An Enhanced Serial Network Spectrum Sensing Scheme for Multiple Antenna Cognitive Radios

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Abstract—In this paper, the problem of primary user detection in cognitive radio networks is faced. To this end, a secondary terminal equipped with multiple antennas is considered to exploit the benefits offered by the spatial diversity. In particular, a two antenna terminal is considered for space and complexity reasons. It is modeled as an enhanced serial network, a distributed detection technique with strong theoretical basis where the processing performed at one antenna is influenced by the processing performed at the other one is considered. The enhanced serial network model is based on the identification of the sub-spaces, denoted as stability region, where the decision problem is not SNR-variant. The analytical expressions for the probability of correct detection and for the probability of false opportunity detection are derived. Numerical results show that the proposed scheme outperforms traditional two antenna terminal solutions in multipath channel.

Index Terms—Cognitive radio, distributed spectrum sensing, distributed detection, serial network, multiple antenna system.

I. INTRODUCTION

Recently, new different wireless services have been deployed. To guarantee the coexistence among them a fixed spectrum allocation policy has been adopted causing lack of free frequency bands [1]. However, the Federal Communication Commission (FCC) has shown that a great part of the radio resources, although licensed, are often underutilized [2], and this has suggested the possibility of considering new techniques which can allow a more efficient spectrum management [1].

In particular, Cognitive Radio (CR) technology has been proposed as a promising solution to improve the radio spectrum utilization by allowing to secondary (cognitive) users to dynamically access to a licensed frequency band if primary (legacy) users are not using it at a given time and in a given location [1]. On the other hand, many problems arise since primary users have to be protected from harmful interference while assuring an adequate level of service at the CR network [3].

For these reasons, the reliable detection of the primary users’ activity, known as spectrum sensing, is a fundamental task in CR networks. Furthermore, primary user transmitted signals can be heavily affected by channel detrimental effects (e.g. additive noise, multipath fading) which can cause an undesirable missed detection of the primary users [1], [4] leading to possible harmful interference to legacy networks.

Although most of the prior researches focus on spectrum sensing considering single antenna at the CR networks [5], recently, the utilization of multiple antenna at the secondary system has gained a lot of attention. In fact, it allows to obtain several benefits such as multipath fading effects mitigation, capacity enhancement, etc. by exploiting the spatial diversity. In spite of various architectures can be designed, cooperative single antenna CRs [1], [6]–[8] and multiple antenna CR [4], [9]–[12] have been considered in the open literature for the detection of a primary user.

In the first case, several single antenna secondary users can cooperate by performing local spectrum sensing and sending the obtained data (e.g. a compressed version of the sampled signal, a local decision), through a control channel, to a fusion center which makes the global decision. The single antenna secondary users lie in different locations in the environment and hence they perceive independent signals allowing to mitigate the multipath fading impairments [1]. For example, in [1], [6], the multiple secondary users are designed as a standard parallel fusion network, where each user independently acts local spectrum sensing. Then, the local decisions are transmitted over a control channel to a data fusion center, where they are combined to yield the global inference [13]. It is shown that this approach outperforms traditional stand-alone single antenna terminal in the detection of a primary user [1], [6]. However, some practical issues arise, as a communication overhead when exchanging local spectrum sensing data, the necessity of a reliable communication channel between the secondary users and the data collector [6], [7], etc. which can limit the application of the cooperative approach to CR networks [1].

Recently, an alternative approach, based on a single secondary user equipped with multiple antennas, has been considered [4], [10]–[12]. It allows to overcome the practical limitations exhibited from the cooperative single antenna CRs by exploiting the spatial diversity derived from the independent signals perceived by the antennas, if they are placed at least one half the wavelength apart [14]. For example, traditional combining techniques such as maximum ratio combining and antenna selection [14] are considered in [10] to improve the detection of the primary user. The reported numerical analyses point out that the considered multiple antenna CR provides better detection performances than single antenna terminal by assuming that the channel coefficients are known at the secondary system. However, this hypothesis is unpractical in real CR networks where cooperation from primary network cannot be assured [9]. In other works, presented in [11]...
and [12], it is assumed that each antenna perceives an independent signal which is then processed without performing any diversity combining to make a local decision. Such decisions have to be fused to yield a global inference. To this end, the AND fusion rule is applied in [12], while a majority voting is considered in [11]. Despite these approaches lead to performance improvements with respect to a single antenna detection, each antenna acts autonomously and does not influence the processing with each others which could prevent a further performance improvements [13].

In this work, to overcome such a limitation, a serial network model [13], a distributed detection technique where the processing at each antenna is influenced by the processing at the other ones, is applied to a multiple antenna secondary system. In particular, a secondary terminal equipped with two antennas is considered since terminals with a low number of antennas are cost and space effective. However, the proposed scheme can be easily extended to terminal equipped with more than two antennas. Moreover, a stability region is introduced to improve the detection of the primary user with respect to that of the traditional serial network model [13]. It is defined as the sub-spaces where the decision problem is independent of the received Signal-to-Noise Ratio (SNR). The analytical expressions for the probability of correct detection and for the probability of false opportunity detection are derived. Finally, a set of numerical simulations are carried out to verify the effectiveness of the proposed two antenna system comparing the obtained performances with those of different two antenna terminals employing the OR fusion rules [8], the AND fusion rule [8], and the traditional serial network model [13], in a heavily corrupted multipath environment.

II. SYSTEM MODEL

In this work, it is assumed that a two antenna secondary system has to reliably detect the activity of a primary user. A binary hypothesis testing problem is considered, for simplicity, and the two hypotheses are denoted by $H_0$ (e.g. primary user absence) and $H_1$ (e.g. primary user presence) associated with the a priori probability $P_0$ and $P_1$, respectively. However, the proposed scheme can be easily extended to the general case of $M$-ary hypotheses testing problem (e.g. the detection of primary users and the associated transmission standard). For example, it can be divided in $\frac{M \times (M-1)}{2}$ binary tests by implementing an one-against-one approach and then by applying a majority voting to make the global decision [7].

Among the different approaches which can be used to fuse the local spectrum sensing data to make a global decision, in this work, the serial network model [13], a distributed detection technique, is applied. It has been selected since it guarantees satisfactory performances in various practical problems [13].

In the considered serial network model, the antennas are connected in series and gather direct observations of the radio spectrum $y_{i}$, $i = 1, 2$. The first antenna obtains a local decision $u_{1}$ based on its own observation $y_{1}$. Such decision is transferred to the second antenna which uses it in addition to its own observation $y_{2}$ to make the global decision $u_{0} = u_{2}$ [13].

Different kinds of observation $y_{i}$ (e.g. sampled signals, compressed versions of sampled signals) can be used as input to a serial network to detect primary users’ activity. In this work, it is assumed that the received signals are processed to extract some features of interest, as shown in Fig. 1. A feature $f_{j}$ is defined as an inherent characteristic which is unique for each class of signals [15]. Some of the most intuitive features proposed in the open literature [7], [15] are instantaneous amplitude, phase, and frequency, cyclic features, etc [7], [15]. Therefore the observation $y_{i} = \{ f_{j} \}$ $j = 1, . . . , N$ is assumed to be an $N$-dimensional vector containing the extracted features $f_{j}$. The dimension $N$ of the observation can affect, even heavily, the complexity of the detection problem, resulting in long detection time.

The Principal Component Analysis (PCA) [16] method, also know as Karhunen-Loeve (K-L) method, is applied in order to reduce the complexity of the considered problem. PCA involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components [16]. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible [16]. In this work, the PCA is applied to the $N$-dimensional vector of the observation $y_{i}$ to reduce it to a scalar observation $y_{ir}$, i.e. containing the obtained principal component. This procedure allows to reduce the model of the observation status from multidimensional probability density functions (pdfs) to monodimensional pdfs, reducing the complexity of the considered problem and the detection time, consequently.

Note that the performances of the detection problem could be deeply influenced by the quality of the observations. In particular, the extracted features, as well as the observations...
\[ y_i \text{ are dependent on the received SNR [7]. However, this} \]
dependance is exploited in the proposed scheme to improve the
performances of the detection of a primary user, differently
from traditional serial networks [13]. To this end, the stability
regions, here defined as different sub-spaces \( \gamma_{i,l}, l = 1, \ldots, \Lambda \)
of the possible values of the received SNR \( \Gamma \) where the
decision problem is stable since it is not SNR-variant, are
introduced.

In order to identify the stability regions an off-line training
phase is carried out. It is usually implemented in supervised
classification (e.g. artificial neural networks, support vector
machines) [7] and consists in using a training set composed by
some observation instances associated with an hypothesis and
a SNR label to identify the stability regions \( \gamma_{i,l} \). In particular,
by applying the central limit theorem (CTL) and assuming
that the dimension \( N \) of the training set is sufficiently large,
it is possible to estimate the conditional pdfs under the
two hypotheses \( p(y_i|H_k, \gamma_{i,l}), k = 0, 1 \) which approach a
normal distribution. Therefore, \( p(y_i|H_k, \gamma_{i,l}) \) are completely
represented by the sample mean \( \mu_{k,l,i} \) and the sample variance
\( \sigma_{k,l,i}^2 \)

\[
\mu_{k,l,i} = \frac{1}{N} \sum_{n=1}^{N} y_i(n) \tag{1}
\]

\[
\sigma_{k,l,i}^2 = \frac{1}{N} \sum_{n=1}^{N} [y_i(n) - \mu_{k,l,i}]^2, \tag{2}
\]

for the \( l \)-th stability region, the \( k \)-th hypothesis at the \( i \)-th
antenna. The stability regions \( \gamma_{i,l} \) are defined as the sub-spaces
of the received SNR where \( \mu_{k,l,i} \) and \( \sigma_{k,l,i}^2 \) do not significantly
vary, i.e.

\[
\gamma_{i,l} \neq \gamma_{i,l+1} \Leftrightarrow \begin{cases}
|\mu_{k,l,i} - \mu_{k,l+1,i}| > \alpha \\
|\sigma_{k,l,i} - \sigma_{k,l+1,i}| > \beta
\end{cases}, \quad \alpha, \beta \in \mathbb{R} \tag{3}
\]

where \( \alpha \) and \( \beta \) are design parameters.

The obtained stability regions and conditional pdfs under the
two hypotheses are then used to derive a decision rule such that
the average cost for making a decision \( u_0 \) is minimized.
By assuming that the observation at the antennas are conditionally
independent, starting from [13], and adding the dependance
from the stability regions, the following Bayesian risk function
is obtained:

\[
\mathcal{R} = p(u_1, u_2, y_1, y_2, H_k|\Gamma)C_{ik} \]

\[
\quad = \sum_{i,j,k} \int P_{ik}C_{ik}p(u_2|u_1, y_1, y_2, H_k, \Gamma) \cdot p(u_1, y_1, y_2|H_k, \Gamma), \tag{4}
\]

where \( C_{ik} \) is the cost for deciding \( H_i \) when \( H_k \) is present.
A fundamental and well known result in distributed binary
hypothesis testing problems is that, if the observations at
the antennas are conditionally independent (as in this case),
the optimal decision rule at each antenna is the likelihood
ratio test (LRT) [13]. Furthermore, since we are modeling
the proposed system as a serial network, at the first antenna a
single threshold has to be derived, while at the second antenna
two thresholds are needed depending on the decision \( u_1 = k, k = 0, 1 \) at the first antenna [13]. The likelihood ratio tests at
the antennas are [13]:

\[
\Lambda(y_1) = \frac{p(y_1|H_1, \gamma_{1,l})}{p(y_1|H_0, \gamma_{1,l})} \overset{H_1}{\gtrless} t_1(\gamma_{1,l}) \tag{5}
\]

\[
\Lambda(y_2) = \frac{p(y_2|H_2, \gamma_{2,l})}{p(y_2|H_0, \gamma_{2,l})} \overset{H_1}{\gtrless} t_2(\gamma_{2,l}).
\]

By assuming the two hypotheses equally likely and the cost
\( C_{ik} = 0 \) if \( i = k \) and \( C_{ik} = 1 \) otherwise, the thresholds
involved in the LRT in (5) at the two antennas, following
the mathematical procedures shown in [13], and adding the
dependence from the stability region \( \gamma_{i,l} \), are expressed by
\[
\begin{cases}
t_1(\gamma_{1,l}) = \frac{p(u_2=1|u_1=1, H_0, \gamma_{1,l}) - p(u_2=1|u_1=0, H_0, \gamma_{1,l})}{p(u_2=1|u_1=1, H_1, \gamma_{1,l}) - p(u_2=1|u_1=0, H_1, \gamma_{1,l})} \\
t_2(\gamma_{2,l}) = \frac{p(u_2=\gamma_{k}^2|H_2, \gamma_{2,l})}{p(u_2=0|H_2, \gamma_{2,l})} \quad k = 0, 1.
\end{cases} \tag{6}
\]

Since the conditional pdfs under the two hypotheses can be
represented by a normal distribution expressed by
\( N(\mu_{k,l,i}, \sigma_{k,l,i}^2) \), the set of three coupled equations, reported
in (6), in the three unknown variables to be simultaneously
solved becomes

\[
\begin{cases}
t_1(\gamma_{1,l}) = Q \left( \frac{t_{1}^0 - \mu_{0,1,i}}{\sigma_{0,1,i}} - Q \left( \frac{t_{1}^0 - \mu_{0,1,i}}{\sigma_{0,1,i}} \right) \right) \\
t_2(\gamma_{2,l}) = Q \left( \frac{t_{2}^0 - \mu_{0,2,i}}{\sigma_{0,2,i}} - Q \left( \frac{t_{2}^0 - \mu_{0,2,i}}{\sigma_{0,2,i}} \right) \right) \\
t_1^0(\gamma_{1,l}) = \frac{Q \left( \frac{t_{1}^0 - \mu_{0,1,i}}{\sigma_{0,1,i}} \right)}{1 - Q \left( \frac{t_{1}^0 - \mu_{0,1,i}}{\sigma_{0,1,i}} \right)} \\
t_2^0(\gamma_{2,l}) = \frac{Q \left( \frac{t_{2}^0 - \mu_{0,2,i}}{\sigma_{0,2,i}} \right)}{1 - Q \left( \frac{t_{2}^0 - \mu_{0,2,i}}{\sigma_{0,2,i}} \right)},
\end{cases} \tag{7}
\]

where \( Q(x) = \int_x^{\infty} e^{-t^2} \, dt \). It is important to remark that
the three thresholds in (7) can be computed in advance during
the off-line training phase. During the on-line detection phase,
it is required to evaluate the received SNR at the antennas
to identify the stability region and then select the thresholds
which are finally used in the LRTs in (5) to make the global
decision. Note that, in the proposed scheme, the received SNR
estimation is necessary to perform the detection. However, it
is out of scope of the present work, and different techniques
have been proposed in the open literature [17], [18] for SNR
estimation purposes.

Differently from [13], the threshold \( t_1 \) at the first antenna
depends on both possible values of the thresholds \( t_{k}^2, k = 0, 1 \)
and on the stability region \( \gamma_{1,2} \) at the second antenna. As
well, the thresholds \( t_{k}^2 \) depend on the threshold \( t_1 \) and on the
stability region \( \gamma_{1,1} \) at the first antenna. Thus, the processing
at one antenna influences the processing at the other one. This
aspect leads to a performance improvement in the detection
of the primary user with respect to other approaches (see
Section III).

Finally, the probability of correct detection \( P_c \) and
the probability of false opportunity detection \( P_{fo} \) are analytically
derived. In particular, \( P_c \) is the probability to correctly detect
the hypothesis present in the monitored environment

\[ P_e = p(u_2 = 1|H_1)P_1 + p(u_2 = 0|H_0)P_0 \]

\[ = P_1[p(u_2 = 1|u_1 = 0, H_1)p(u_1 = 0|H_1) + p(u_2 = 1|u_1 = 1, H_1)p(u_1 = 1|H_1)] \]

\[ + P_0[p(u_2 = 0|u_1 = 0, H_0)p(u_1 = 0|H_0) + p(u_2 = 0|u_1 = 1, H_0)p(u_1 = 1|H_0)] \]

\[ = P_1\left\{ Q\left(\frac{t_1 - \mu_{1,1,1}}{\sigma_{1,1,1}}\right) \cdot \left[1 - Q\left(\frac{t_1 - \mu_{1,1,1}}{\sigma_{1,1,1}}\right)\right] \right\} \]

\[ + Q\left(\frac{t_2 - \mu_{1,1,2}}{\sigma_{1,1,2}}\right) \cdot Q\left(\frac{t_1 - \mu_{1,1,1}}{\sigma_{1,1,1}}\right) \]

\[ + P_0\left\{ \left[1 - Q\left(\frac{t_2 - \mu_{0,1,2}}{\sigma_{0,1,2}}\right)\right] \cdot \left[1 - Q\left(\frac{t_1 - \mu_{0,1,1}}{\sigma_{0,1,1}}\right)\right] \right\} \]

\[ + Q\left(\frac{t_2 - \mu_{0,1,2}}{\sigma_{0,1,2}}\right) \cdot Q\left(\frac{t_1 - \mu_{0,1,1}}{\sigma_{0,1,1}}\right). \]

(8)

Moreover, \( P_{f_0} \) is the probability to declare the absence of a primary user when a primary user is actually present

\[ P_{f_0} = p(u_2 = 0|H_1) \]

\[ = p(u_2 = 0|u_1 = 0, H_1)p(u_1 = 0|H_1) + p(u_2 = 0|u_1 = 1, H_1)p(u_1 = 1|H_1) \]

\[ = Q\left(\frac{t_0 - \mu_{0,1,2}}{\sigma_{0,1,2}}\right) \cdot \left[1 - Q\left(\frac{t_1 - \mu_{0,1,1}}{\sigma_{0,1,1}}\right)\right] \]

\[ + Q\left(\frac{t_2 - \mu_{0,1,2}}{\sigma_{0,1,2}}\right) \cdot Q\left(\frac{t_1 - \mu_{0,1,1}}{\sigma_{0,1,1}}\right). \]

(9)

Such probability is of fundamental importance in practice. In fact, it represents the probability to miss the detection of the primary user and hence to cause possible interference, with secondary transmissions, to the primary network.

As a final remark, it is important to note that the proposed scheme can be easily derived for secondary terminals equipped with \( I \)-antennas. In this case, \( 2I - 1 \) thresholds have to be obtained by the simultaneous solution of \( 2I - 1 \) coupled equations [13].

### III. NUMERICAL RESULTS AND DISCUSSIONS

In order to evaluate the effectiveness of the proposed solution, the performances of the two antenna CR described in Section II are compared with those of different two antenna CRs employing the OR fusion rules [8], the AND fusion rule [8], and the classical serial network model [13]. It is assumed that the primary user can transmit by similar OFDM-based techniques, i.e. IEEE 802.11a (WiFi) and IEEE 802.16e (WiMAX) [7]. In case of silent primary user (i.e. no transmissions) only noise is received by the two antenna CR. A detection problem in which the secondary terminal has not only to identify the primary user’s activity but also the used transmission standard is considered. To face this detection problem, it is decomposed into three binary tests (i.e. WiFi-noise, WiMAX-noise, WiFi-WiMAX) to apply the scheme proposed in Section II. Then a majority voting is applied to the outputs of the three binary tests to make the global decision.

The same processing algorithm proposed in [7] for the required feature extraction phase (see Fig. 1) is applied to the considered systems to provide a fair comparison. A deeply presentation of the algorithm is out of scope of the present work, however, it is briefly summarized. It is assumed that both primary and secondary users are moving in a given environment and that the transmitted signal are affected by Additive White Gaussian Noise (AWGN) and by multipath effects by implementing the COST 207 - Bad Urban channel model [19]. A Doppler frequency of \( f_d = 100 \text{ Hz} \) is assumed in our simulations. The primary signal is received by each antenna of the secondary terminal and is sampled to obtain a digital signal. It is processed to obtain the Spectral Correlation Function (SCF) [7] which allows to evaluate the correlation among the spectral components of the received signal. For example, the SCF for a WiFi signal is reported in Fig. 2. It exhibits some periodical peaks in fixed position, known in the open literature as cyclic features [7], due to the pilot carriers embedded in both signals of interest. Then, the projection of

![Fig. 2. Estimated SCF for a WiFi signal with SNR = 10 dB.](image)

![Fig. 3. Estimated projection of SCF for a WiFi signal (red), for a WiMAX signal (green) with a SNR = 10 dB, and for no transmission (blue).](image)
which shows the projections for the three signals of interest. Finally, two features which represent the bidimensional observation vector $y_i$, are extracted from the evaluated projections and are reported in Fig. 4. As discussed in Section II, the PCA method is applied to the bidimensional vector of the observation to reduce it to a scalar value $y_i$.

A set of 5000 observations $y_i$ has been generated for each considered SNR $\in \{-15, -10, -5, 0, 5, 10, 15\}$ dB and for each considered class of signal $S \in \{\text{WiFi, WiMAX, noise}\}$, by collecting the received signal for 3 ms. Then, an off-line training phase is performed by using 2500 observations $y_i$, $\alpha = 0.3$ and $\beta = 0.2$ for each considered SNR and class of signal, to evaluate $\mu_{k,l,i}$, $\sigma^2_{k,l,i}$, and $\gamma_{l,i}$, $l = 1, 2, 3$. Such parameters completely represent the conditional pdfs under the hypotheses which are reported in Fig. 5 for a SNR $= 10$ dB. Then the thresholds $t_1$, $\nu^2_1$ and $t_2^2$ needed for the LRT in (5) are obtained by the simultaneous solution of (7). A few sample values for $\mu_{k,l,i}$ and $\sigma^2_{k,l,i}$ are reported in Table I for different SNRs. It is shown that the received SNRs highly affect the estimated values and consequently the thresholds evaluation in (7). This motivates the introduction of the stability regions in (3) allowing to improve the detection performances.

Fig. 6 shows the probability of correct detection $P_c$ for the considered systems. As expected, the performances increase as the SNR increases. The proposed two antenna terminal allows to increase $P_c$ with respect to the other considered approaches, especially at low SNR. In particular, if the proposed two antenna terminal is considered and SNR $= -5$ dB, then $P_c$ increases of 0.30 with respect to the one obtained by the two antenna terminal employing the OR fusion rule [20].

<table>
<thead>
<tr>
<th>Transmitted signal</th>
<th>SNR [dB]</th>
<th>Sample mean $\mu$</th>
<th>Sample variance $\sigma^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>WiFi</td>
<td>-10</td>
<td>0.746</td>
<td>1.704</td>
</tr>
<tr>
<td>WiFi</td>
<td>10</td>
<td>-1.322</td>
<td>0.145</td>
</tr>
<tr>
<td>WiMAX</td>
<td>-10</td>
<td>-0.223</td>
<td>0.283</td>
</tr>
<tr>
<td>WiMAX</td>
<td>10</td>
<td>0.355</td>
<td>0.046</td>
</tr>
</tbody>
</table>

The probability of false opportunity detection $P_{fo}$ is reported in Fig. 7 for the considered systems. As expected, even in this case, the performances increase as the SNR increases. Moreover, it is shown that the proposed two antenna
terminal allows to significantly reduce $P_{fo}$. For example, if the proposed two antenna terminal and a SNR=−10 dB are considered the $P_{fo}$ decreases of about 0.4 with respect to the one obtained by the other considered approaches.

It is important to note that, in general, the proposed scheme outperforms the other considered systems. In particular, in Table II the general probability of correct detection and the general probability of false opportunity detection are reported outperforms the other considered systems. In particular, in Table II the general probability of correct detection and the general probability of false opportunity detection are reported independently from the received SNR. It is shown that the proposed two antenna terminal has better performances than other considered systems.

<table>
<thead>
<tr>
<th>CR</th>
<th>$P_c$</th>
<th>$P_{fo}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>proposed two antenna</td>
<td>0.8278</td>
<td>0.0915</td>
</tr>
<tr>
<td>two antenna serial network [13]</td>
<td>0.8069</td>
<td>0.1867</td>
</tr>
<tr>
<td>two antenna OR fusion rule [8]</td>
<td>0.7499</td>
<td>0.2227</td>
</tr>
<tr>
<td>two antenna AND fusion rule [8]</td>
<td>0.6567</td>
<td>0.2944</td>
</tr>
</tbody>
</table>

In the reported simulations, to provide a fair comparison with the single antenna terminal, it assumed that the received SNR at the two antennas is the same. However, other simulations have been carried out in terms of different received SNR at the antennas and the proposed scheme have provided similar results.

Finally, note that both considered probabilities, obtained through simulations, approach the analytical solution obtained by implementing (8) and (9).

IV. Conclusions

In this paper, a two antenna CR has been modeled as a serial network, a distributed detection technique where the processing at one antenna is affected by the processing at the other one. Furthermore, to improve the detection performances, a stability region based on the received SNR is introduced. The proposed scheme outperforms different two antenna terminals employing the OR fusion rule, the AND fusion rule, and the classical serial network model, as proved by the reported numerical results. In particular, the probability of correct detection increases with respect to the one obtained by the other approaches and, at the same time, the probability of false opportunity detection significantly decreases.

REFERENCES