Cognitive Tracking in IEEE 802.22 Symbiotic Radars

Pietro Stinco, Maria S. Greco, Fulvio Gini
Dept. of Ingegneria dell'Informazione, University of Pisa
Pisa, Italy
{pietro.stino, maria.greco, fulvio.gini}@iet.unipi.it

Braham Himed
RF Technology Branch, Air Force Research Lab
WPAFB, OH 45433, USA
braham.himed@us.af.mil

Abstract—**This paper focuses on a Symbiotic Radar, that is a Passive Radar which is an integral part of a communication network. The Symbiotic Radar exploits the signals of opportunity emitted by the Base Station (BS) and the Customer Premise Equipments (CPE) of an IEEE 802.22 WRAN. The radar is linked to the BS and suggests the best CPEs that must be scheduled to transmit. This selection is performed by a cognitive passive tracking algorithm that exploits the feedback information contained in the target state prediction to improve the tracking performance. The proposed algorithm has been designed with the consideration that the communication capabilities of the whole network must be preserved.**

Keywords - Cognitive Tracking; Cognitive Radio; Passive Radar; Symbiotic Radar; IEEE 802.22; ComRadE system.

I. INTRODUCTION

Communication systems are proliferating at incredible rates, resulting in spectrally dense environments and fierce competition for frequency bands that traditionally has been exclusively allocated to radar systems as primary legal users. To cope with the issue of spectrum crowding, future radar systems, as well as communication systems, should be able to coexist with other radiating systems anticipating their behavior and properly reacting to avoid interference. To this end, they need critical and new methodologies based upon cognition as an enabling technology [1],[2].

The IEEE 802.22 is a new standard [3] based on Cognitive Radio techniques for WRAN (Wireless Regional Area Network) that exploits, in a non-interfering and opportunistic basis, the unused channels in the VHF and UHF bands allocated to the television. The architecture of the IEEE 802.22 network is composed of a Base Station (BS) that covers a cell with a radius up to 30 Km providing high-speed Internet service for up to 512 fixed or portable Customer Premise Equipment (CPE) devices or groups of devices.

In [4], [5] and [6] it is shown how it is possible to exploit the IEEE 802.22 devices as transmitters of opportunity for Passive Radar (PR) systems. In particular, [4] studies the foliage penetration capabilities of a PR, defined as commensal radar, that exploits the signal emitted by the BS as the signal of opportunity, while [5] and [6] show how to combine the opportunity signals of the BS and the CPEs for target detection and target parameters estimation, respectively.

In this work, we introduce the concept of a Symbiotic Radar (SR) where the PR is an integral part of the IEEE 802.22 WRAN. The SR exploits the signal emitted by the BS and the CPEs for surveillance purposes but it is also linked to the BS to suggest the best CPEs that must be scheduled to transmit to improve the target tracking performance. In particular, the IEEE 802.22 WRAN is composed by collaborative CPEs that can also be used for surveillance purposes. As an example, the CPEs can be wireless cameras or infra-red cameras. The SR, that can also be considered as a CPE, provides full surveillance coverage during night and day and in all weather conditions using radar technology. Such system can also be defined as a ComRadE system, where Com stands for communication, Rad stands for radar, while the whole word ComRadE recalls that the communication and the radar systems are "friend" or "ally" systems.

The main advantage of a symbiotic radar, which is part of an IEEE 802.22 WRAN, is that the whole system can be installed anywhere, without any license to transmit and without interfere with other radiating systems. As a matter of fact, the SR is passive and does not bring any radar transmitter hardware while the IEEE 802.22 standard is based on cognitive radio technique. Moreover, both the SR and the IEEE 802.22 devices are very low power consuming systems that can be powered with solar panel or small wind turbines. For this reason, the whole system can also be installed in remote areas where the electricity grid is inexistent or dated and fragile.

As mentioned, the SR is linked to the BS and suggests the best CPEs that must be scheduled to transmit in order to improve target tracking performance. This concept is directly linked to the cognitive tracking algorithm introduced by Haykin [7],[8] where, exploiting the perception-action cycle, the receiver feeds the transmitter with a feedback information that is processed to select the best transmitted waveform. In the particular case of a passive radar that exploits the signals of opportunity emitted by the BS and the CPEs, and noting that its performance depends on the position of the target with respect to the locations of the transmitter and receiver (bistatic geometry), the feedback information contained in target state prediction is exploited for the selection of the best transmitters of opportunity. Over the years, a huge variety of filters have been proposed for target tracking [9]. In this paper we consider the Extended Kalman Filter (EKF) combined with a cognitive algorithm for the selection of the best set of CPEs.

The algorithm is designed such that the communication capabilities of the whole network are preserved. The numerical results show that the proposed cognitive tracking algorithm improves the performance of the symbiotic radar while preserving the communication capabilities of the ComRadE system.

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II. Cognitive Passive Tracking

The IEEE 802.22 emitters operate in the white space bands of the TV signal in the frequency range of 54-862 MHz. The standard specifies three operation modes depending on the bandwidth of the channel: 6 MHz, 7 MHz, and 8 MHz. Without loss of generality, we considered the 6 MHz based channel. In an IEEE 802.22 cell, a single BS controls the medium access and manages multiple CPEs. The timeline is divided into superframes of time duration 160 ms. Each superframe is composed by 16 frames of 10 ms, each of which is formed by two parts: a downstream (DS) subframe, where the BS transmits and the CPEs receive, and an upstream (US) subframe, where the M scheduled CPEs transmit to the BS. The upstream transmissions are shared by CPEs on a demand basis, according to an Orthogonal Frequency Division Multiple Access (OFDMA) scheme where information is modulated on orthogonal subcarriers using Inverse Fast Fourier Transforms (IFFT) of size 2048 [3].

Fig. 1 shows the IEEE 802.22 WRAN scenario analyzed in this paper. The network is composed by a BS that provides Internet access to 32 CPEs. The SR is not co-located with the BS and can control the BS to suggest the best cooperative CPEs that must be scheduled to transmit for target tracking performance improvement. The figure also shows the target trajectory in absence of process noise.

Let define the state vector as $\mathbf{x}_k=[x_k\ \dot{x}_k\ y_k\ \dot{y}_k\ ]^T$, where (x_k, y_k) is the location of the target, assumed to be on the x-y plane, and $(\dot{x}_k, \dot{y}_k)$ is the target velocity vector. Let also assume that the target motion equation is described by the following dynamic target state [10], [11]:

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{n}_{k-1}, \tag{1}$$

$$\mathbf{F} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{2}$$

where T is the superframe duration while $\mathbf{n}_k$ models the process noise, which takes into account mismodeling effects or unforeseen disturbance in the target motion. We assume that $\mathbf{n}_k$ is a zero-mean Gaussian distributed vector with covariance matrix [10]:

$$\mathbf{Q} = q\begin{bmatrix} T^3/3 & T^2/2 & 0 & 0 \\ T^2/2 & T & 0 & 0 \\ 0 & 0 & T^3/3 & T^2/2 \\ 0 & 0 & T^2/2 & T \end{bmatrix} \tag{3}$$

where q is a deterministic parameter which takes into account the process noise power.

The available measurements at time k are collected in the column vector $\mathbf{z}_k=[r_k^{(0)}\ \zeta_k^{(0)}\ \ldots\ r_k^{(M)}\ \zeta_k^{(M)}\ \theta_k]^T$, whose components are the range from receiver to target $r_k^{(0)}$ and the bistatic velocity $\zeta_k^{(0)}$, obtained by exploiting the signal emitted by the BS in the DS, the set of ranges $\{r_k^{(1)},\ldots, r_k^{(M)}\}$ and bistatic velocities $\{\zeta_k^{(1)},\ldots, \zeta_k^{(M)}\}$, obtained exploiting the M

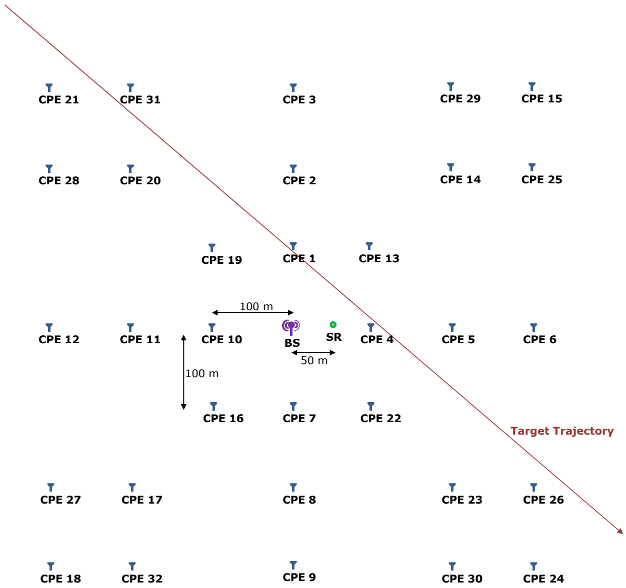

Fig. 1 – The analyzed scenario.

CPEs, that are scheduled to transmit in the US, and the Direction of Arrival (DOA) of the target echo θ_k.

The relationship between the measurement vector and the target state is given by

$$\mathbf{z}_k = \mathbf{h}_k(\mathbf{x}_k) + \mathbf{w}_k. \tag{4}$$

The explicit expression of $\mathbf{h}_k(\mathbf{x}_k)$ is given in [12]; $\mathbf{w}_k$ is the measurement noise, independent of the process noise $\mathbf{n}_k$. The measurement noise is assumed to be Gaussian distributed with zero mean and covariance matrix $\mathbf{R}_k$.

In bistatic radar systems the accuracy of the estimate of range and bistatic velocity heavily depends on the geometry of the scenario, i.e. the position of the target with respect to the radar receiver and the transmitter of opportunity that is exploited, as well on the signal to noise ratio (SNR), which is itself dependent on the geometry. The expression of $\mathbf{R}_k$ is reported in [6],[12]. Note that this covariance matrix is a function of time since the bistatic geometry changes along the target trajectory.

As discussed, to estimate the state vector $\mathbf{x}_k$ from the measurements $\mathbf{z}_k$, we use the EKF, where the target state estimates are computed recursively as follow [9]:

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{G}_k\left(\mathbf{z}_k - \mathbf{h}_k\left(\hat{\mathbf{x}}_{k|k-1}\right)\right) \tag{5}$$

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}\hat{\mathbf{x}}_{k-1|k-1} \tag{6}$$

$$\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1} + \mathbf{G}_k\mathbf{S}_k\mathbf{G}_k^T \tag{7}$$

$$\mathbf{P}_{k|k-1} = \mathbf{Q} + \mathbf{F}\mathbf{P}_{k-1|k-1}\mathbf{F}^T \tag{8}$$

$$\mathbf{S}_k = \hat{\mathbf{H}}_k\mathbf{P}_{k|k-1}\hat{\mathbf{H}}_k^T + \mathbf{R}_k \tag{9}$$

$$\mathbf{G}_k = \mathbf{P}_{k|k-1}\hat{\mathbf{H}}_k^T\mathbf{S}_k^{-1} \tag{10}$$

where $\hat{\mathbf{H}}_k$ is the matrix obtained by the linearization of the non linear function $\mathbf{h}_k(\mathbf{x}_k)$ and is defined as the Jacobian evaluated at $\hat{\mathbf{x}}_{k|k-1}$:

$$\hat{\mathbf{H}}_k = \left[\nabla_{\mathbf{x}_k} \mathbf{h}_k^T(\mathbf{x}_k)\right]^T\Big|_{\mathbf{x}_k=\hat{\mathbf{x}}_{k|k-1}}. \tag{11}$$

The explicit expression of $\hat{\mathbf{H}}_k$ is given in [12].

Now let us consider how the perception-action cycle defined by Haykin [7] can be applied for cognitive passive tracking. The perception-action cycle is the fundamental function of a cognitive tracker. For active radar systems, at each step k, the transmitter modifies the transmitted signal (action) minimizing a specific cost function that depends on the feedback information. This information is evaluated by the receiver and provides a compressed measure of information contained in the radar returns (perception).

Clearly, a passive radar does not have any radar transmitter on its own and hence it is not able to modify the transmitted signal. However, the Symbiotic Radar is integrated with the communication network and hence it controls the BS and selects the CPEs that give the best performance for the target state estimation. In other words, similarly to cognitive active radars that select the best transmitted waveform, the SR exploits the feedback information to select the best transmitters of opportunity that minimize a pre-defined cost function.

In [13],[14] we described how it is possible to exploit the Cramér-Rao Bounds (CRB) of the range and bistatic velocity, which depend on the geometry and are strictly related to the measurement covariance matrix $\mathbf{R}_k$, to select the best transmitters of opportunity. In particular, the CRB can be evaluated off-line and, exploiting this information, for each point of the surveillance area, the SR a-priori knows which is the best CPE that provides the minimum error in the measurement of range and bistatic velocity. Hence, it can rank the CPEs from best to worst.

The perception-action cycle is based on the minimization of a predefined cost function. In [7] it is shown that the cost function that minimizes the mean square error (MSE) of target state prediction is the trace of the prediction of the target state covariance matrix $\mathbf{P}_{k+1|k}$. This function is minimized when the transmitters of opportunity are the BS and all the M scheduled CPEs are those that minimize the measurement error, i.e. the CPEs that in the prediction point $\hat{\mathbf{x}}_{k+1|k}$ gives the lowest CRBs of the range and bistatic velocity.

Let S_{ideal} denotes this ideal set of M+1 transmitters of opportunity, the minimum value of the cost function is given by $Trace\{\mathbf{P}_{k+1|k}(S_{ideal})\}$. Clearly, not all the available M slots in the US frame can be allocated for target tracking purposes, since the communication functionalities of the network must be preserved.

Let S_m indicates the set of M+1 transmitters composed by the BS, the m CPEs (selected by the SR) that give the best performance in estimating the range and bistatic velocity, and the M-m CPEs selected by the BS for communication purposes. The cognitive passive tracking algorithm selects the set of transmitters for the subsequent frame by finding the minimum number m that guarantees a cost function such that

$$\lambda \cdot Trace\left\{\mathbf{P}_{k+1|k}(S_m)\right\} \le Trace\left\{\mathbf{P}_{k+1|k}(S_{ideal})\right\}, \tag{12}$$

where $0 \le \lambda < 1$; note that when $\lambda=0$ the tracking is purely passive and the SR does not select any CPE to improve the performance. The search of the minimum number m of CPEs starts from 1, i.e. exploiting the CPE that gives minimum error in estimating range and bistatic velocity, and it stops when $m=M/2$, i.e. when the 50% of the available slots in the US are allocated to the best CPEs. Clearly, if the CPEs scheduled to transmit for communication purposes are in favorable bistatic geometry, they are also exploited by the SR for target tracking.

III. SIMULATION RESULTS

This section shows the performance of the proposed cognitive passive tracking algorithm for the scenario in Fig. 1. The SR is at the origin of the Cartesian coordinate system while, in absence of process noise, the target is moving from [-400 m, 400 m] to [400 m, -250 m], with speed 8.33 m/s.

In the Monte Carlo runs the process noise power q has been fixed to q=0.01. Among the 32 CPEs in the network, only M=8 can be scheduled to transmit in each superframe. According to the proposed algorithm, to improve the target tracking performance, the SR can select up to $M/2$=4 collaborative CPEs.

Figs. 2 and 3 show the Root Mean Square Error (RMSE) of the target position and velocity, which are measured as follows:

$$RMSE_{position} = \sqrt{\frac{1}{MC}\sum_{mc=1}^{MC}\left(x^{(mc)} - \hat{x}_{k|k}^{(mc)}\right)^2 + \left(y^{(mc)} - \hat{y}_{k|k}^{(mc)}\right)^2}, \tag{13}$$

$$RMSE_{velocity} = \sqrt{\frac{1}{MC}\sum_{mc=1}^{MC}\left(\dot{x}^{(mc)} - \hat{\dot{x}}_{k|k}^{(mc)}\right)^2 + \left(\dot{y}^{(mc)} - \hat{\dot{y}}_{k|k}^{(mc)}\right)^2}. \tag{14}$$

The results have been obtained through 10^4 Monte Carlo runs for values of λ={0, 0.8, 0.9, 0.95, 0.99, 0.999}.

The results obtained with λ=0 indicate the performance of a passive radar that does not exploit the cognitive perception-action cycle described in the previous section. As a term of comparison, the figures also show the following bounds on the target position and velocity estimates:

$$B_{position} = \sqrt{\frac{1}{MC}\sum_{mc=1}^{MC}\left[\mathbf{P}_{k|k}^{(mc)}\right]_{1,1} + \left[\mathbf{P}_{k|k}^{(mc)}\right]_{3,3}}, \tag{15}$$

$$B_{velocity} = \sqrt{\frac{1}{MC}\sum_{mc=1}^{MC}\left[\mathbf{P}_{k|k}^{(mc)}\right]_{2,2} + \left[\mathbf{P}_{k|k}^{(mc)}\right]_{4,4}}. \tag{16}$$

These bounds are the CRB of the target state estimate when the relation in (4) between the target state $\mathbf{x}_k$ and the measurement vector $\mathbf{z}_k$ is linear, i.e. $\mathbf{h}_k(\mathbf{x}_k)=\hat{\mathbf{H}}_k$.

The degradation of the performance for k=400:500 is related to the fact that in this time range the target approaches the SR. For the resulting geometry, the nonlinearity in (4) is severe and the non-Gaussianity of the true posterior density is

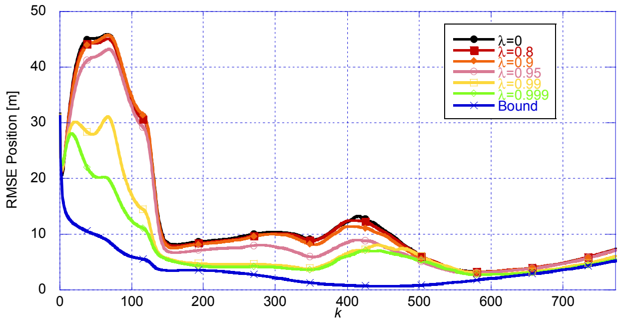

Fig. 2 – RMSE of target position for λ={0, 0.8, 0.9, 0.95, 0.99, 0.999}.

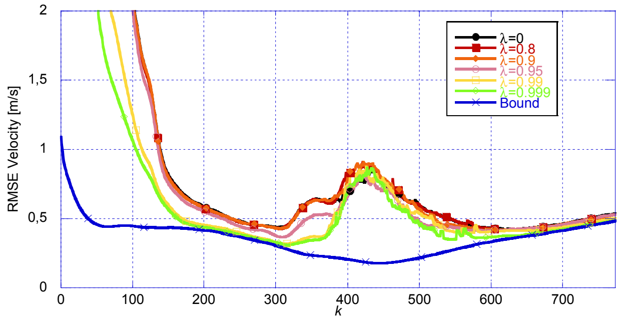

Fig. 3 – RMSE of target velocity for λ={0, 0.8, 0.9, 0.95, 0.99, 0.999}.

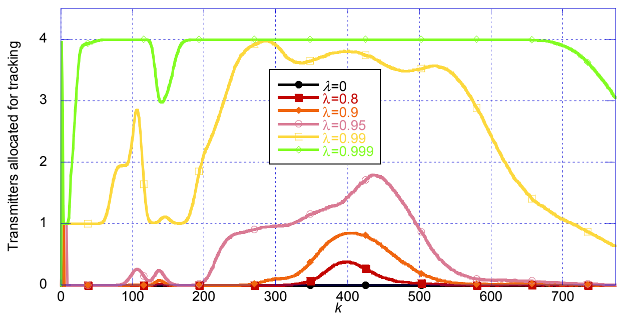

Fig. 4 – Mean number of CPEs scheduled to transmit by the SR.

stronger [9]. This phenomenon is more pronounced for low values of λ.

From these numerical results, it is apparent that there is a substantial gain using the cognitive tracking algorithm with respect to the purely passive tracking. Note also that in the analyzed scenario there are only 32 CPEs, the performance in the case λ=0 are comparable with the other ones since there is a high probability that the 8 CPEs scheduled to transmit have good bistatic geometries. The performance of the cognitive algorithm is more prominent when the IEEE 802.22 WRAN is composed by a huge number of CPEs. As discussed in previous section, the proposed algorithm has been designed also to preserve the communication capabilities of the network. Fig. 4 shows the mean number of CPEs scheduled to transmit by the SR along the target trajectory to improve the required tracking performance. Clearly, when λ=0 the tracking is passive and the SR does not schedule any CPE while when λ tends to one, the SR tends to schedule all the available $M/2$ CPEs. Note also that for the particular case of λ=0.95, the mean number of scheduled CPEs is not greater than 2 and the resulting performances are substantially lower than in the case of λ=0.

IV. CONCLUSIONS

In this work we introduced the concept of a Symbiotic Radar (SR), that is defined as a passive radar which is an integral part of a communication network. We focused on the particular case of an IEEE 802.22 WRAN. This choice has been made considering that both the SR, which is a passive system, and the IEEE 802.22 devices, that exploit cognitive radio techniques, can be installed everywhere without any license to transmit and without interfere with other radiating systems. We defined a cognitive passive tracking algorithm inspired by the perception-action cycle introduced by Haykin [7] where the SR control the BS and can select the best CPEs that must be scheduled to transmit in each frame to improve the target tracking performance. The proposed algorithm has been also designed to preserve the communication capabilities of the network. The obtained results show that there is a substantial gain using the proposed algorithm with respect to a passive radar that does not select the CPEs of opportunity even in the case in which the resources allocated to the SR are very low.

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