Efficient Evidence-based Decision Fusion Scheme for CSS in Cognitive Radio Networks

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ABSTRACT In this paper, an evidence based decision fusion cooperative spectrum sensing (CSS) schemes has been considered for overcoming the hidden terminal problem, improving reliability, and increasing SU agility. Under practical conditions, the combination of conflicting evidences with the classical Dempster Shafer theory (DS theory) rule may produce counter-intuitive results when combining the secondary users (SUs) sensing data evidence leading to poor CSS performance. In order to overcome and minimise the effect of conflicting data, and to enhance performance of the CSS system, a novel efficient evidence-based decision fusion scheme CSS is proposed. The approach is based on the credibility of evidence from the SUs sensing decision, which represents the similarity or the relation among the different SUs sensing data evidence, and a dissociability degree measure which indicates the quality or clarity of the SUs sensing data evidence. Furthermore, a weighted averaging factor determined by the credibility and dissociability of the SU sensing data evidence is proposed. Simulation results presented show that under practical conditions the proposed scheme enhances the performance of the CSS system when compared to traditional fusion rules that do not take into account the difference in local sensing reliability between the SUs.

INDEX TERMS Cognitive radio, cooperative spectrum sensing, data fusion, Dempter-Shafter theory, credibility, ambiguity measure.

I. INTRODUCTION

In wireless channels, the hidden terminal problem which can lead to very low signal-to-noise ratio (SNR) at the secondary users (SUs) is one of the biggest challenges of implementing spectrum sensing. In a case, whereby a single SU sensing is shadowed, in severe multipath fading and shadowing effects, the SU may not reliably detect the primary user (PU) signal and access the channel when there is a primary signal present causing interference to the licensed PU [1, 2]. To overcome the hidden terminal problem and increase the spectrum sensing reliability, CSS has been studied in [2-12]. In general, CSS can be classified as either being centralised or distributed. Centralised CSS operates in two categories as follows: *a)* the observations are pre-processed by the SUs to produce their measurement or test statistics. From the reported measurement, the fusion center FC makes the final judgment [8, 13-20]; *b)* the FC processes the total received samples forwarded from each SU to make the final decision [9-11, 19, 21, 22]. Category *b)* requires a large portion of overhead as SUs report their collected samples. Therefore, the gain from cooperation may be exhausted by the overhead of communication. Thus, category *a)* attracts wider interest, hence, this work focuses on the fusion rule in category *a)* centralised CSS where the FC makes a final sensing decision based on the Basic Probability Assignment (BPA) of the sensing data received from each involved SU. The detection probability and false alarm probability are determined by the fusion rule.

In [4], an optimal data fusion rule, originally mentioned in [23], was applied by combining with a counting rule. Though it gave a good detection performance when the channel state changes, it required a long time period to converge which under practical condition can lead to poor performance. In [5] an optimal half voting rule was proposed, but only gave a good performance under impractical condition i.e. when identical threshold for all SUs are considered. In [3] a method was proposed for combining all SUs spectrum decisions and their self-assessed credibility of each decision by means of Dempster Shafer theory (DS theory) of evidence, which is suitable for fast-changing radio frequency (RF) environments, due to its ability to assign uncertainty to propositions. However, under practical conditions, illogical results may be obtained by the DS theory combination rule when the conflicts between SUs sensing data are high [24-26], leading to low performance. In [6] a method was proposed to try to overcome this problem by assigning a relative relationship between SUs to adjust the credibility of the decision. It directly sets the weight for each user by assuming certain knowledge of each SUs average SNR, which is not easily obtained, especially in low a SNR regime.

Unfortunately, the combination of conflicting evidences with the classical DS theory rule may produce counter-intuitive results when combining the SUs sensing data evidence leading to poor CSS performance. Hence, in order to minimise the effect of conflicting data along the trend of research in [25-29], a novel efficient evidence-based decision fusion scheme CSS is proposed in this paper. This approach is based on the credibility of evidence from the SUs which represents the similarity or the relation among different SUs sensing data evidence, and a dissociability degree measure which indicates the quality or clarity of the SUs sensing data evidence. Furthermore, a weighted averaging factor determined by the credibility and dissociability of the SU sensing data evidence is proposed.

In most of the previous work on CSS that considers weighted contribution from each user, the focus was on the following: (i) how to obtain the optimal weight for each user based on some performance criteria, by assuming knowledge of the local probabilities of false alarm and detection of each local detector which may not be known in practice, [30, 31] (ii) directly setting the weight for each user by assuming certain knowledge of each user's SNR, which is not easy obtainable, especially in low SNR a regime [6, 11, 32, 33]. Contrary to previous works, this work does not assume any knowledge of the performance of each SU detector, but rather uses the local decisions made by the SUs to estimate the BPA for each SU. The BPAs are obtained without the knowledge of each SUs SNR, which makes the proposed evidence-based scheme more practical and efficient.

In this paper, a CR network with one PU and multiple SUs, which are operated in a time-slotted mode, have been considered. In general, the current CSS research including the hard decision fusion rule [8, 9, 16, 34] and soft decision rule[35], assume that the received average SNRs are approximately the same at each of the SU. This assumption simplifies the calculation of the final sensing performance, including the probability of detection and probability of false alarm [51-53]. On the other hand, when considering the channel shadowing effect, it cannot handle the practical inhomogeneous situations, where the average SNR varies among cooperative users. Instead of treating all sensing terminals indiscriminatingly, the proposed scheme treats each SU in the CR network in a practical independent manner by assigning a credibility value and a dissociability measure to the SUs sensing data evidence. The proposed approach has been used to overcome and minimise the effect of conflicting SUs sensing data evidence in prior works [3,6] when using a classical DS theory combination rule. An example in which the proposed scheme can be implemented is IEEE 802.22, it is a standard for wireless regional area network (WRAN) using white spaces in the television (TV) frequency spectrum, the standard is intended for cognitive operation in the digital TV bands, among others.

The main contributions of this paper can be summarised as follows:

- We propose a novel efficient evidence-based decision fusion scheme CSS for CR networks that uses both the credibility of SUs sensing data evidence and dissociability degree measure of SUs sensing data evidence.
- We derive novel analytic expressions for the credibility of evidence from the SUs sensing data, which represents the relation among different SUs sensing data evidence.
- We formulate the correlation coefficients between the local decisions using a distance of evidence rule and a correlation matrix (CM), which gives an insight into the agreement between the sensing decisions evidence. We evaluate and deriving expressions for a dissociability degree measure of evidence from the SUs sensing data, which indicates the quality or clarity of the SUs sensing data evidence.
- We present detailed simulations, which validate our analysis. The results demonstrates that the proposed scheme significantly improved performance for CSS when compared to traditional and start of the art sechemes.

The rest of this paper is organised as follows: A CSS system model and the detection problems for local sensing at SUs are presented in Section II. A review of DS theory of evidence has been presented in Section III. In Section IV, the proposed evidence based CSS scheme DS combination algorithm is introduced. In Section V, the proposed BPA estimation of the SUs sensing data is presented including the evaluation of the credibility and dissociability degrees are presented, respectively. The critical analysis of the modified combination rule and the analysis of the final decision are detailed in Section VI and a summary of the proposed algorithm is outlined. Simulation results and analysis are presented through receiver operating characteristics (ROC) curves, and other performance related curves in Section VII. Finally, conclusions are drawn in Section VIII.

II. SYSTEM MODEL

A. COOPERATIVE SPECTRUM SENSING

To investigate, design and analyse a general system model which will be used for the rest of this paper is described in this section.

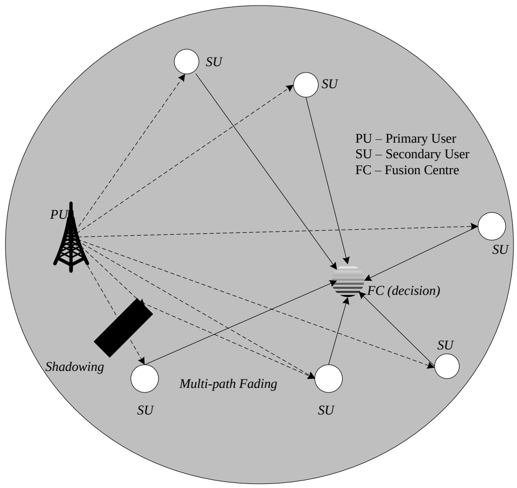

Figure 1. General system model: cooperative spectrum sensing

The CSS scheme considered for detecting PU's signal is shown in Figure 1. Each SU performs a local sensing process and subsequently reports the sensing data to the FC. The global decision on the occupation of the PU signal is made at the FC. The spectrum sensing frame in Figure 2 describes the process.

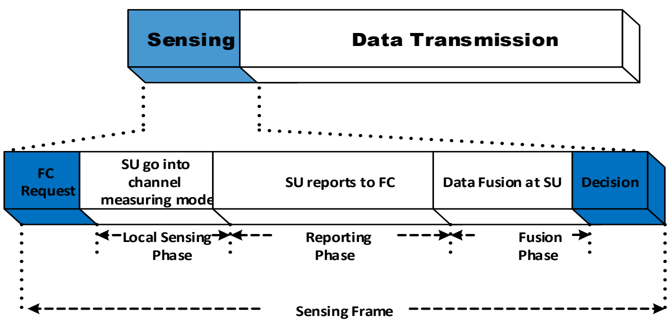

Figure 2. System model cooperative spectrum sensing frame.

The sensing frame starts with the FC sending a sensing request message to the SUs. All the individual SUs enter into a quiet mode i.e. none utilise the channel and perform local spectrum sensing in the sensing phase. Each SU using a reporting mechanism then sends their sensing data to the FC in the reporting phase. Hence, the SUs send their local sensing information in intervals of one's per sensing frame.

B. SPECTRUM SENSING

Individual SUs perform local spectrum sensing in a distributed manner for detecting the PU signal. Local sensing is in effect a binary hypotheses testing predicament. Comparing the different algorithms for spectrum sensing, energy detection has been established to be the least complex detection scheme that reduces overhead, and is quickly able to detect the PU signal, even if the PU signal is unknown [36]. In this paper, energy detection is considered for local spectrum sensing. To measure the value of a single power in a practical frequency band in time domain, a band pass filter is applied to the received primary signal at the SUs and the power of the signal samples is subsequently measured as shown in Figure 3.

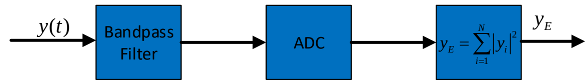

Figure 3. Block Diagram of an energy detection scheme.

The decision statistic is an estimation of the received signal power which is given at each SU by the sensing matrix:

$$y_E = \sum_{i=1}^{N} |y_i|^2 \tag{1}$$

where y_i is the i-th sample of received signal and $N = 2TW$, where T and W are correspondent to detection time and signal bandwidth in Hz, respectively. It was proved in [37] that the probability density function (PDF) of the received PUs signal energy at an SU y_E, is a Chi-square distribution such that

$$f(y_E) = \begin{cases} \chi_N^2, & H_0 \\ \chi_N^2(N\gamma), & H_1 \end{cases} \tag{2}$$

where H_0 and H_1 are the hypotheses of indicating a vacant channel and occupied channel of the PU's signal, respectively, χ_N^2 is the central Chi-square distribution with N degree of freedom, and $\chi_N^2(N\gamma)$ is a non-central Chi-square distribution with N degree of freedom and a non-centrality parameter $N\gamma$. γ is the SNR of the PU signal at the SUs. In the absence of knowledge of the PU signal, when the number of required samples N is relatively large, y_E can be approximated as a Gaussian random variable under both hypotheses H_0 and H_1, with mean μ_1, μ_0 and variance σ_1^2, σ_0^2, respectively, such that [36]:

$$\begin{cases} \mu_0 = N, & \sigma_0^2 = 2N \\ \mu_1 = N(\gamma+1), & \sigma_1^2 = 2N(2\gamma+1) \end{cases} \tag{3}$$

where the γ is a constant in a non-fading additive white Gaussian noise (AWGN) environment. However, in a fading channel scenario, the SNR γ is a random variable [14, 36, 38, 39].

In order to increase detection reliability of a CR network, a CSS scheme is considered instead of a single SU as illustrated in Figure 1. The SUs conduct local spectrum sensing by applying an energy detector to measure the PU's signal energy in each sensing frame. After the spectrum sensing process, each SU computes its own local detection and the decision along with a corresponding credibility denoted by *crd* are then transmitted to the FC, where a global decision is made. The whole CSS process can be categorised into two stages:

1. Local sensing at the SUs.
2. Final decision at the FC.

C. LOCAL SPECTRUM SENSING ALGORITHM

The detection problem can be represented as follows [40]:

$$\begin{cases} H_0: & y(t) = n(t) \\ H_1: & y(t) = h(t)s(t) + n(t) \end{cases} \tag{4}$$

for $t = 1, \ldots, M$, where t represents the discrete time index and M denotes the number of observation, H_0 and H_1 are correspond to hypotheses of absence and presence of the PU signal, respectively, $y(t)$ represents the received data at the *i*-th SU, $h(t)$ represents the channel gain, $s(t)$ is the PU's transmitted signal and $n(t)$ is the additive white Gaussian noise. The following assumptions are made:

- The PU, SUs and FC are considered to be in the same region where they share a common spectrum allocation.
- The channels corresponding to the different SUs are independent.
- The noise $n(t)$ is an independent complex Gaussian random variable.
- The PU's signal $s(t)$ is an independent random process.
- The PU's signal $s(t)$ is independent of the noise $n(t)$.

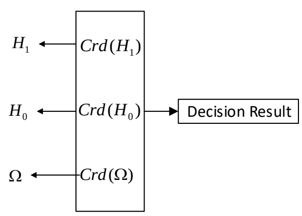

Figure 4. Decision Result Construction at the *i-th* SU.

Different SUs are presented with unique credibility based on their local sensing owing to changes in channel conditions between the PU and SUs. Therefore, the parameter "credibility" Crd is a variable that changes with corresponding channel condition h_i and the distance D_i between the PU and the *i*-th SU.

$$Crd_i = f(h_i, D_i) \tag{5}$$

where Crd_i represents the detection credibility from the *i*-th SU. Each SU has different possibilities for hypotheses H_0 and H_1, and a total credibility for its detection. Therefore, the detection result can be divided into three parts as illustrated in Figure 4, where $Crd(H_0)$ and $Crd(H_1)$ are the credibility for hypotheses H_0, and H_1 to be true based on local sensing at the *i*-th SU, respectively. $\Omega = \{H_1, H_2\}$ can be interpreted that either hypothesis could be true. Therefore, $Crd(\Omega)$ conveys total uncertainty of local detection at the *i*-th SU.

D. FINAL DECISION AT THE FUSION CENTRE

Having analysed the decisions and their associated credibility Crd_i, at each *i*-th SU, the FC has the task of combining the received data using the DS theory of evidence combination which an adequate choice (see Section III). But the combination of conflicting evidences with the classical DS theory combination rule may produce counter-intuitive results when combining the SUs sensing data evidence. Hence, it is proposed that the FC employs an enhanced DS theory combination scheme in softly combing the two types of data, and making a final decision on whether the PU is present.

III. A REVIEW OF DEMPSTER-SHAFER EVIDENCE THEORY

DS theory is an approach to represent uncertain knowledge and to accomplish the uncertainty reasoning [41]. It has become an important method in data fusion [41]. DS theory of evidence has attracted much attention in a wide variety of fields such as intelligence, identification, automotive, fuzzy and wireless communication [25-28]. Due to the stochastic characteristics of wireless communication channels, there is uncertainty in local detection results at SUs. Considering that DS theory is used in managing uncertainty, it is a good choice for decision making in CR systems [3, 6, 24, 25,29, 36, 43, 48]. In this section, a brief review of DS theory of evidence is carried out. A more complete introduction can be found in Shafer's original work [42].

A. Basic Probability Assignment (BPA)

Let $\Omega = \{A_1, A_2, \ldots A_n\}$ be a finite set of mutually exclusive possible hypotheses, referred to as the *frame of discernment*. The power set 2^Ω is the set of all subsets of Ω including itself and the null set $\varnothing$ [26]. DS theory assigns a mass (degree of belief) to each subset in the power set 2^Ω. While traditional probability theory employs a measure of probability to assign to each atomic hypothesis A_i in the frame of discernment, the mass in DS theory is assigned not only to each atomic hypothesis, but also to combinations of hypotheses. Hence, each subset in the power set is assigned a mass. The function m, that assigns a mass in the range of [0, 1] to each subset *A*, is called Basic Probability Assignment (BPA). This function satisfies the following conditions [26]:

$$m(\varnothing) = 0, \tag{6}$$

and

$$\sum_{A \subseteq \Omega} m(A) = 1. \tag{7}$$

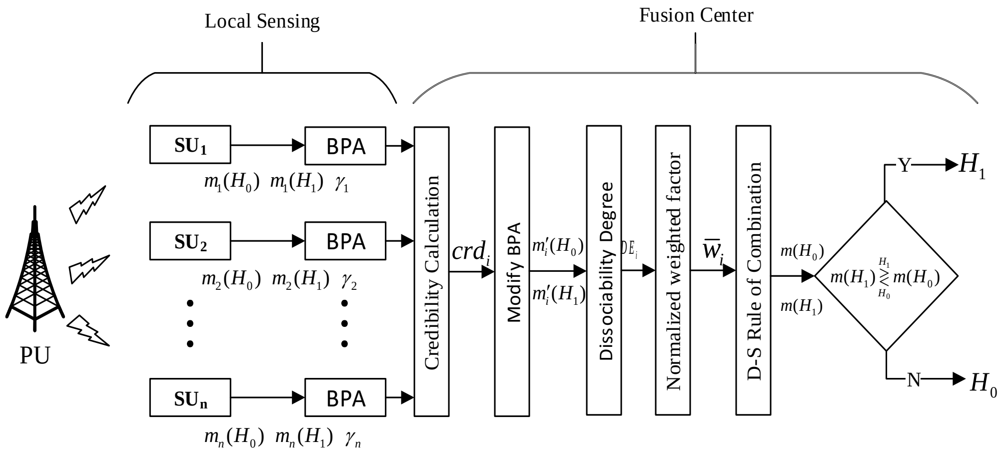

Figure 5. Evidence-based Decision Fusion Scheme for CSS.

The value of a mass (roughly equivalent to probability) is the belief that supports hypothesis *A*, but does not support any subsets of *A*. Associated with m are a belief or credibility function *bel* and a plausibility function *pl* and are defined to characterise the uncertainty and the support of certain hypotheses. These two measures, derived from the mass values, are respectively defined as a map from a set of hypotheses to an interval [0, 1] for all $A \subseteq \Omega$ as follows [29]:

$$bel(A) = \sum_{B|B \subseteq A} m(B) \tag{8}$$

and the plausibility functions as:

$$\begin{aligned} pl(A) &= \sum_{B|B \cap A \neq \varnothing} m(B) \\ &= 1 - bel(A) \end{aligned}, \tag{9}$$

bel(A) can be understood to be a global measure of the believe that hypothesis *A* is true, while *pl(A)* can be summarised as the amount of belief that could potentially be placed in *A*, if further information becomes available [27]. The pignistic transformation maps a belief function *m* to the pignistic probability function. The pignistic transformation of a belief function *m* on $\Omega = \{A_1, A_2, ...A_n\}$ is given by [24]:

$$BetP(A) = \sum_{B \subseteq \Omega} \frac{|A \cap B|}{|B|} \frac{m(B)}{1 - m(\varnothing)}, \quad \forall A \subseteq \Omega \tag{10}$$

where $|A|$ is the cardinality of set A. In a particular case where $m(\varnothing) = 0$ and $A \in \Omega$, i.e., A is a singleton of Ω,

$$BetP(A) = \sum_{A \in B} \frac{m(B)}{|B|}, A = A_1, ..., A_n, \quad B \subseteq \Omega \tag{11}$$

B. DS THEORY COMBINATION RULE

The mass function from different information sources, m_j where $(j = 1, ..., d)$ are combined with DS rule of combination, also called an orthogonal sum. The result is a new mass function [26]:

$$m(A_k) = (m_1 \oplus m_2 \oplus ... \oplus m_d)(A_k) \tag{12}$$

where symbol $\oplus$ means the direct sum. $m(A_k)$ incorporates the joint information provided by the sources, given by [26]:

$$m(A_k) = \frac{1}{1-K} \sum_{A_1 \cap A_2 ... A_d = A_k} \left(\prod_{1 \le j \le d} (m_j(A_j)) \right) \tag{13}$$

where

$$K = \sum_{A_1 \cap A_2 ... A_d = \varnothing} \left(\prod_{1 \le j \le d} (m_j(A_j)) \right) \tag{14}$$

K represents a measure of conflict between the different sources or contracting mass assignments, and it is introduced as a normalisation factor. In a practical system of evidence combination, the different evidence to be combined are not always concordant, there may be conflicts among them. This stems from the fact that in DS theory rule of combination, the conflicting mass assignments are discarded which may lead to counterintuitive behaviors among SUs conflicting mass assignments [26].

IV. COOPERATIVE SPECTRUM SENSING BASED ON EVIDENCE THEORY

The DS combination rule is commutative and associative, and can be extended to combining multiple evidences in CSS sequentially [26]. After receiving all the sensing decisions with corresponding credibility Crd_i from the *i*-th SUs, according to DS theory of evidence combination, the FC makes a final decision on the observed band. This process can be categorised into steps, illustrated by the evidence-based decision fusion scheme for CSS block diagram in Figure 5.

A. BPA ESTIMATION IN CSS

In order to apply the DS theory of evidence to make a final decision, the frame of discernment denoted by Ω is defined as $\{H_1, H_0, \Omega\}$, where Ω denotes either hypotheses is true. After each sensing period, each SU will estimate its self-assessed decision credibility, which is equivalent to the BPA assignment for the two hypotheses H_0 and H_1, respectively. The DS combination rule is commutative and associative hence, an appropriate BPA function is a cumulative distribution function (CDF) instead of a PDF given by [26, 28]:

$$H_0 : m_i\left(y_{E_i} \mid H_0\right) = \int_{y=y_{E_i}}^{\infty} \frac{1}{\sqrt{2\pi\sigma_{0i}^2}} \exp\left(-\frac{\left(y-\mu_{0i}\right)^2}{2\sigma_{0i}^2}\right) dy \quad (15)$$

$$H_1 : m_i\left(y_{E_i} \mid H_1\right) = \int_{y=-\infty}^{y_{E_i}} \frac{1}{\sqrt{2\pi\sigma_{1i}^2}} \exp\left(-\frac{\left(y-\mu_{1i}\right)^2}{2\sigma_{1i}^2}\right) dy \quad (16)$$

where $m(.)$ is equivalent to $Crd(.)$, which is described in Section II.C, $m_i\left(y_{E_i} \middle| H_0\right)$ and $m_i\left(y_{E_i} \middle| H_1\right)$ are the BPAs of hypothesis H_0 and H_1 of the *i*-th SU, respectively. Using these functions, the BPA of hypotheses H_0 and H_1 are unique for each test statistics value y_{E_i} and vary in such a way that the larger y_{E_i} is the larger $m_i\left(y_{E_i} \middle| H_1\right)$ and the smaller $m_i\left(y_{E_i} \middle| H_0\right)$ are and vice versa [28]. The credibility from individual SUs and uncertainty are subject to the following constraint [3]:

$$m_i(H_1) + m_i(H_0) + m_i(\Omega) = 1 \quad (17)$$

B. BPA CREDIBILITY DEGREE

Instead of combining all the SUs self-assessed BPA which assumes they are all equal, the BPA of each SU should be assigned a credibility to highlight the reliability of the different SUs sensing data, for improving sensing accuracy. Subsequently, an additional stage at the FC to calculate the credibility of each BPA is proposed.

Generally, if all the self-assessed BPA evidence is assigned credibility, that piece of evidence should be more important and has more effect on the final fusion decision. On the contrary, if the self-assessed BPA evidence is highly conflicting with other bodies of evidence, this BPA should be less important and has little effect on the final fusion decision. To establish the credibility value of each self-assessed BPA, the correlation coefficients between the self-assessed BPAs are used. Using a distance of evidence rule as defined in [43], the distance of evidence between each BPA is given by:

$$d_{BPA}(m_i(H_0), m_i(H_1)) = \sqrt{\frac{1}{2}(m_i(H_0) - m_i(H_1))^T \underline{\underline{\mathbf{D}}}(m_i(H_0) - m_i(H_1))} \quad (18)$$

where $m_i(H_0)$ and $m_i(H_1)$ are the BPAs of the *i*-th SU and the Jaccard matrix $\mathbf{D}$ is a $2^{|\Omega|} \times 2^{|\Omega|}$ matrix to measure the conflict of the focal elements in $m_i(H_0)$ and $m_i(H_1)$, whose elements are [43]:

$$\mathbf{D}(A,B) = \frac{|A \cap B|}{|A \cup B|}, A, B \subseteq \Omega. \quad (19)$$

The introduction of the matrix has the advantage of taking the similarity between the BPAs into consideration. To describe the similarity between the BPAs, the correlation coefficient is defined as [44]:

$$c[m_i(H_0), m_i(H_1)] = \frac{\langle m_i(H_0), m_i(H_1)\rangle}{\|m_i(H_0)\| \cdot \|m_i(H_1)\|}, \quad (20)$$

where $m_i(H_0)$ and $m_i(H_1)$ have the same definition as in (18). Considering the similarity among the subsets of Ω, matrix $\mathbf{D}$ is used to modify the BPA from the *i*-th SU:

$$\begin{cases} m_i'(H_0) = m_i(H_0)\mathbf{D} \\ m_i'(H_1) = m_i(H_1)\mathbf{D} \end{cases}. \quad (21)$$

Therefore, using Equation (20) and Equation (21) the correlation coefficient can be redefined as:

$$c[m_i(H_0), m_i(H_1)] = \frac{\langle m_i'(H_0), m_i'(H_1)\rangle}{\|m_i'(H_0)\| \cdot \|m_i'(H_1)\|}. \quad (22)$$

$c[m_i(H_0), m_i(H_1)]$ satisfies the following requirement [44]:

- $0 \le c[m_i(H_0), m_i(H_1)] \le 1$
- $c[m_i(H_0), m_i(H_1)] = c[m_i(H_1), m_i(H_0)]$
- $c[m_i(H_0), m_i(H_1)] = 1 \Leftrightarrow m_i(H_0) = m_i(H_1)$
- $c[m_i(H_0), m_i(H_1)] = 0 \Leftrightarrow (\cup A_i) \cap (\cup B_j) = \varnothing$,

where A_i and B_j are focal elements of $m_i(H_0)$ and $m_i(H_1)$, respectively.

Let the number of BPAs be *n*. Subsequently, after all the degrees of similarity between the BPAs have been obtained, a correlation matrix (**CM**), which gives an insight into the agreement between the BPAs evidence is given by:

$$\mathbf{CM} = \begin{bmatrix} c[m_1(H_0), m_1(H_1)] & c[m_1(H_0), m_2(H_1)] & \cdots & c[m_1(H_0), m_n(H_1)] \\ c[m_2(H_0), m_1(H_1)] & c[m_2(H_0), m_2(H_1)] & \cdots & c[m_2(H_0), m_n(H_1)] \\ \vdots & \vdots & \ddots & \vdots \\ c[m_n(H_0), m_1(H_1)] & c[m_n(H_0), m_2(H_1)] & \cdots & c[m_n(H_0), m_n(H_1)] \end{bmatrix} \quad (23)$$

where the diagonal element $c[m_i(H_0),\ m_i(H_1)]=1$. The credibility degree of the BPA of $m_i(H_0)$ and $m_i(H_1)$ is given by:

$$Crd_i = \frac{1}{n-1}\sum_{i=1}^{n} c[m_i(H_0), m_i(H_1)]\,. \tag{24}$$

The credibility vector consisting of the credibility of all the BPAs from the SUs is defined by:

$$\mathbf{CRD} = [Crd_{1,} Crd_{2,} ..., Crd_{n,}]^{\mathrm{T}}, \tag{25}$$

therefore, the following formulation can be obtained:

$$\mathbf{CRD} = \frac{1}{n-1}(\mathbf{CM} - \mathbf{E}_{n\times n})\mathbf{I}_{n\times 1} \tag{26}$$

where $\mathbf{E}_{n\times n}$ and $\mathbf{I}_{n\times 1}$ are *n*-dimensional identity matrix and *n*-dimensional unit column vector, respectively.

C. BPA DISSOCIABILITY DEGREE

The sensing decisions evidence dissociability denoted by *DE* is a function from a BPA *m* to $[0,1]$, it expresses the degree of the BPA focusing to the singletons of the focal elements. When the classification results are described in terms of BPAs, the BPAs dissociability can be constructed by the determined principle in multiclass classification. Generally, when the BPA from each SU to each class is nearly equal, the classification ability is poor. The greater the differences that exist among the BPA, the more reasonable decisions that can be made. Therefore, the dissociability cannot reach 1 unless the BPA is a categorical BPA, satisfying:

$$m(A) = \begin{cases} 1 & if\ \ A = A^*, \\ 0 & \text{otherwise.} \end{cases} \tag{27}$$

where A^* is one of the singletons in discriminate frame, thus $A^* \in \Omega, \Omega$ is the discriminate frame. If the belief function focuses on all the singletons on A equally, the dissociability is 0. Therefore, the dissociability degree *DE* can be defined as [45, 46]:

$$DE(m) = 1 + \frac{1}{\ln(M)}\sum_{A\in A} BetP_m(A)\ln(BetP_m(A)) \tag{28}$$

where $BetP_m(A) = \sum_{B\subseteq A} \frac{|A\cap A|}{|B|}\frac{m(B)}{1-m(\varnothing)}$ is the pignistic probability, and M is the cardinality of Ω.

V. CSS BASED ON EVIDENCE THEORY PROPOSED COMBINATION RULE

It has been shown that credibility of evidence represents the relation among different sensing decisions evidence and the dissociability measure indicates the quality of the sensing decisions evidence. If both of the two factors are taken into consideration together, a better performance can be expected. Hence, a novel combination approach based on a modified weighted average BPA evidence is proposed.

The weighted factor is generated by the credibility and dissociability of the BPAs evidence. Both can be derived based on the BPAs, thus no extra priori knowledge is needed. The weighted factor *w* is determined by both credibility *Crd* and dissociability *DE* as follows:

$$w : (Crd, DE) \mapsto [0,1] \tag{29}$$

If the SUs BPA has a relatively high credibility degree, defined based on the correlation coefficient between BPAs and one of them has a higher dissociability than the others, it should be more credible. That is because such credible BPA evidence is relatively less uncertainty at the same time. Such BPAs should have a larger weight. On the contrary, suppose that the SUs BPA are relatively incredible and if one of them has lower dissociability than the others, it should be more incredible and should be assigned to a less value of weight. However, for a BPA with a higher dissociability but lower credibility, lower weighted factor should be assigned to it. This indicates that the conflict between this BPA and others may be high. On the other hand, zero dissociability reflects the probability assigned to each singleton is equal, thus its weighted factor is mainly determined by credibility. The requirements for *w* can be summarised as:

i) $\frac{\delta w}{\partial(Crd)} > 0, \frac{\delta w}{\partial(DE)} > 0$
ii) $0 \le w \le 1$
iii) $w(1,1) = 1$
iv) $w(0, DE) = 0$
v) $w(Crd, 0) = \lambda \cdot Crd, 0 < \lambda < 1$

where δw, $\partial(Crd)$ and $\partial(DE)$ denote change in *w*, change *Crd* and change in *DE*, respectively. Hence, the modified weights can be defined as follows:

$$w = \frac{1}{2}(Crd + crd \cdot DE^{-Crd}). \tag{30}$$

The factor $1/2$ is needed in equation to normalise w and to guarantee that $0 \le w \le 1$. The weighted factor w_i for each BPA can be normalised by:

$$\bar{w} = w_i \,/ \sum_{i=1}^{n} w_i. \tag{31}$$

If all the BPAs evidence is available at the same time, the masses can be averaged and the combined masses calculated by combining the average values multiple times [47]. Thus, the BPA for the weighted averaged evidence $\bar{m}$ can be given by:

$$\bar{m}(A) = \sum_{i=1}^{n} \bar{w} \cdot m_i(A), \quad A \in \Omega \tag{32}$$

If there are n pieces of evidence, the averaged BPA must be combined $(n-1)$.

VI. FINAL DECISION

According to DS theory of evidence, the combination of the averaged BPA can be obtained by [42]:

$$m(H_0) = \bar{m}_1 \oplus \bar{m}_2 \oplus ... \oplus \bar{m}_n(H_0) = \frac{\sum_{A_1 \cap A_2 \cap ... A_n = H_0} \prod_{i=1}^{n} \bar{m}_i(A_i)}{1-K} \quad (33)$$

$$m(H_1) = \bar{m}_1 \oplus \bar{m}_2 \oplus ... \oplus \bar{m}_n(H_1) = \frac{\sum_{A_1 \cap A_2 \cap ... A_n = H_1} \prod_{i=1}^{n} \bar{m}_i(A_i)}{1-K} \quad (34)$$

where

$$k = \sum_{A_1 \cap A_2 \cap ... A_n = \varnothing} \prod_{i=1}^{n} \bar{m}_i(A_i) \quad (35)$$

In conclusion, the final decision computed at the FC is given as:

$$H_1 : m(H_1) > m(H_0) \quad (36)$$

$$H_0 : m(H_0) > m(H_1)\,, \quad (37)$$

which can be expressed in a compact form as:

$$m(H_1) \underset{H_0}{\overset{H_1}{\gtrless}} m(H_0)\,. \quad (38)$$

The proposed evidence-based decision fusion scheme for CSS is summarized in Table I.

VII. SIMULATION RESULTS AND ANALYSIS

This section is used to evaluate the performance of the proposed evidence based CSS scheme, where simulation results are shown to compare the proposed approach with other related approaches based on the receiver operating characteristic (ROC) and probability of detection curves in relation to SNR curves. The effects of different parameters on the proposed algorithm were examined, such as the SUs with independent channels, channel availability and different values of the SNR. For the simulation in this paper, the PU network is assumed to be a DVB-T2 signal [48], the bandwidth of the PU signal is 8 MHz and modulation type is QPSK. The average occupancy rate for the PU is set to 50%, i.e. the probability of presence and absence of the PU signal is fixed to an equal probability (0.5), respectively.

The simulation is based on the Monte Carlo method in MATLAB with 100,000 iterations. AWGN and Rayleigh channels are considered, there are six SUs spread in the network to perform local spectrum sensing. A summary of the simulation parameters for analysing the developed CSS algorithm's performance evaluation are shown in Table II.

TABLE I
Proposed Evidence-Based Decision Fusion Scheme for CSS in CR Networks

Algorithm 1: Proposed evidence-based decision fusion scheme for css in cr networks	
Input	y_{E_i}
Output	H_1, H_0
Step 1:	// using (1) compute local spectrum sensing statistic //(energy detector) y_{E_i}
Step 2:	//using (16) and (17) compute the cumulative evidence //probability $m_i\left(y_{E_i}\middle\vert H_1\right)$, $m_i\left(y_{E_i}\middle\vert H_0\right)$, $m_i(\Omega)$
Step 3:	// using (18) compute the distance of evidence between //each BPA $d_{BPA}(m_i(H_0), m_i(H_1))$
Step 4:	// using (21) compute modification of BPA $m_i'(H_0)$, $m_i'(H_1)$
Step 5:	//using (22) compute the redefinition of correlation matrix $c[m_i(H_0), m_i(H_1)]$
Step 6:	// using (23) and (24) compute the credibility vector **CRD**
Step 7:	// using (28) compute dissociability of each BPA $DE(m)$
Step 8:	//using (30) and (31) compute weighted factor and //normalised the //weighted factor w, $\bar{w}$
Step 9:	//using (32) compute the average BPAs $\bar{m}(A)$
Step 10:	//using (33) and (34) compute the combination of the //weighted averaged evidence $m(H_0)$ *and* $m(H_1)$
Step 11:	//using (38) compute final decision If $m(H_1) > m(H_0)$ //then test supports H_1 else $m(H_0) > m(H_1)$ //test supports H_0

TABLE II
SIMULATION PARAMETERS FOR THE DEVELOPED EVIDENCE BASED CSS

Parameter	**Value**
PU bandwidth	8 MHz
Local sensing	25 μs
Frame length	60
FEC blocks per frame	50
Channel condition	AWGN, Rayleigh
SNR range	-20dB to -8dB
Iterations	100,000
Number of SUs	6
PU average occupancy rate	0.5 (50%)

Figure 6 and Figure 7 show the ROC curves, highlighting the performance of the proposed evidence based scheme and energy detection result at each SU under AWGN and Rayleigh fading channels, respectively. A sensing time of 25 μs was considered. Energy detection is adopted as the local detection at the SUs. There are six SUs considered in the system. A practical scenario has been considered, where the six distributed SUs endure different channel conditions. The received signal condition at the six SUs are respectively -10 dB, -12 dB, -14 dB, -16 dB, -18 dB and -20 dB. It is shown in both Figure 6 and Figure 7 that the proposed CSS schemes which considers all the six SUs, outperforms any of the single standalone SUs. For example, when the probability of false alarm under a Rayleigh channel is 0.1, the probability of detection improves by approximately 18% considering a single SU with channel conditions of -10 dB.

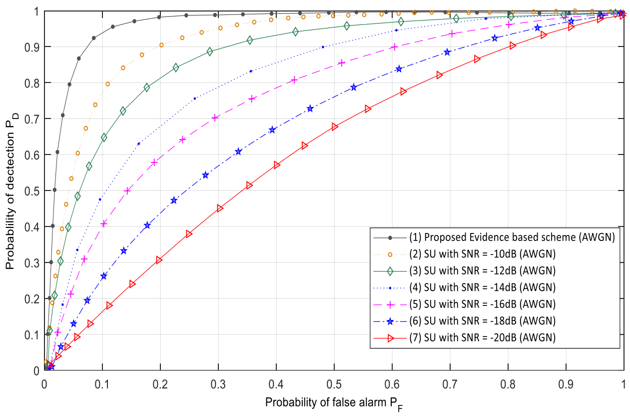

Figure 6. ROC curves of the proposed scheme and the local sensing results (energy detection) at each SU over AGWN channel.

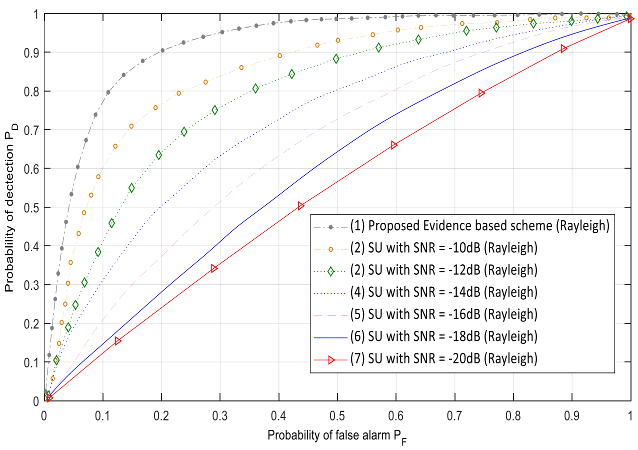

Figure 7. ROC curves of the proposed scheme and the local sensing results (energy detection) at each SU over Rayleigh fading.

Figure 8 and Figure 9 show the ROC curves, highlighting the performance of the proposed evidence based scheme compared to the AND rule, OR rule, CV rule [23], DS theory fusion [3] and enhanced DS theory fusion [6] under AWGN and Rayleigh fading channels, respectively. Six distributed SUs with diffrent distance measures to the PU are considered. Without loss of generality, the SNRs of the received PU signals at the SUs are assumed to be - 10*dB*, -12*dB*, -14*dB*, -16*dB*, -18*dB* and -20*dB*, respectively. Under these conditions, Figure 8 and Figure 9 show the ROC curves of different fusion rules, which can be split into two groups. The first group: AND rule, OR rule, and CV rule are considered as traditional hard decision CSS schemes [18, 49]. As discussed in [2], hard decision have the fewest communication overhead (1-bit hard decision for CSS), but the sensing performance are evidently worse [18, 49]. The ROC curves of the AND rule, the OR rule, and the CV rule have performances than those of the other algorithms highlighted in Figure 8 and Figure 9.

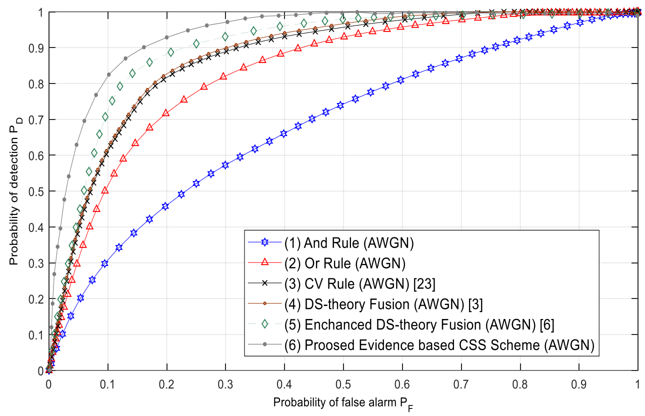

Figure 8. ROC comparison between the proposed scheme, AND rule, OR rule, CV rule [23], DS theory fusion [3] and Enhanced DS theory fusion [6] over AGWN channel.

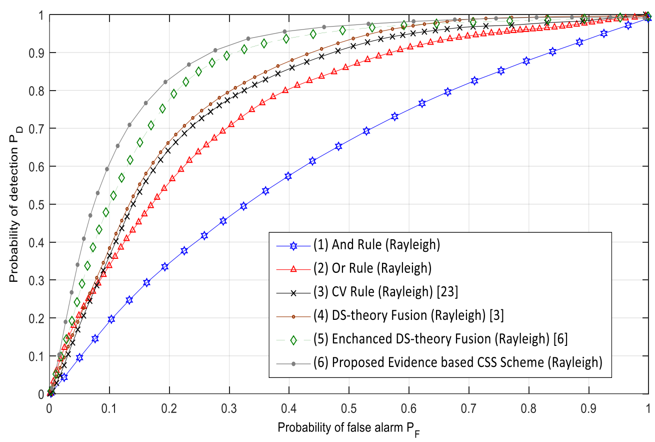

Figure 9. ROC comparison between the proposed scheme, AND rule, OR rule, CV rule [23], DS theory fusion [3] and enhanced DS theory fusion [6] over Rayleigh channel.

For example, under AWGN conditions, when the probability of false alarm is 0.1 the probability of detection for AND rule, the OR rule, and the CV rule are approximately 0.3, 0.5 and 0.6, respectively.

The second group of CSS algorithms, DS theory fusion and enhanced DS theory fusion scheme can be considered as soft decision scheme, they utilise the BPA of the sensing data to be sent to the FC, and hence have a higher detection performance than the first group for a chosen false alarm probability value. The proposed algorithm falls under the second group, it utilises the BPA of the local sensing observation and fusion decisions are made at the FC. The results of this second group correspond with the maximum ROC curves. The proposed scheme has a better performance than both the DS theory fusion and enhanced DS theory fusion scheme. For example, under AWGN conditions, when the probability of false alarm is 0.1 the probability of detection for the DS theory fusion, enhanced DS theory fusion and the proposed scheme are approximately 0.62, 0.72 and 0.82, respectively. The improvement is approximately 10%, while a similar improvement of approximately 9% under Rayleigh conditions can be observed.

In general, it can be observed that spectrum sensing detection slightly decreases under Rayleigh channel conditions when compared to AWGN conditions. For example, in Figure 8 and Figure 9, taking the proposed scheme into consideration, when the probability of false alarm is 0.2 the probability of detection under Rayleigh channels when compared to AWGN decrease by approximately 10%.

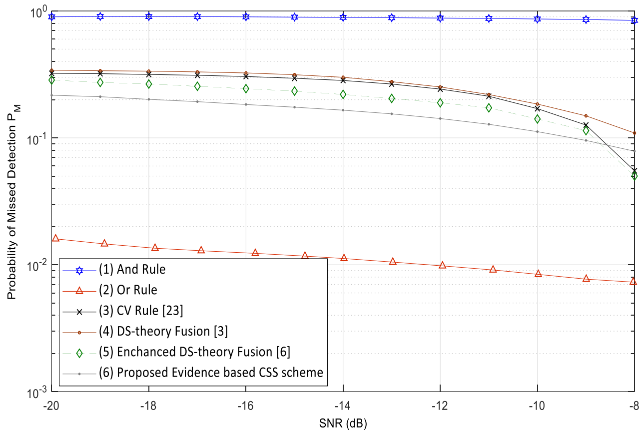

Figure 10. Probability of missed detection comparison between AND rule, OR rule, CV rule [23], DS theory fusion [3], Enhanced DS theory fusion [6] and the proposed evidence based CSS scheme.

In Figure 10, the probability of missed detection of the AND rule, OR rule, CV rule, DS theory fusion, Enhanced DS theory fusion and the proposed scheme are highlighted. Six distributed SUs with diffrent distance measures to the PU are considered under AWGN conditions. In order to evaulate the proposed scheme in a practial situaton, it is assumed that the first SU channel conditions is changed from -20 dB to -8dB, which is representable of a CSS problem, where an SU experiences fading. The next five SUs have the same AWGN channel with SNR = - 16dB. It is shown in Figure 10, that under the above conditions, the probability of missed detection P_M of the OR rule is always the smallest and vice versa for the AND rule which indicates unsuitable performance in a practical scenario. The proposed scheme gives a lower probability of missed theory fusion due to the effective BFA function, credibility adjustment, dissociability and weight combination algorithm among the SUs. For example, at SNR = -18 dB, the missed detection of the proposed scheme reduced by approximately 7% when compared to the enhanced DS theory fusion.

VIII. CONCLUSION

In this paper, a novel evidence based decision fusion scheme CSS for CR networks that uses both a credibility of SUs sensing data evidence and dissociability degree measure has been proposed. Furthermore, a weighted averaging factor determined by the credibility and dissociability of the SU sensing data evidence has also been proposed. The proposed approach has been used to overcome and minimise the effect of conflicting SUs sensing data evidence when using a classical DS theory combination rule.

A CR network with one PU and multiple SUs, which are operated in a time-slotted mode, have been considered. Instead of treating all sensing terminals indiscriminatingly, the proposed scheme treats each SU in the CR network in a practical independent manner by assigning a credibility value and a dissociability measure to the SUs BPA evidence. Local spectrum sensing was carried out at each SU using an energy detector to estimate the received signal power. An appropriate BPA function as a form of cumulative density function (CDF) was used. Instead of combining all the SUs (self-assessed BPA which means treating all BPA's equally), the BPAs of each SU are modified by a credibility evidence to improved sensing accuracy. Subsequently, an enhanced stage to the FC was proposed.

To establish the credibility value which represents the relation among different sensing decisions evidence of each SU sensing decision, the distance of evidence between each BPA was derived using a distance of evidence rule. Afterwards, to describe the similarity between the SUs, a correlation coefficient was defined. A matrix was used to modify the BPA from each SU. Subsequently, after all the degrees of similarity between the BPAs had been obtained, a correlation matrix and credibility vectors consisting of the BPAs were expressed. To ascertain the quality of the BPA evidence a dissociability measure *DE* was formulated using a pignistic probability. Finally, weighted factor has been generated based on the credibility and dissociability of the BPAs with no extra priori knowledge needed. The combination of the averaged BPAs evidence was also obtained using the DS evidence theory combination rule.

Simulations were performed under AWGN and Rayleigh fading, respectively. The results have demonstrated that under practical condition the proposed scheme significantly improved performance for CSS when compared to the AND rule, OR rule, which do not take into account the difference in local sensing reliability between SUs. Also when comparing against the CV rule, DS theory fusion and enhanced DS theory fusion there is an improved performance in CSS. The missed detection probability of the proposed scheme decreased by approximately 7% when compared to the enhanced DS theory fusion.

In this paper, two important design criteria for CSS were focused on, which are the sensing reliability, and SU agility. The simulation results showed that the proposed scheme yields a significant improvement in the detection probability as well as a considerable reduction in the missed detection probability without any prior knowledge of the primary system by utilising DS theory. However, the main drawback of the proposed scheme as well as other soft data fusions (including the CSS scheme used in [3]) are the bandwidth required for transmitting the sensing data.

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