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Cognitive UWB: interference mitigation by spectral control

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Abstract — **Introducing cognitive principles in the design of a wireless network appears as an attractive option when considering the emerging scenario of coexisting networks. In this paper we introduce cognitive features in a network of IEEE 802.15.4a devices, and show that significant improvements in terms of network lifetime can be achieved by allowing the devices to adapt their behavior to the unpredictable changes of the operating environment.**

I. INTRODUCTION

The object of this paper is to analyze the impact of introducing cognitive mechanisms in the design of a self-organizing network of wireless devices. Cognitive radio is an innovative concept based on the idea of a radio device aware of the scenario in which it operates, and thus capable to adapt its behaviour to the changes of the operating environment [1][2]. As a matter of fact, cognitive features are particularly attractive in those scenarios where the devices must cope with interfered propagation environments, as it happens in the case of multiple and heterogeneous wireless networks that coexist and share a common radio resource.

This paper is organized as follows. Section II introduces the system model and formalizes the problem under examination. Section III defines the proposed approach for modelling network dynamics. Section IV presents the results of simulation, and Section V concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

The system model considered in this work consists of a self-organizing network of low-power, low-cost and low-rate wireless devices, as those considered in the framework of the IEEE 802.15.4 standard [3]. In this context, we consider the case of nodes that adopt Impulse Radio (IR) UWB at the physical layer, as proposed in the recently formed IEEE 802.15.4a Task Group [4]. UWB radio signals must in principle coexist with other radio signals, and thereby devices must cope with the problem of interference provoked by other communication systems. In such scenario, our goal is twofold: *i*) design of the rules for the formation of the network; *ii*) introduction of cognition in the network with the aim of improving robustness against interference.

A. Physical Layer

The UWB signal format is the one typical of Impulse Radio (IR) signals, with Time-Hopping coding (TH) and binary Pulse Position Modulation (PPM) [5]. The signal $s(t)$ transmitted by a reference transmitter TX can be described by the following expression:

$$s(t) = \sqrt{P_{TX} T_S} \sum_j p_w(t - jT_S - c_j - a_j \varepsilon) \qquad (1)$$

where P_{TX} is the average transmitted power, T_S is the pulse repetition period, $p_w(t)$ is the energy-normalized pulse shape, $c_j < T_S$ is the TH code value for pulse j, a_j is the data symbol carried by pulse j, and ε is the PPM shift. Note that the bit interval T_b is: $T_b = N_S T_S$, where N_S is the number of transmitted pulses per bit. We assume that transmission power P_{TX} is upper-bounded by a specified maximum power level, indicated as P_{MAX}, which may derive from technological limitat

ion or regulatory recommendations [6]. As predictable from Eq.(1), different pulse waveforms can be selected for transmitting data over the wireless channel. These waveforms lead to different spectral shapes for the transmitted signals, so that the UWB signal can be adapted to different interference scenarios.

A general flat Additive White Gaussian Noise (AWGN) channel model is assumed. In the presence of external interference and Multi User Interference (MUI), the signal $r(t)$ at the input of a reference receiver RX writes:

$$r(t) = \sqrt{P_{RX} T_S} \sum_j p_w(t - jT_S - c_j - a_j \varepsilon - \tau) + n_e(t) + n_{mui}(t) \qquad (2)$$

where P_{RX} is the average received power after propagation over the link between TX and RX, τ is the propagation delay, $n_e(t)$ accounts for thermal noise and external interference provoked by wireless devices that operate outside the network, and $n_{mui}(t)$ accounts for MUI. We adopt at RX a coherent correlator followed by a Maximum Likelihood detector. Soft decision detection is performed, so that the decision variable $Z(x)$ that is present at the correlator output after the xth bit interval is given by:

$$Z(x) = \int_{\tau + xT_b}^{\tau + (x+1)T_b} r(t)\, m_w(t - \tau)\, dt \qquad (3)$$

where $m_w(t)$ is the correlator mask for the xth transmitted bit:

$$m_w(t) = \sum_{j=0}^{N_S - 1} \left[p_w(t - jT_S - c_j) - p_w(t - jT_S - c_j - \varepsilon) \right] \qquad (4)$$

Introducing Eq.(2) into Eq.(3) leads to a decision variable for the xth bit that is given by $Z(x) = Z_u + Z_e + Z_{mui}$, where Z_u, Z_e, and Z_{mui} are the useful contribution, the external noise contribution, and the MUI contribution, respectively. For this receiver architecture, system performance can be expressed in terms of the signal to noise ratio SNR that is measured at the correlator output, which is defined as follows:

$$SNR = E_u /(\eta_e + \eta_{mui}) \tag{5}$$

where E_u is the received useful energy per bit for the reference link, η_e is the variance of the Z_e contribution, and η_{mui} is the variance of the Z_{mui} contribution introduced by the other active nodes.

B. Network Architecture and Multiple Access

We suppose that all network nodes communicate through one elected node, denoted as the Conscious Node of the network (CNode). Network architecture is thus centralized in the CNode and therefore our analysis is focused on the set up of the uplink connections. In the downlink, in fact, proper orthogonality of signals makes the problem irrelevant. The CNode implements the cognitive paradigm and plays the role of network coordinator. Time Hopping (TH) coding is used for discriminating among users, according to a method that is commonly indicated as TH Impulse Radio (TH-IR) [7]. Data exchange between the CNode and any other node requires the set-up of a specific channel of communication that is identified by a unique TH code. In such system, the performance of a given link between one active node and the CNode is expressed by Eq.(5), where we can substitute [1]: $E_u = (N_S)^2 P_{RX} T_S$, $\eta_e = N_S \eta_p(w)$, $\eta_{mui} = (N-1) N_S \sigma_m{}^2(w) P_{RX}$, where $\eta_p(w)$ is the variance of noise collected for one single pulse, N is the number of active nodes in the network, and $\sigma_m{}^2(w)$ is a MUI weight defined as follows:

$$\sigma_m^2(w) = \int_{-\infty}^{+\infty} \left[\int_{-\infty}^{+\infty} p_w(t+z) \left[p_w(t) - p_w(t-\varepsilon) \right] dt \right]^2 dz \tag{6}$$

One obtains:

$$SNR = \frac{1}{R_b} \frac{P_{RX}}{\eta_p(w) + \sigma_m^2(w)(N-1) P_{RX}} \tag{7}$$

where $R_b = 1/T_b$. Depending on the characteristics of both $n_e(t)$ and $n_{mui}(t)$, different analytical relations can be found between the SNR value in Eq.(7) and the average Bit Error Rate (BER) that can be estimated for each single uplink. Under the assumption that both $n_e(t)$ and $n_{mui}(t)$ can be modelled as white Gaussian random processes, one has:

$$\text{BER} = (1/2)\, erfc\left(\sqrt{SNR/2}\right) \tag{8}$$

C. Packet Structure and Traffic Modeling

The SNR in Eq.(7) provides a measure of the link quality in the presence of both noise and MUI. A prerequisite for correct detection of transmitted data, however, is the synchronization between TX and RX. This task is generally achieved by grouping information bits into packets, and by providing each packet with a proper synchronization trailer that allows the receiver to estimate the τ value [8]. For fixed length of the synchronization trailer, performance of the synchronization procedure depends on the signal to noise ratio that is measured on the single pulse. We will denote this quantity as SNR_p, and will assume that a link between TX and RX can be established provided that SNR_p is at least equal to a threshold value SNR_0, which is a system parameter that measures the sensitivity of the receiver with respect to synchronization. Note that by Eq. (7) one can derive SNR_p by substituting $R_b = 1/T_s$. The CNode can thus support N active connections with N nodes in the network provided that:

$$SNR_p = \frac{T_S P_{RX}}{\eta_p(w) + \sigma_m^2(w)(N-1) P_{RX}} \geq SNR_0 \tag{9}$$

Note in Eqs. (7) and (9) how both synchronization performance and the quality of the uplink connections depend on the waveform $p_w(t)$ that is adopted for transmission.

With respect to traffic modeling, we assume that two types of traffic sources may access the system for transmitting data, denoted as QoS-aware sources (Q sources) and Best Effort sources (B sources). A Q source is fully characterized in terms of generated traffic and required QoS, while a B source does not require any a-priori specification neither in terms of transmission rate nor in terms of QoS. For a full characterization of the adopted traffic model, we cross-refer to [9], which contains a list of all the parameters that can be associated to Q and B sources.

III. Network Dynamics

As indicated in Section II, devices communicate by exchanging data with the CNode, which routes data to other nodes that are located inside its coverage area. We assume that any device has the capability of becoming the CNode of the network, but we will consider in this work a static scenario where we suppose that the role of the CNode is played by the first node coming to life in the network.

As proposed in [9], network dynamics for the proposed system model can be well described by the hybrid system formalism. Hybrid systems are powerful abstractions for modeling complex systems, and have been the subject of intense research in the past few years by both the control and the computer-science communities [10]. Based on the hybrid system formalism, the network can be modeled as a finite-state automaton, where each discrete state q_N of the automaton corresponds to the presence of N active nodes and one CNode.

In state q_N, the CNode has activated N links with N active nodes and interacts with the external environment by application of cognitive mechanisms. Specifically, we assume that the CNode has the capability of continuously sensing its surrounding environment and of determining the noise floor perceived by its receiver. Based on environment sensing, the CNode estimates the values of $\eta_p(w)$ and $\sigma_m{}^2(w)$ and then computes the value of minimum power $P_{min}(w)$ that must be received from each node in order to guarantee for each connection the condition in (9), that is:

$$P_{min}(w) = \frac{\eta_p(w)}{T_S} \left(\frac{1}{SNR_0} - \frac{\sigma_m^2(w)(N-1)}{T_S} \right) \tag{10}$$

If M different waveforms are available at the physical layer, the CNode can apply Eq.(10) in order to determine the waveform that better adapts to the environment. Such waveform is the one leading to the smallest $P_{\min}(w)$ value, for $w = 1, ..., M$. The CNode can thus determine two factors: the waveform $p_{w*}(t)$ to be currently used by nodes and the corresponding $P_{\min}(w^*)$. This information is stored in a specific control message $K(t,q_N)$ and communicated to the active nodes using piggybacking. In parallel, the CNode evaluates the eventual transition to state q_{N+1} and determines the corresponding $K(t,q_{N+1})$. This message is broadcasted over a specific broadcast control channel. Each active node receives $K(t,q_N)$ and also estimates the attenuation A_j characterizing its path to the CNode. Based on this information, each node selects the waveform w^*, adjusts the transmission power to $P_{TXj} = A_j P_{min}(w^*)$, and then determines the bit rate to be used in its future transmissions to the CNode. The procedure for bit rate selection depends on the class of traffic of the source, and is fully described in [9]. By listening to $K(t,q_{N+1})$, the node can also evaluate whether it is willing to move to state q_{N+1}. A transition to state q_{N+1} could in fact be impeded by a Q node that might not be in the condition of hitting its QoS with $N+1$ active devices. This mechanism automatically limits the number of active nodes in the network. In the presented model, the transition from state q_N to state q_{N-1} is associated with the disconnection of one node from the network. This disconnection can be provoked by one of the two following events: *i*) a node leaves the network because its activity is terminated; *ii*) changes in the environment and in radio propagation are no more compliant with node's requirements. The transition from state q_N and state q_{N+1} correspond to the admission in the network of a new device, which takes place if: *i*) all active nodes agree to the transition; ii) a candidate node that listens to $K(t,q_{N+1})$ agrees in accepting those constraints.

IV. Simulation Analysis

The goal of this analysis is to quantify by simulation the impact on network performance which derives from the application of different schemes of cognition at the CNode.

A. Simulation Scenario

We consider a scenario that consists of one CNode located at the centre of a circular area A with radius R. Area A is populated by N active nodes and N_i potential interfering devices, that are divided into N_a active interferers and N_s silent interferers (Figure 1).

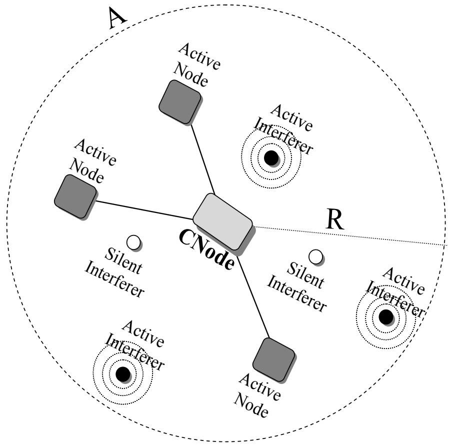

Figure 1 - Simulation scenario composed by one CNode (light rectangle), N active nodes (squares), and N_i potential interferers, divided into N_a active interferers (dark circles) and N_s silent interferers (light circles).

We assume that the active users are transmitting data towards the CNode during the whole duration of the simulation period of time T. At time τ, in particular, the jth active node ($j = 1, \ldots, N$) is transmitting an UWB signal with power $P_j(\tau) = A_j(\tau)P_{min}(\tau)$, where we indicate with $P_{min}(\tau)$ and $A_j(\tau)$ the requested power at the CNode and the attenuation of the jth uplink at time τ, respectively. According to the procedure introduced in Section III, we denote with $p_w(t)$ the waveform that is adopted by the N active nodes at time τ. Such waveform is determined by the CNode based on the evaluation process that is described in Section III. In the proposed scenario, we assume that waveform $p_w(t)$ can be selected among a set of M different waveforms $p_1(t), \ldots, p_M(t)$ represented by the first six odd derivatives of the Gaussian pulse, and that waveform selection is performed periodically based on the analysis of the external environment. Specifically, we assume that the CNode may order a change in the adopted waveform only at multiples of a given interval $\Delta\tau_1$, which accounts for the time that is required by each active node for modifying the characteristics of the pulse shaper. In this simulation, we do not foresee the arrival of candidate nodes or departure of any active node from the network.

Unlike the active nodes, interfering devices do not transmit continuously. At each instant of simulation, each interfering device can assume one of two possible states: *i*) *active*, that is, the device is transmitting with a given power, bandwidth, and frequency of operation; *ii*) *silent*, that is, the device is not generating any signal that is perceivable by the CNode. Transition from one state to the other is random; each device j is associated in fact with two fixed transition probabilities PA_j and PS_j, where PA_j indicates the probability to move from *silent* to *active*, and PS_j indicates the probability to move from *active* to *silent*. In the proposed simulation, changes in the state of the interfering devices are determined periodically, with period $\Delta\tau_2$. At each multiple of $\Delta\tau_2$, the jth interfering device switches-on with probability PA_j if it was *silent*, or switches-off with probability PS_j if it was *active*. In order to stress the CNode with continuous changes in the interference pattern, we modify the position of an interfering device every time it switches from *silent* to *active*. We also assume that the N_i interfering devices are divided into H different classes of interferers. The generic class h (with $h = 1, \ldots, H$) is composed by n_h devices (with $\Sigma_h n_h = N_i$). All the interferers that belong to class h generate RF signals with same transmission parameters, that is, transmission power P_h, and transmission bandwidth W_h centered around a central frequency f_h. In addition, all devices within class h have same transition probabilities PA_h and PS_h.

B. The three levels of cognition

As stated above, the aim of this simulation is to verify to which extent network performance may be affected by modifications in the cognitive capabilities of the CNode. In order to reach this goal, we will consider three different types of CNode for the simulation.

In the first case, called *full cognition*, we consider a CNode that is always capable to quantify the different levels of interference that are measured at the receiver in correspondence of the M available waveforms. The CNode is thus always capable of selecting the waveform that minimizes the value of the requested power $P_{min}(\tau)$, and, as such, the waveform that minimizes transmission power for the active nodes. This case corresponds to the maximum complexity that can be associated to the CNode, since a parallel bank of M receivers is required for performing the radio scene analysis.

In the second case, denoted as *intermediate cognition*, we consider a CNode with reduced cognitive capabilities. Specifically, we assume that at time $\tau_k = k\Delta\tau_1$ the CNode is capable to quantify the level of interference that is measured at the receiver in correspondence of a sub-set of the M available waveforms. This sub-set consists of the waveform $p_m(t)$ that was used in the time interval $[\tau_k - \Delta\tau_1, \tau_k]$, and the two adjacent waveforms $p_{m-1}(t)$ and $p_{m+1}(t)$. Obviously, waveform $p_{m-1}(t)$ is taken into account if $m > 1$, and waveform $p_{m+1}(t)$ is taken into account if $m < M-1$. Within this sub-set, the CNode selects that waveform leading to the lower $P_{min}(\tau)$. Because of the limited cognitive capabilities of the CNode, $P_{min}(\tau)$ might be higher than what would be obtained if all the M waveforms were considered for selection. As a consequence, we expect a decrease in performance for the whole network, that can be quantified in an increase of transmission power for the active nodes. As a trade-off, however, a smaller amount of processing is required at the CNode compared to the full cognition case, since a smaller number of parallel receivers is necessary for the selection process with respect to the case of full cognition.

The last case corresponds to *no cognition*, that is, a simpler CNode randomly selects a waveform $p_m(t)$ at the beginning of network operation and does not perform any further selection during network lifetime. At each instant τ, the CNode quantifies the amount of received power $P_{min}(\tau)$ that is required from active nodes, but does not make any effort in optimizing transmission parameters based on the varying interference pattern. In this sense, the CNode is *adaptive* but not *cognitive*, because it is not aware of the environment, and does not evaluate among several strategies for improving the utilization of the wireless resource. This CNode, however, has lowest complexity, since only one receiver block is required.

C. Simulation Settings

Performance under the three cognitive options described in Section IV.C was analyzed by simulation of two different network scenarios denoted as *case A* and *case B*. Simulation parameters for the *A* and *B* scenarios are provided in Tables 1 and 2. In both cases, 20 external devices generate narrowband interfering signals located around 2, 4, 6 and 8 GHz. In *case A*, all interfering devices are characterized by an average active time and an average silent time of 100 µs. In *case B*, transitions between the two states are more frequent with respect to *case A*, since interfering devices are characterized by an average active time and an average silent time of 10 µs. For each active interfering device, the value of the received power at the CNode is computed by considering free-space path loss attenuation.

During the simulation period, we reproduce the activity of the CNode according to the three options described in Section IV.C. At time τ, in particular, we compute the three values of $P_{min}(\tau)$ that correspond to the application of *full cognition*, *intermediate cognition*, and *no cognition*. These $P_{min}(\tau)$ values are then converted into three corresponding transmission power levels P_{TX} by assuming a reference active node whose uplink is characterized by a constant attenuation of 80 dB. Finally, transmission power levels are converted into three values of energy that would be consumed by the reference node in correspondence to the three cognitive options.

Parameter	*Symbol*	*Value*
Radius of the circular area	R	10 m
Number of active nodes	N	10
Number of potential interfering devices	N_i	20
Number of classes of interferers	H	4
Number of available waveforms	M	6
Requested SNR for synchronization	SNR_0	3 dB
Thermal noise power density	η_p	–200 dBW/Hz
Average pulse repetition period	T_S	50 ns
Duration of the simulation	T	1 ms
Minimum time between two changes of transmitted waveform	$\Delta\tau_1$	10 µs
Minimum time between two changes in the state of an interferer	$\Delta\tau_2$	10 µs

Table 1 – Simulation parameters for *case A* and *case B*.

Parameter	*Symbol*	*Value*			
		Class			
		1	*2*	*3*	*4*
Number of devices per class	n_h	5	5	5	5
Transition probability from *silent* to *active* state	PA_h	0.01 (*case A*)	0.01 (*case A*)	0.01 (*case A*)	0.01 (*case A*)
		0.1 (*case B*)	0.1 (*case B*)	0.1 (*case B*)	0.1 (*case B*)
Transition probability	PS_h	0.01	0.01	0.01	0.01

from *active* to *silent* state		(*case A*) 0.1 (*case B*)	(*case A*) 0.1 (*case B*)	(*case A*) 0.1 (*case B*)	(*case A*) 0.1 (*case B*)
Transmission power in mW	P_h	2	2	2	2
Transmission bandwidth in MHz	W_h	1	1	1	1
Central frequency in GHz	f_h	2	4	6	8

Table 2 – Simulation parameters for the 4 classes of interferers.

D. Simulation Results

Simulation of the two cases described in Section IV.C provided the results presented in Figure 2 (*case A*) and Figure 3 (*case B*). In both figures, we plot the energy consumed by the reference node as a function of time. In each figure, different curves correspond to the different levels of cognition that are implemented at the CNode. As expected, the energy values that correspond to no cognition (black circles) are always higher than those obtained by introducing cognition in the network. Specifically, simulation of *case A* indicates that the reference node with full cognition has consumed at the end of the simulation period an amount of energy which is only the 9.25% of that consumed with no cognition. This percentage reduces to 8.62% in *case B*. Similar results are observed for intermediate cognition: this option requires in *case A* an amount of energy that is only the 12.34% of that measured with no cognition; this percentage reduces to 11.37% when moving from *case A* to *case B*. Interestingly, energy consumption with intermediate cognition is proximal to that of full cognition. This result indicates that a significant increase in network lifetime may be achieved even by adopting sub-optimal algorithms with moderate complexity, provided that the rules of operation are adjusted in some extent to the state of the external environment. Preliminary investigations obtained by varying the transmission parameters in Tables 1 and 2 seam to lead to similar network behavior.

As a final comment, we observe that energy consumption with full and intermediate cognition increases quite linearly with time in both cases *A* and *B*. On the contrary, energy consumption with no cognition is irregular and concentrated in specific instants of time, in particular for *case B* which is characterized by more rapid changes of the interference pattern. This result shows that adaptation by itself may allow the network to counteract external perturbations, but at the price of additional and sometimes significant energy consumption. When adaptation is enriched with cognitive capabilities, the network can really achieve high robustness to rapid and unpredictable external perturbations without paying the price of a reduced lifetime for the nodes.

V. Conclusions

In this work we analyzed the possibility of introducing cognitive mechanism in the design of a self-organizing network of low-rate and low-power IR UWB devices. Different cognitive strategies, corresponding to different levels of complexity for the nodes, were compared in terms of performance in mitigating both external and internal interference. Simulation results showed that the application of cognitive mechanism evidently improves network performance, even in the case of sub-optimal algorithms with moderate complexity.

Acknowledgment

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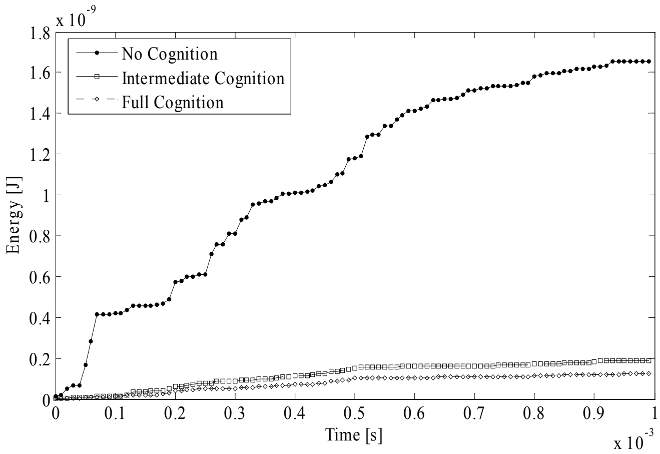

Figure 2 – Energy consumed by the reference active node in *case A*, expressed as a function of time for the three strategies under examination: full cognition (white diamonds), intermediate cognition (white squares), and no cognition (black circles).

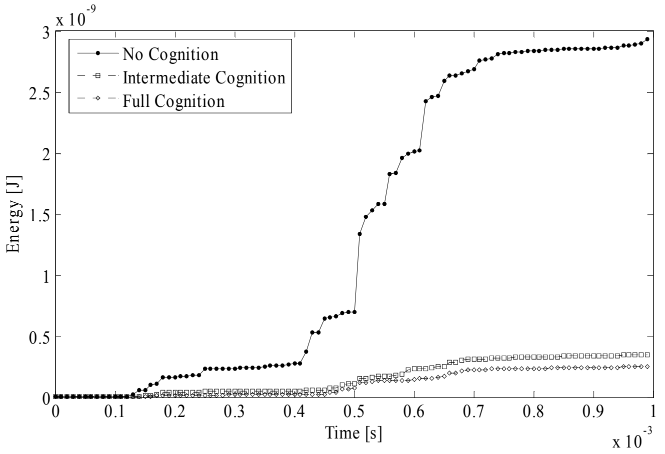

Figure 3 - Energy consumed by the reference active node in *case B*, expressed as a function of time for the three strategies under examination: full cognition (white diamonds), intermediate cognition (white squares), and no cognition (black circles).