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Research Article

Cooperative Spectrum Sensing Performance-overhead Tradeoff in Cognitive Radio Network under Bandwidth Constraint

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Abstract: In cognitive radio network unlicensed users continuously scan a vast range of frequencies to detect 'white spaces' or 'spectrum holes' that are temporarily and spatially not being used for communications by licensed user and this process is known as spectrum sensing. In order to execute the cooperative spectrum sensing among cognitive radio users, data fusion schemes are superior to that of decision fusion ones in terms of the detection performance but suffer from the disadvantage of huge traffic overhead when bandwidth constraint of communication channels is taken into account. In this study, a cluster-based data and decision fusion approach is implemented to jointly exploit the advantages of both and a selective optimal weight setting algorithm is proposed by utilizing normal and modified deflection coefficients maximization under Neyman-Pearson criterion in order to obtain a final decision about the presence of primary users. The simulations show promising results as the novel hybridization process visibly reduces the network traffic overhead while exhibiting a highly satisfactory detection performance in CRN. Impairments in wireless network environment like shadowing, fading and noise uncertainty are also taken into consideration while optimizing performance of proposed model.

Keywords: Cooperative sensing, data fusion, decision fusion, deflection coefficient, selective weight

INTRODUCTION

The static spectrum policy is failing to cope up with the ever increasing spectrum demands by mobile and wireless applications and guarantee desired Quality of Service. Moreover, current studies show that some frequency bands in the spectrum are heavily congested while other bands are largely unoccupied most of the time (Commission, 2002). The Cognitive Radio (CR) is proposed as a key technology to dynamically allocate the spectrum bands (Haykin, 2005). CR is inherently able to adaptively and opportunistically transmit and receive data in a changing radio environment and share the temporarily and spatially available wireless channel with licensed users as long as the Primary Users (PUs) are not interfered with. The CR users are classified as Secondary Users (SUs) with lower priority than the PUs who are obviously, licensees, or alternatively, users of existing technologies on unlicensed bands. The fundamental requirement for SUs is to exploit an efficient Spectrum Sensing (SS) technique that can reliably monitor the PUs' activities and quickly vacate the band once a PU attempts to use that. It is thus necessary to invent a fast and highly robust algorithm to determine whether a frequency band is available or being occupied. This is the area of SS for CR.

Many substantial researches are going on to improve the SS performance. By its very nature as a soft fusion scheme, an optimal linear operation framework for SS in order to accurately detect the weak PU signal is presented in Niu and Varshney (2005) whereas optimal weighting solutions are provided for fusing the individual sensing data coming from each cooperative node in Zhang *et al*. (2008). Associated with channel sensing the higher the P_d, the better PU can be protected and on the other hand, the lower the P_f, the more chances the channel can be reused. Peh and Liang (2007) and El-Saleh *et al*. (2009) showed that the achievable maximum P_d under a targeted P_f and the minimum achievable P_f under a targeted P_d could be achieved by cooperating an optimum number of users with the highest PU's SNR rather than cooperating all users in the network.

In Van and Koo (2009) decision fusion methods worked well in reporting channels experiencing Rayleigh fading, shadowing and Additive White Gaussian Noise (AWGN) but there is still some performance loss due to hardening the decisions depending on only single threshold value and therefore, suffer from significant loss of information. Meanwhile, Li and Li (2011) investigates the soft combining based CSS performance in more actual occasion of both

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imperfect sensing channels and reporting channels by using the modified deflection coefficient that maximize the detection probability for a given false alarm probability. In El-Saleh *et al*. (2010), a deflection coefficient based hybrid SDF-HDF CS clustering scheme is proposed to exploit the advantages of reduced overhead of HDF and the superior detection performance of SDF.

Chen *et al*. (2010) proposes an optimal CSS scheme based on linear coherent Multiple Access Channel (MAC) in CR to maximize the sensing performance under the interference temperature constraint. In MAC, the channel is modelled as a coherent sum of signals sent by users, hence precise synchronization between FC and SUs demands lots of feedback channels and consumes large bandwidth. To overcome this problem, in Chen and Zhang (2010) a CSS scheme based on linear Parallel Access Channel (PAC) is proposed to maximize the sensing performance by searching the optimal number and set of SUs in cooperation and controlling their weighting coefficients. Calculating optimal weighting coefficients may not be always affordable due to high computational complexity. In order to obtain weighting coefficients with reduced computational complexity, maximization of deflection criteria can be used as in Jamali *et al*. (2011).

All the papers studied generally stressed on detection performance optimization of CR, where only a few of them discussed about the communication overhead for deploying such system. In real communication environment, there is a bandwidth constraint regarding information sharing among CRs to make a correct detection of PU. Many current SS algorithms do not meet these requirements. In our paper, we jointly explore performance optimization as well as overhead reduction under bandwidth constraints in CRN. Hence, this study is proposing a novel Cluster-based Cooperative SS (CCSS) scheme to improve detection performance by maximizing selective weighted deflection coefficients with respect to overhead reduction by limiting cooperation among only a certain number of potential SUs.

The following section contains system deployment and mathematical assumptions. Performance of proposed SS scheme with existing Maximal Ratio Combining (MRC) and Equal Gain Combining (EGC) based data fusion schemes as well as OR-rule based decision fusion scheme is then assessed through simulations utilizing signals derived from the proposed mathematical model.

MATHEMATICAL MODELLING

For a cognitive ad hoc network, cluster based architectures are promising to reduce congestion in channel access by separating local and remote traffic (Hossain *et al*., 2009). We assume that geographically nearby SUs are grouped into a cluster governed by a Cluster Head (CH), while each SU serves as relay in the sense that they receive different versions of a probable PU transmission and N CHs of the N clusters report their decisions to a common Base Station (BS). A Cluster-based Cooperative Spectrum Sensing (CCSS) is used to improve the detection reliability and realize a space diversity scheme to tackle hidden terminal and channel attenuation problems.

Table 1: Potential combinations of data and decision fusion

Fusion	1	2	3	4
Intra-cluster	Decision	Weighted data	Selective weighted data	Selective weighted data
Inter-cluster	Decision	Weighted data	Weighted data	Decision

CSS is performed on a hierarchical architecture through two levels of user cooperation. The low-level cooperation is carried out within each cluster (intra-cluster) while the high-level one is accomplished outside the cluster among the CHs (inter-cluster).

After receiving a signal from PU over a decision interval, each SU calculates the observation energy using selective weighted-data fusion at CHs amplifies it under transmission power constraint and sends the aggregated result to FC/BS through a common reporting channel for a final decision to be taken by data or decision fusion. Data fusion is employed followed by decision fusion. The justification is that once the decision is taken by each SU, all the sensing information will be lost.

To obtain final decision about the presence of PU, we present few possible fusion methods as shown in Table 1. According to fusion 1, when the channels are of stringently limited bandwidth, both intra-cluster and inter-cluster cooperation are required to be implemented in HDF at the cost of severe performance degradation. Fusion 2 and 3, where both intra-cluster and inter-cluster cooperation are implemented in SDF, are expected to show the best detection performance among these.

However, according to the traffic overhead analysis by El-Saleh *et al*. (2010), if each SU transmits its real values to FC, theoretically, infinite bits are required resulting in a very wide bandwidth, especially when M and N are large and will eventually incur huge overhead. Hence, these methods are appropriate only when the control and reporting channels are of ample bandwidth. Fusion 4 shows a fair balance between performance and overhead since SDF and HDF are both used to obtain the final decision at BS.

Now justification for proposal of fusion 3 and 4 using selective weight comes into focus. If every SU transmits the real value of its observation using SDF, it will result in a large demand of communication bandwidth on the reporting channel, which is practically not feasible. Even when the HDF schemes are adopted at FC, a large number of SUs still yields the total number of sensing bits transmitted to FC prohibitively huge. The consumption of system resources, e.g., the total transmission power of the cooperative SUs and the amount of overhead traffic in the CRN, grows approximately linearly with the number of SUs. To solve this problem, we propose a selective DCM weighting where only sensing information of a particular SU contributing to the largest optimal weight (NDC or MDC) inside each cluster is used in data fusion at FC. This will significantly reduce the traffic overhead over reporting channel since apparently only *N* users are sending their observations to FC instead of *M *N*.

Moreover, shadow fading is correlated for closely spaced SUs; hence, it is desired to select SUs that are sufficiently spatially separated (Hu and Blum, 2001). Hence, sensing reliability may be degraded for this cluster-based scheme if one cluster contains too many close CUs. To solve this problem, the proposed selective weighting scheme can be regarded as an optimal solution without any loss of reliability of detection performance. However, fusion 4 is supposed to render slight degradation in performance compared to fusion 3 since we used OR-rule for decision fusion in inter-cluster cooperation.

PROBLEM FORMULATION

Figure 1 shows the proposed general deployment of the CRN with three main sequential links: the PU-SU link, the SU-CH link and finally the CH-BS link, termed as sensing channel, control channel and reporting channel respectively.

In order to formulate a practical CCSS model for CRN we assume both the signal and the noise to be Wide Sense Stationary (WSS) over sufficient time intervals to perform detection, to have circularly symmetric Gaussian distributions (zero relation matrix and zero mean) and be statistically independent of each other. The density function depends only on the magnitude but not on the argument. As such, the magnitude of standard complex normal random variable will have the Rayleigh distribution and the squared magnitude will have the Exponential distribution, whereas the argument will be distributed uniformly on $[-\pi, \pi]$.

The channel gains are also assumed independent of each other, known and constant over each sensing period. This can be justified by the slow-changing nature over the link where the delay requirement is short compared to the channel coherence time that is also called the quasi-static scenario (Hoven *et al*., 2005). Now we represent the general notations used in this study:

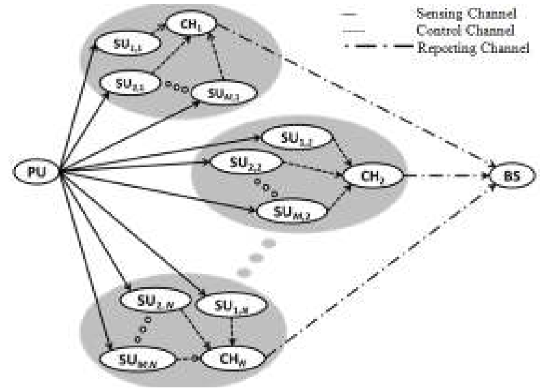

Fig. 1: Deployment of cluster-based CSS in CRN

$CN\sim N(0,\sigma^2)$	=	Circularly symmetric complex Gaussian distribution with zero mean and variance σ^2
H_o and H_1	=	PU is absent and present separately
n	=	1, 2, …, K; K is the number of samples of the received signal
i	=	1, 2, …, M; M is the number of cooperative SUs per cluster
j	=	1, 2, …, N; N is the number of CHs in CRN
P_{Ti}	=	Transmit power of the i^{th} SU
$x_i[n]$	=	Received sampled signal at the i^{th} SU
$S[n]$	=	PU transmitted signal with $CN\sim N(0, \sigma_p^2)$
$W_i[n]$	=	i^{th} sensing channel noise (AWGN) with $CN\sim N(0, \sigma_{si}^2)$
$N_i[n]$	=	i^{th} control channel noise (AWGN) with $CN\sim N(0, \sigma_{ci}^2)$
g_i, h_i, l_j	=	Sensing, control and reporting channel gain respectively, which accommodate any uncertainty such as multipath fading, shadowing and propagation path loss

Characterization of sensing channel: The observed signal at the i^{th} SU is usually represented as a binary hypothesis test:

$$x_i\,[n|H_0] = W_i[n] \quad (1)$$

$$x_i\,[n|H_1] = g_i S[n] + W_i[n] \quad (2)$$

The corresponding energy observed at i^{th} SU is:

$$X_i = \sum_{n=1}^{K} |x_i[n]|^2 \quad (3)$$

Characterization of control channel: Now each SU, serving as relays in an Amplify-And-Forward (AAF) manner, transmit their individual energy measurements of PUs' signal, X_i, to the j^{th} corresponding CH through a dedicated control channel with a weighting factor ω_i under transmit power constraint in an orthogonal manner.

The signal received by corresponding j^{th} CH from the i^{th} SU is:

$$Y_i = \omega_i(P_{Ti}\, h_i X_i + N_i) \quad (4)$$

$\omega_i \geq 0$ satisfying $\|\vec{\omega}\| = 1$, which is used to optimize the detection performance.

The weighting factor for the signal from a particular SU represents its contribution to the cluster decision. For example, if a SU signal generates a high deflection coefficient that may lead to correct detection on its own, it should be assigned a larger weight. For those SUs experiencing deep fading or shadowing, their weights are decreased in order to reduce their negative contribution to the decision fusion.

Weighted data fusion at cluster head: Next all individual test statistics from M SUs are used to linearly formulate the resultant test statistic of the j^{th} cluster, Z_j, given as:

$$Z_j = \sum_{i=1}^{M} Y_i \quad (5)$$

Since Y_i is a linear sum of a large number of samples K of some independent signals, it follows a normal distribution according to the Central Limit Theorem with the mean and variance as follows:

$$\mu_{i,0} = \frac{1}{M*K}\sum_{i=1}^{M}\sum_{n=1}^{K}\omega_i\,(P_{Ti}h_i\sigma_{si}^2 + \sigma_{ci}^2) = w^T\mu_0 \quad (6)$$

$$\mu_{i,1} = \frac{1}{M*K}\sum_{i=1}^{M}\sum_{n=1}^{K}\omega_i\,[P_{Ti}h_i\,(g_i\sigma_p^2 + \sigma_{si}^2) + \sigma_{ci}^2] = w^T\mu_1 \quad (7)$$

$$\sigma_{i,0}^2 = \mathbf{2}\sum_{i=1}^{M}\sum_{n=1}^{K}\omega_i^2\,\,(P_{Ti}h_i\sigma_{si}^2 + \sigma_{ci}^2)^2 = w^T\textstyle\sum_0 w \quad (8)$$

$$\sigma_{i,1}^2 = 2\sum_{i=1}^{M}\sum_{n=1}^{K}\omega_i^2\,\,[P_{Ti}h_i(g_i\sigma_p^2 + \sigma_{si}^2) + \sigma_{ci}^2]^2 = w^T\textstyle\sum_1 w \quad (9)$$

Let,

$$\mu_0 = \frac{1}{M*K}\sum_{i=1}^{M}\sum_{n=1}^{K}(P_{Ti}h_i\sigma_{si}^2 + \sigma_{ci}^2)$$

$$\mu_1 = \frac{1}{M*K}\sum_{i=1}^{M}\sum_{n=1}^{K}[P_{Ti}h_i\big(g_i\sigma_p^2 + \sigma_{si}^2\big) + \sigma_{ci}^2]$$

$$\textstyle\sum_0 = 2\sum_{i=1}^{M}\sum_{n=1}^{K}(P_{Ti}h_i\sigma_{si}^2 + \sigma_{ci}^2)^2$$

$$\textstyle\sum_1 = 2\sum_{i=1}^{M}\sum_{n=1}^{K}[P_{Ti}h_i\big(g_i\sigma_p^2 + \sigma_{si}^2\big) + \sigma_{ci}^2]^{\,2}$$

Considering that global threshold at the CH is β_j, the likelihood ratio is $Z_j \gtrless_{H_0}^{H_1} \beta_j$. As such, the overall probability of detection, P_d for the j^{th} cluster can be written as:

$$P_{d,j} = P(Z_j > \beta_j | H_1) = Q\left(\frac{\beta_j - E\,(Z_j|H_1)}{\sqrt{var\,(Z_j|H_1)}}\right) = Q\left(\frac{\beta_j - w^T\mu_1}{\sqrt{w^T\sum_1 w}}\right) \quad (10)$$

In CSS, the main metric of sensing performance is either minimization of P_f (high spectrum utilization) or maximization of the P_d (low interference to PU), which can be hardly both reached since they are converse variables. In this study, we mainly maximize P_d by controlling the weighting vector while meeting a certain requirement on the P_f under Neyman-Pearson criterion. Then for a given P_f, P_d can be written as:

$$P_{d,j} = Q\left(\frac{Q^{-1}(\overline{P_f})\sqrt{w^T\sum_0 w} + w^T[\mu_0 - \mu_1]}{\sqrt{w^T\sum_1 w}}\right)$$
$$= Q\left(\frac{Q^{-1}(\overline{P_f})\sqrt{w^T\sum_0 w} - w^T\Delta]}{\sqrt{w^T\sum_1 w}}\right) \quad (11)$$

Let,

$$\Delta = \frac{1}{M*K}\sum_{i=1}^{M}\sum_{n=1}^{K}P_{Ri}h_i\,g_i\sigma_p^2 \text{ and } \Delta = [\Delta_1, \Delta_2, ..., \Delta_M]^T$$

Characterization of reporting channel: Assume that the reporting channel corresponding to the j^{th} CH is a Binary Symmetric Channel (BSC) with a probability of reporting error, $P_{e,j}$ and decision fusion rule is employed at the BS to make a global decision. The cluster decisions will be forwarded from N CHs to BS through dedicated reporting channels in an orthogonal manner.

Decision fusion at base station: Using OR rule, it is shown that the global probability of detection, Q_d, of the whole CRN are given by:

$$Q_d = 1 - \prod_{j=1}^{N}[\big(1 - P_{d,j}\big)(1 - P_{e,j}) + P_{d,j}P_{e,j}] \quad (12)$$

Assume, for simplicity, all CHs of the reporting channel are similar to each other resulting in $P_{d,j} = P_d$ and probabilities of reporting errors are identical (i.e., P_e) for all CHs, then:

$$Q_d = 1 - [(1 - P_d)(1 - P_e) + P_dP_e]^N \quad (13)$$

When all reporting channels are perfect (i.e., no error):

$$Q_d = 1 - (1 - P_d)^N \quad (14)$$

PERFORMANCE OPTIMIZATION

Calculating optimal ω vector will result in high computational complexity, which may not be always affordable. In order to set the ω with reduced computational complexity, Deflection Coefficient (DC) can be used as it is a good measurement of the detection performance and can be exploited for performance optimization. The Deflection Coefficient Maximization (DCM) based selective optimal weight setting scheme can be realized by the Normal DCM (NDCM) or the Modified DCM (MDCM).

To measure the effect of the PDFs on the detection performance at CHs under hypothesis H_0 and H_1, NDC and MDC is introduced, respectively:

$$d_n^2 = \frac{[\mu_{i,1} - \mu_{i,0}]^2}{\sigma_{i,0}^2} = \frac{[w^T(\mu_0 - \mu_1)]^2}{\sigma_{i,0}^2} = \frac{(w^T\Delta)^2}{w^T\sum_0 w} \quad (15)$$

$$d_m^2 = \frac{[\mu_{i,1} - \mu_{i,0}]^2}{\sigma_{i,1}^2} = \frac{[w^T(\mu_0 - \mu_1)]^2}{\sigma_{i,1}^2} = \frac{(w^T \Delta)^2}{w^T \Sigma_1 w} \quad (16)$$

Normalizing each weighting co-efficient, according to El-Saleh *et al.* (2010), we obtain the optimal weighting vector as:

$$\omega^*_{opt,NDC\_CH} = \omega_{opt,NDC} \,/\, ||\omega_{opt,NDC}|| = \Sigma_0^{-1} \Delta \quad (17)$$

$$\omega^*_{opt,MDC\_CH} = \omega_{opt,MDC} \,/\, ||\omega_{opt,MDC}|| = \Sigma_1^{-1} \Delta \quad (18)$$

The detection performance after performing data-fusion at CHs is thus given according to (Hossain *et al.*, 2009):

$$P_{d,j(NDC)} = Q\left(\frac{Q^{-1}(\overline{P_f})\sqrt{\Delta^T \Sigma_0^{-1} \Delta} - \Delta^T \Sigma_0^{-1} \Delta}{\sqrt{\Delta^T \Sigma_0^{-2} \Sigma_1 \Delta}}\right) \quad (19)$$

$$P_{d,j(MDC)} = Q\left(\frac{Q^{-1}(\overline{P_f})\sqrt{\Delta^T \Sigma_1^{-2} \Sigma_0 \Delta} - \Delta^T \Sigma_1^{-1} \Delta}{\sqrt{\Delta^T \Sigma_1^{-1} \Delta}}\right) \quad (20)$$

For a given $\overline{P_f}$, P_d is maximized in the sense that the distance between the centers of two PDFs under hypotheses H_0 and H_1 is pushed apart from each other to the maximum by this weighting vector ω^*_{opt} hence, detection performance is optimized. Finally, Q_d after performing decisionfusion at FC/BS are thus given as:

$$Q_{d\_BS} = 1 - \prod_{j=1}^{N}[(1 - P_{d,j})(1 - P_{e,j}) + P_{d,j}P_{e,j}] \quad (21)$$

Performance evaluation of the proposed CRN: In this section, the proposed data weighting schemes performed at CH stages are first simulated and compared. Next, the proposed weighting of data and decision fusion methods in CSS scenarios, where the individual decisions reported by the CHs to the BS are combined using OR rule, is simulated and compared under different scenarios. The effect of varying M is observed as well as the effect of varying P_e of the reporting channels. The default sensing time and sensed bandwidth are set as T_s = 25 μs and B = 6 MHz, respectively. The relay transmit power is set to 12 dBm and the channel gains are $\{g_i\}$, $\{h_i\}$ and $\{l_i\}$ of the sensing, control and reporting channels respectively and are normally distributed but remain constant within each sensing interval T_s, as T_s is sufficiently small. The simulation results are obtained from 10^5 realizations of channel gains and signal and noise variances and then the ROC curves are averaged.

Evaluation of intra-cluster CSS at CHs: By plotting P_d vs. P_f at the CH of single cluster, ROC curve is obtained as in Fig. 2 to observe and compare the overall effect of various weight-setting algorithms used in weighted data fusion schemes at CHs.

The Equal Gain Combination (EGC) based scheme, as expected, is inferior to all weight setting algorithms and shows poor performance due to fixed ω_i assigned to the measurement of each SU at the CH, which can be same as in case of non-weighted scheme. It does not require any channel state information, but still exhibits much better performance than the conventional OR HDF.

Another widely used weight based on SNR (MRC) gives a better ROC compared to that of EGC using the formulas in El-Saleh *et al.* (2010) due to its adaptability. Comparing the effects of DC maximization, it is observed that selective NDC is slightly better than that of MDC and both outperform conventional EGC and MRC.

Since selective NDC gives us superior optimization performance than any other schemes compared, comparison of ROC under NDCM will be considered onwards. Next, we investigate the effect of varying the number of cooperative SUs in a cluster as shown in Fig. 3.

Obviously, performance improves well when M in the cluster increases. when M = 1, which is also equivalent to the case of non-cooperation, ROC curve is very near to the line of no discrimination, where there is no difference between signal and noise. This yields the worst result. As M increases, separation between the signal and noise increases and detection performance of ROC curve improves as well.

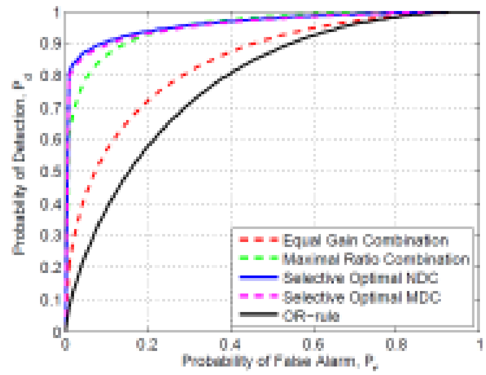

Fig. 2: Performance of various data fusion schemes at CHs

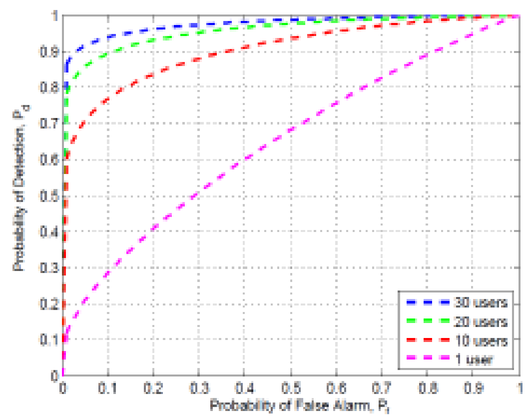

Fig. 3: ROC curve for various no of users inside a cluster

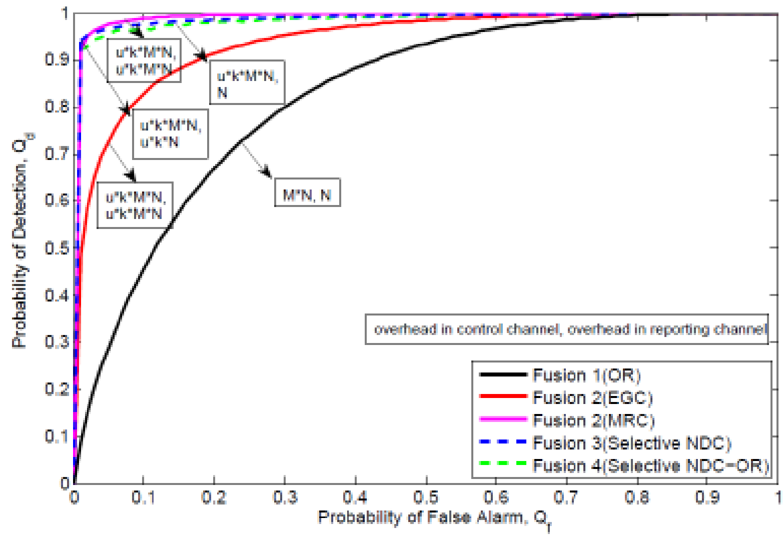

Fig. 4: Comparison of different fusion schemes at BS

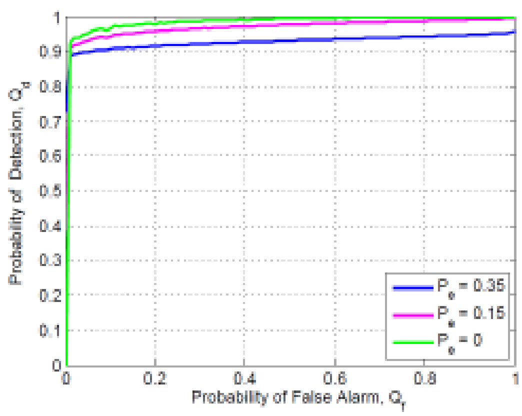

Fig. 5: Detection performance for different P_e at reporting channel

Table 2: Traffic overhead analysis for different fusion schemes

Hybrid scenario	Number of bits transmitted over control channel	Number of bits transmitted over reporting channel
Fusion 1	$M \times N$	N
Fusion 2	$u \times k \times M \times N$	$u \times k \times M \times N$
Fusion 3	$u \times k \times M \times N$	$u \times k \times N$
Fusion 4	$u \times k \times M \times N$	N

Evaluation of inter-cluster CSS at BS: Fusion methods in Table 2 are employed for 3 CHs consisting of 5, 15 and 30 SUs in each cluster respectively. Each fusion method performance is displayed together with the no of bits of overhead they incur. Fusion 1 based on OR rule and result in worst performance among these, but have the advantage of least traffic overhead. MRC based data fusion 2 shows the best result in case of performance comparison in Fig. 4. Our proposed selective optimal NDC based data fusion 3 shows a better result than MRC in low Q_f region (until 0.02). As Q_f goes higher, it shows a near-optimum result that is very close to MRC, For example, when Q_f = 0.1, the ratio of $\frac{Q_{d(MRC)}}{Q_{d(selective\ NDC)}}$ = 1.01. On the other hand, it has M times lesser overhead compared to MRC in support of negligible performance degradation. Furthermore, to reduce overhead in fusion 4 we deploy OR-rule followed by selective optimal NDC based data fusion. It shows a little more degraded performance than the previous 2, but greatly reduces bandwidth consumption.

However, it is clear that performance of our proposed fusion 3 & 4 is still in acceptable margins and can be improved further by increasing no of cluster, N and/or choosing an optimal no of SUs inside a cluster, M. Figure 5 is simulated based on fusion 4 including different P_e in the reporting channel from 3 CHs to BS according to El-Saleh *et al*. (2010).

As expected, the performance degrades as the reporting error increases. When P_e = 0, (13) reduces to (14) and thus the best result, i.e., highest Q_d is achieved due to the error free reporting channel. As P_e increases, Q_d also decreases which in not desired.

Traffic overhead analysis: Table 2 presents a traffic overhead analysis for the potential combinations as presented in Table 2. Consider that during a specific sensing interval each SU in a particular cluster quantizes K signal samples needs with u bits per sample resulting in transmission of $u \times k$ bits with data and only 1-bit with decision to the corresponding CH. Now, we calculate the overhead traffic by the total number of bits that needs to be reported from each SU all the way to the BS in Table 2.

It is clear that fusion 1 scenario offers the lowest overhead traffic, but unfortunately, the detection performance of HDF scheme is not as good as the fusion 2 as shown in Fig. 2 and 4. However, when M and N go large, using fusion 2 will lead to require large bandwidth. Thus, fusion 3 scenario presents a balance between these two conflicting objectives; maximizing the detection performance and minimizing the overhead traffic. Using proposed selective optimal weighting algorithm, only 1 SU with the highest optimal weight is sending its sensing information to FC during inter-cluster cooperation, so it is apprehensible that M is 1 in this case. Hence, a reduction of M times comparing to fusion 2 in case of data fusion is noticeable with only a little performance degradation. In fusion 4, decision fusion is made using OR-rule by further reducing no of bits to a great extent at the cost of a little more performance degradation compared to fusion 3, which is desired when there is a constraint on bandwidth availability on reporting channel.

CONCLUSION

The CSS is widely used in CRN in order to reduce the sensing time and the sensitivity requirements on an individual CR under destructive channel effects. In the proposed CCSS scenario, optimization of P_d is investigated with resorting to allocation of an optimal weight, by maximizing NDC and MDC, to individual cooperative SUs, but only a particular SU from each cluster having the highest optimal weight gets the opportunity to contribute to obtain the final decision about the presence of PU at BS. The performance of the proposed hybrid fusion scheme has been simulated and compared with other conventional schemes. Simulation also proved that performance degrades with increased reporting error. Finally, the presented traffic overhead analysis shows an excellent compromise between the detection performance and radio resources under bandwidth constraints when selective optimal NDC-based weighted data fusion is used followed by OR-rule based decision fusion. By characterizing the tradeoff as an optimization problem, the approximation of optimal number of intra and/or inter clusters users can be obtained which can minimize the cooperation overhead without any performance loss of reliability.

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