transmitter.

Following Sections III and IV, we can summarize the CRR waveform design algorithm as follows.

1) The current \( R_H \) and \( R_n \) can be estimated through successive measurements with orthogonal UWB sequences or radar waveforms \( x \in S \) as discussed in Section IV-A.
2) An estimate for $y_{t+1}$ is obtained using (2) and Step 1. We then choose the PPM delay $\zeta$ as discussed in Section III-A and design the UWB-PPM ensemble $\mathcal{S}$. We then select $x_{t+1} \in \mathcal{S}$ to be transmitted based on the MI minimization approach and (19).

3) The CRR waveform is transmitted carrying the communication source and destination identity information in the preamble of the data frame. The communication link can either be between two different CRR nodes or between a CRR node and a remote sensor monitoring the phenomenon-of-interest induced by the target.

4) Backscattered signal is collected and passed through a matched filter bank or a correlation receiver, which uniquely identifies the orthogonal sequence out of the ensemble $\mathcal{S}$ and demodulates the PPM signal.

5) The radar signal is used to extract the target parameters like target range, velocity, and impulse response. The estimates for $R_H$ and $R_n$ are updated using the current received signal and are relayed back to the MI minimization module.

6) The process is repeated iteratively.

V. SIMULATION RESULTS AND DISCUSSION

A. Simulation Setup

As discussed before, we employ the CRR waveform comprising the orthogonal sequences of Gaussian UWB-PPM pulses $x_t$ over the transmitting antenna elements. For simulation purposes, we set the PPM delay $\zeta$ such that the cross-correlation coefficient between the transmission waveforms is no greater than 0.4. In this way we have an acceptable BER for communications. Furthermore, orthogonality between the distinct CRR waveforms is maintained for radar waveform optimization purposes. This CRR signal is matched filtered at the receiver, which essentially cross-correlates the incoming signal with delayed version of the transmitted signal in order to estimate the propagation delay. The PPM data are separately demodulated and the radar signal processing is carried out by the target impulse response and parameter estimation module. As described in the previous sections, the target channel covariance matrix is estimated and the noise variance is also determined in order to help the MI minimization module to decide upon the best UWB sequence to be used for transmission in the subsequent time interval. The frequency of transmission of these UWB pulses is 4 GHz and the sampling frequency is 10 GHz.
B. Target Range Estimation

In order to estimate the target range or in other words the Time Of Arrival (TOA) of the back-scattered signal it is essential to determine the value of the Pulse Repetition Interval (PRI) between successive Gaussian pulses in an UWB sequence. In this work we assume, perfect synchronization between different CRR units and we also assume a multipath channel with the existence of Line Of Sight (LOS) as a major component in the back-scattered signal. We adopt a multipath channel model as mentioned in [10] for the proposed CRR waveform design under IEEE 802.15.4 MAC layer as shown in [11].

To find the target distance the CRR node will try to estimate the actual time delay \( \tau_d \) using correlation. The transmitted signal is delayed by time \( \tau_n \) and is cross-correlated with the target return to give the cross-correlation product.

\[
R_{yx}(\tau_d - \tau_n) = E[x_t^T(\tau - \tau_n)y_t(\tau - \tau_d)]
\]

(20)

The maximum value for (20) will only be achieved when \( \tau_d = \tau_n \). Hence, in order to estimate the time delay, the maximum of \( R_{yx} \) is evaluated by varying the value of \( \tau_n \) at the receiver and cross-correlating with the received signal. Systems utilizing the UWB-OFDM signals for joint communication-radar applications [7]–[9] share a common drawback. The auto-correlation (related to the range resolution of the radar) of the UWB-OFDM signal depends both on the location of the notch as well as the OFDM signal bandwidth [7]. Hence, it can be seen that although the radar target range estimation is unaffected by the presence of the OFDM signal, its range resolution does depend on the notch bandwidth into which the OFDM signal is embedded. On the other hand, in the proposed UWB-PPM design, the communication and radar signals can both mutually coexist by sharing the same frequency band. Hence, the range resolution of the radar is not affected by the communication signal design parameters.

Fig. 3(a) shows the range resolution of the target and the surrounding clutter. For this simulation the target and the clutter were assumed to be stationary. This range profile represents the classification of the target and non-target scatterers into range bins, which is achieved by continually interrogating the stationary environment with CRR waveforms chosen by the MI minimization algorithm. At each iteration we choose the waveform that would produce the least correlated output. The range resolution result in Fig. 3(a) is obtained at the end of 10 such iterations of MI minimization. As seen from Fig.
3(a), the target is located at a distance of approximately 38 m from the CRR node. Over the CRR links, three or more distinct CRR nodes can share the target relative distance information and triangulate its location. Fig 3(b) indicates the range profile of the radar scene on a temporal domain. The range is resolved continually for a duration of 4 seconds where the target and its surroundings are stationary. As seen from the plot, the target is clearly distinguishable from the non-target scatterers. Again, such clear resolution in the ranges of the target and non-target scatterers is achieved after 10 iterations of the algorithm.

C. MI Minimization Simulation

Fig. 3(c) represents the MI minimization algorithm for different levels of SNR. For a stationary radar scene, we compute the MI and minimize it over each iteration by choosing the best possible transmission sequence. These iterations are carried out for each fixed value of SNR. At high SNRs, since the radar signal is stronger than the AWGN, the backscatter is dependent on the target and non-target scatterers. In order to gain more information on the radar scene, we can minimize the MI between the expected and received signals by choosing the best possible signals for transmission. However, at low SNRs, the signals are not only subject to the radar scene uncertainty, but also to the AWGN. Hence, we cannot minimize the MI sufficiently, and the best transmission sequence for the next time instant is not always selected. As we can see from the plot, at high noise floors the estimation of $R_H$ will be poor and hence minimization of MI cannot be achieved. Since MI cannot be minimized with iterations the waveform selection algorithm fails to select an optimum waveform and hence will produce statistically dependent back-scattered signals. Hence there would not be any gain in the information pertaining to the target scene and hence the waveform selection approach would fail to provide any performance gain.

D. Target Detection Probability

Fig 3(d) indicates the probability of target detection in the presence of AWGN and clutter interference. We use the performance measure of signal-to-clutter-and-noise ratio (SCNR) in order to evaluate the probability of target detection. Specifically, SCNR indicates the strength of the target return against the strength of the signal from clutter sources also corrupted by noise. For a particular CRR waveform and a stationary radar scene, 1000 simulations were run for each value of SCNR and the probability of successful detection of the target was plotted based on the hypothesis testing method.
employing the optimal Neyman-Pearson detector algorithm in [12]. Then the next CRR waveform was chosen according to the MI minimization algorithm and the process was repeated for 50 iterations. As seen from the plot, the MI minimization algorithm converges after 50 iterations yielding a detection probability of 0.9 at 8 dB of SCNR value as compared to 17 dB achieved at the first iteration. However, as we increase the number of iterations, the probability of detection does not show further improvement after 50 iterations for a stationary target.

E. Communication BER and Throughput Performance

Fig. 4(a) shows the performance of the CRR waveform design from a communications perspective. The plot indicates the BER for different systems, which have been investigated in the literature for joint communication-radar networks. The proposed CRR waveform solution can be modified by incorporating additional modulation levels for PPM, e.g., 16 or 4-ary PPM. However, as we go on increasing the delay between the radar pulses in order to send constellation of signals, the orthogonality of the UWB sequences is affected. Consequently, choosing the appropriate Euclidean distance or the delay for PPM results in a tradeoff between communication and radar signal design requirements. As seen from the plot and also described in [7]–[9], UWB-OFDM signals offer better bit error performance when we adopt data redundancy bits for error control. However, the proposed UWB-PPM design performs comparably to these schemes even without redundant bits added.

Fig. 4(b) shows the throughput analysis for the CRR waveform as compared to other UWB-OFDM signal designs. UWB communications in general achieve high data rate over short distances. As the distance between the communicating nodes increases the throughput falls. The CRR waveform design offers a data rate of just about 200 Mbps at a distance of 20 m, which is better than that offered by the 4-carrier uncoded UWB-OFDM.

F. Mobile Target Scene Simulation

Fig. 4(c) shows the target and clutter range profile for a dynamic radar environment, in which the target and clutter sources are in relative motion with respect to the observing CRR node. The simulation was carried out with a relative velocity of 3.5 m/s. By choosing CRR waveforms based on the estimated target impulse response and ensuring that at each instance of reception the received signals are uncorrelated from each other, the proposed MI minimization algorithm is able to achieve resolvable target and clutter returns at the 10th iteration as shown in Fig. 4(c)-(d). In Fig. 4(d) we
observe that the target and the surrounding clutter are distinctly resolved into different range bins even if the radar scene is dynamic. The MI minimization algorithm is self-corrective since it updates the estimated value of the target channel covariance matrix and also the noise variance at each step. This result demonstrates the effectiveness of the proposed MI minimization algorithm over dynamic radar scenes with mobile targets and clutter.

G. Ranging And Detection Error In Multipath Channel

Fig. 5(a) displays the average power delay profile of the UWB channel model mentioned in [10]. Throughout this simulation we utilize this channel model. Time is measured relative to the first arriving multipath, and the amplitude of each vertical line represents the energy gain of each 2 ns delay bin. On average, over 92% of total energy arrives within 100 ns. This means that a PRI greater than 100 ns would experience very little Inter Symbol Interference (ISI). Also, on average, over 95% of pulses dissipate their energy after about 120 ns and over 99% of pulses after about 160 ns. We set PRI above 200 ns for our methods to avoid ISI.

As described earlier, we intend to estimate the delay $\tau$ which will maximize $R_{yx}$. We therefore perform peak detection on $R_{yx}$ to obtain an estimate for the TOA and hence the range of the target.

Fig. 5(b) indicates the ranging error in the multi-path channel with respect to the SCNR. Throughout this simulation we assume that LOS is a major component of the back-scattered signal. In this simulation we compare the performance of the ranging based on mean TOA from the received signal and from the TOA determined by the peak detection of $R_{yx}$. Hence this result indicates the ranging error with respect to the TOA variations caused due to the presence of multi-path channel. As we can see from the plot, for low SCNR value the ranging error based on TOA from peak detection of $R_{yx}$ is better as compared to the one based on mean TOA estimate. We also compare this result with the Cramer-Rao Lower Bound (CRLB) on UWB ranging error for TOA estimation method at bandwidth of 1 GHz as shown in [23]. As seen from the plot the proposed TOA estimation scheme achieves ranging error close to CRLB at higher values of SCNR. Hence as long as the LOS component is present in the multi-path, the ranging error performance of the proposed method is optimal.

Fig. 5(c) represents the effect of PRI on the ranging error. As described earlier, the PRI is assumed to be greater than 200 ns and hence the effect of ISI due to multipath channel is negligible. As can be seen from the plot the ranging error sharply increases as we decrease the PRI below 200 ns. Above this value the ranging error reduces with increase in the PRI. Fig 5(d) shows the performance
gain in terms of probability of target detection, achieved by the MI minimization approach. In this simulation, we test the probability of target detection with regards to the varying waveforms selected by the proposed approach and an arbitrary static waveform chosen in order to estimate the target parameters over successive iterations. Since we have assumed that the target RCS fluctuates according to the Swerling III case, the MI minimization approach always selects distinct waveforms which would produce statistically independent received signals over time and hence it adapts its signal better to the fluctuating RCS of the target. The static waveform on the other hand inspite of multiple iterations is unable to match its waveform to the fluctuating target response and hence the probability of detection of the target in this case is sub-optimal.

VI. Conclusion

We have developed a joint communication-radar waveform design solution for the CRR network. As indicated by the simulation results, the CRR waveform optimization approach promises better target impulse response extraction and range resolution. From a communications perspective, the proposed CRR waveform design also promises high data rate performance over short ranges. The radar and communication signals share the same spectral and temporal domains using the current design strategy. This approach was based upon constant learning of the target environment and adapting the transmission waveform characteristics to suit the dynamic target scene. Such a cognitive approach ensures maximum information extraction from the radar scene and better target discrimination capability. The proposed unified system would constitute a unique cost-efficient platform for future intelligent surveillance applications, for which both environment sensing along with the allocation of ad hoc communication links are essential. Such systems can be used in mission-critical and military applications for addressing the remote surveillance and communication issues simultaneously. It is envisaged that the future personal communication and tracking devices will have comprehensive radar-like function, such as spectrum sensing and localization, in addition to multi-mode and multi-band communication capability.

References


Appendix A

Proof of (11) in Section IV-B

Let us assume that \( y \) as defined in Section IV-B follows a multivariate normal distribution with mean vector \( \mu \) and covariance matrix \( \Sigma \). Thus the joint probability density function of \( y \) is

\[
f_y(y) = \frac{1}{(\sqrt{2\pi})^N |\Sigma|^\frac{1}{2}} \exp \left[ -\frac{(y - \mu)^T \Sigma^{-1} (y - \mu)}{2} \right]
\]  

(21)

We want to prove that the joint entropy is given by

\[
H(y|x) = \frac{1}{2} \ln \left( (2\pi e)^N |\Sigma| \right) \text{ nats}
\]

(22)

Proof:

\[
H(y|x) = - \int f(y) \left\{ -\frac{(y - \mu)^T \Sigma^{-1} (y - \mu)}{2} - \ln \left( \left( \sqrt{2\pi} \right)^N |\Sigma|^{\frac{1}{2}} \right) \right\} \, dy
\]

\[
= \frac{1}{2} E \left[ \sum_{i,j} (y_i - \mu_i)(\Sigma^{-1})_{ij}(y_j - \mu_j) \right] + \frac{1}{2} \ln \left( (2\pi)^N |\Sigma| \right)
\]

\[
= \frac{1}{2} E \left[ \sum_{i,j} (y_i - \mu_i)(y_j - \mu_j)(\Sigma^{-1})_{ij} \right] + \frac{1}{2} \ln \left( (2\pi)^N |\Sigma| \right)
\]

\[
= \frac{1}{2} \sum_{i,j} E[(y_j - \mu_j)(y_i - \mu_i)(\Sigma^{-1})_{ij}] + \frac{1}{2} \ln \left( (2\pi)^N |\Sigma| \right)
\]

\[
= \frac{1}{2} \sum_{i,j} \sum_{j} \Sigma_{ji}(\Sigma^{-1})_{ij} + \frac{1}{2} \ln \left( (2\pi)^N |\Sigma| \right)
\]

\[
= \frac{1}{2} \sum_{j} (\Sigma\Sigma^{-1})_{jj} + \frac{1}{2} \ln \left( (2\pi)^N |\Sigma| \right)
\]

\[
= \frac{1}{2} \sum_{j} 1_{jj} + \frac{1}{2} \ln \left( (2\pi)^N |\Sigma| \right)
\]

\[
= \frac{N}{2} + \frac{1}{2} \ln \left( (2\pi)^N |\Sigma| \right)
\]

\[
= \frac{1}{2} \ln \left( (2\pi e)^N |\Sigma| \right) \text{ nats}
\]

This completes the proof.
Fig. 1. (a) Coexistence of communication and radar functionalities in a CRR network, and (b) CRR node architecture.
Fig. 2. (a) 16-bit CRR transmission waveform obtained from the column vector of the Walsh-Hadamard code matrix and the PPM data, (b) orthogonality of CRR waveforms, and (c) spectrum of received CRR signal at a reference distance of 20 m at 5 GHz center frequency.
Fig. 3. (a) Static target and non-target (clutter) scatterers resolved after 10 iterations of MI minimization at a CRR node, (b) target and clutter returns after 10 iterations of MI minimization, (c) minimization of MI algorithm at different SNRs, and (d) probability of target detection against SCNR for various iterations of the MI minimization algorithm.
Fig. 4. (a) BER of different joint communication-radar waveform designs, (b) throughput performance against distance from a particular CRR node, (c) target range profile for a target velocity = 3.5 m/s for 4 s time duration after 10 iterations of MI minimization, and (d) target and clutter returns after 10 iterations of MI minimization.
Fig. 5. (a) UWB channel model as shown in [10], (b) Average ranging error based on TOA estimation in the multi-path UWB channel, (c) Average ranging error against PRI in the multi-path UWB channel, and (d) Probability of detection of waveform selection based on MI minimization and static waveform assignment both at the end of 50 iterations.