Censored Cooperative Spectrum Sensing in Cognitive Radio Network

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Abstract: - The ever-increasing demand for higher data rates in wireless communications has motivated the introduction of cognitive radio. Current research scope on cognitive radio network mainly focuses on improving performance of primary users' detection, which requires a large number of secondary users for reliable detection and hence, resulting in a high sensing & transmission energy consumption and very wide bandwidth of reporting channel. An energy-efficient 'censor before cooperation' algorithm is proposed for smart selection of secondary users in a distributed two-layered cognitive radio network based on their individual weights obtained by maximizing deflection coefficients. The core of the concept relies on selecting an optimal number and set of users, termed as active users, who can efficiently sense the primary users and censoring the bad performing secondary users, termed as passive users, from cooperation. The MATLAB simulation results show the superiority of the proposed spectrum sensing algorithm to other fusion schemes derived under Neyman-Pearson framework in terms of detection performance. Besides, this algorithm greatly reduces communication overhead because sensing information is transmitted only from active users to a fusion center while the passive users to not transmit anything out of the cluster. Transmission energy is also conserved in relation with the passive users. Erroneous reporting channels are assumed, which gives a practical touch to the system model.

Key-Words: - Cluster, cognitive radio network, censored cooperative sensing, deflection coefficient, energy fusion

1 Introduction
Traditionally, the spectrum is licensed to users by government agencies in a static manner where the licensee has exclusive right to access the allocated band. However, with increasing demand for the spectrum and scarcity of vacant bands, a spectrum policy reform is highly expected. Current studies show that some frequency bands in the spectrum are heavily congested while other bands are largely unoccupied most of the time [1].

The cognitive radio (CR) [2] is proposed as a key technology to exploit these underutilized spectral resources by reusing unused spectrum in an opportunistic manner. The crucial requirement for CRs is to act as secondary users (SUs) and to exploit an efficient spectrum sensing (SS) technique that can reliably monitor the primary users' (PU) activities and quickly vacate the band once a PU has been detected. It is thus the key for the development of CR to invent fast and highly robust ways of determining whether a PU is present or not. Thus, SS is one of the most essential components of CR.

Among various SS methods such as matched filter, feature detection and wavelet detection, energy detection is the most common method due to its low computational complexity which is also utilized in this paper [3]. The benefits of cooperation in SS are illustrated in [4] when the number of CR is arbitrarily large. G. Ganesan shows that by allowing the SUs operating in the same band to cooperate the detection time can be reduced and thus overall agility can be increased.

When using techniques such as those described in [5] [6] [7], as the number of SUs grows, the energy consumption of the CR network (CRN) increases, but the performance generally saturates. Hence, techniques have been developed to improve the energy efficiency in cooperative CRN. A popular energy-aware cooperative spectrum sensing (CSS) technique is censoring. In energy detection based censored CSS, local decision is based on the locally collected energy, and the SU will not send anything when outside this region. In [8] it is shown that the number of SUs has a large effect on the sensing performance if the SUs are few. However, once the number of active SUs reaches a certain number, the sensing performance is only marginally increased if additional SUs are used. [9] shows that cooperating all SUs in the network does not necessarily lead to attain the optimum performance,
but instead, it is achieved by cooperating a certain number of users who possess the highest PU’s signal-to-noise ratio values at their receivers.

Clustering has also been proposed in networks to improve the energy efficiency [10], and it can easily be used in CRN as well. For CSS specifically, this method reduces the average communication range to pass on information to the fusion center (FC), and thus diminishes the average transmission energy, but it also allows for taking intermediate decisions about the presence or absence of the PU (soft or hard) at the cluster heads (CHs) [11]. In [12], confidence voting is proposed as a kind of censoring mechanism that can be used within every cluster to reduce the transmission energy even more. The idea is that a SU sends results to the CH only if it is confident, and it gains confidence when its result accords with the cluster consensus, and loses confidence otherwise.

Current research trends focus on detection methods and not on user selection. In order to sustain confidence in sensing, the number of users will have to be increased. In turn, the sensing performance decreases in the sense that the risk of missing a spectrum opportunity, and/or the risk of causing interference to PU, will increase. Furthermore, the total power consumption of the sensing goes up. It is thus, desirable to use as few users as possible, while still having enough for the sensing to be reliable. In this sense, selecting the appropriate users from a cluster to engage in CSS should be addressed as a point of optimization while ensuring a high reliability of the sensing and having a low battery consumption of the SUs.

A new scheme is considered for two-layer cluster-based distributed detection based on a ‘censoring before cooperation’ or ‘send/no-send’ viewpoint. A number of intra-cluster SUs are exclusively allowed to participate in CSS based on their sensing observations so that only users containing ‘informative’ observations send those to CH, and those containing ‘uninformative’ observations are censored.

The following section contains the system deployment and assumptions. Next, performance of the proposed censored CSS (CCSS) scheme is assessed with maximal ratio combining (MRC) and equal gain combining (EGC) based conventional energy combining schemes as well as the OR-rule based hard combining scheme through simulations utilizing signals derived from the proposed mathematical model.

2 Mathematical Model

It is assumed that geographically nearby M 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. CSS is performed on a hierarchical architecture of these user clusters, through two layers of 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).

In order to formulate a practical CCSS model for CRN, both the signal and the noise are assumed to be have circularly symmetric Gaussian distributions and be statistically independent of each other. 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. The general notations used in this paper are as follows:

\[ CN \sim N(0, \sigma_p^2) \] is circularly symmetric complex Gaussian distribution with zero mean and variance \( \sigma_p^2 \). \( H_p \) and \( H_t \) represent PU is absent and present separately, \( n \) is 1, 2, ..., \( K \); \( K \) is the number of samples of received signal, \( i \) is 1, 2, ..., \( M \); \( M \) is the number of SUs per cluster, \( j \) is 1, 2, ..., \( N \); \( N \) is the number of CHs in CRN, \( P_{T_i} \) is transmit power of the \( i^{th} \) SU. \( x_{i[n]} \) is received sampled signal at the \( i^{th} \) SU, \( S[n] \) is PU transmitted signal with \( CN \sim N(0, \sigma_p^2) \), \( W[n] \) is \( i^{th} \) sensing channel noise (AWGN) with \( CN \sim N(0, \sigma_{n_i}^2) \). \( N_{[n]} \) is \( i^{th} \) Control channel noise (AWGN) with \( CN \sim N(0, \sigma_{c_{[i]}}^2) \), \( g_i \) and \( h_i \) are sensing, control and reporting channel gains, respectively, which accommodate any uncertainty such as multipath fading, shadowing, and propagation path loss. The channel gains are assumed independent of each other, known and constant over each sensing period.

![Fig. 1. Deployment of CCSS in a CRN](image-url)
Fig. 1 shows the general deployment of the cognitive radio network (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.

### 2.1 Intra-cluster CSS at CHs

The observed signal at the $i^{th}$ SU is usually represented as a binary hypothesis test.

$$x_i[n | H_0] = W_i[n]$$

$$x_i[n | H_1] = g_i S[n] + W_i[n]$$

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

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

After receiving a signal from PU over a decision interval each SU, serving as a relay in an amplify-and-forward (AAF) manner, transmits its individual energy measurements of PUs’ signal, to the $j^{th}$ corresponding CH through a dedicated control channel in an orthogonal manner. The signal received by corresponding $j^{th}$ CH from $i^{th}$ SU is

$$Y_j = P_{f_i} h_i X_i + N_i$$

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

Next all individual test statistics from $M$ SUs are used to linearly formulate the resultant test statistic of the $j^{th}$ cluster, $Z_j$, with a weighting factor $\omega_j$, given as

$$Z_j = \sum_{i=1}^{M} \omega_i Y_i$$

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:

$$\mu_{i,0} = \frac{1}{M} \sum_{i=1}^{M} \sum_{n=1}^{K} \omega_i (P_{f_i} h_i \sigma_p^2 + \sigma_{s_i}^2) = w^T \mu_0$$

$$\mu_{i,1} = \frac{1}{M} \sum_{i=1}^{M} \sum_{n=1}^{K} \omega_i [P_{f_i} h_i (g_i \sigma_p^2 + \sigma_{s_i}^2) + \sigma_{c_i}^2] = w^T \mu_1$$

$$\sigma_{i,0}^2 = 2\sum_{i=1}^{M} \sum_{n=1}^{K} \omega^2_i (P_{f_i} h_i \sigma_{s_i}^2 + \sigma_{c_i}^2)^2 = w^T \Sigma_0 w$$

$$\sigma_{i,1}^2 = 2\sum_{i=1}^{M} \sum_{n=1}^{K} \omega^2_i [P_{f_i} h_i (g_i \sigma_p^2 + \sigma_{s_i}^2) + \sigma_{c_i}^2]^2 = w^T \Sigma_1 w$$

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 making.

In this paper, $P_f$ is maximized by controlling the weighting vector while meeting a certain requirement on $P_f$ under Neyman-Pearson criterion. Then, for a given $P_f$, $P_d$ can be written as

$$P_{d,f} = Q\left(\frac{Q^{-1}(P_f)}{\sqrt{\sum_{i=1}^{M} \sum_{n=1}^{K} \omega_i (g_i \sigma_p^2 + \sigma_{s_i}^2)}}\right)$$

where, $\Delta = \frac{1}{M \Sigma_{n=1}^{K} \sum_{i=1}^{M} P_{f_i} h_i g_i \sigma_p^2}$

### 2.2 Inter-cluster CSS at CHs

Next, the energy measurements will be forwarded from $N$ CHs to BS/FC through dedicated reporting channels in an orthogonal manner for a final decision to be taken by soft or hard combining. Using OR rule, it is shown that the global probability of detection, $Q_d$, of the whole CRN is given by:

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

It is assumed, for simplicity, that all CHs of the reporting channel are similar to each other resulting in $P_{d,j} = P_d$:

$$Q_d = 1 - [(1 - P_f)(1 - P_e) + P_d P_e]^N$$

and when all reporting channels are perfect (i.e. no error), $Q_d$ of the whole CRN is given by:

$$Q_d = 1 - (1 - P_d)^N$$

### 3 Performance Optimization

#### 3.1 Selecting optimal weight

In order to set $\omega$ 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 [7]. The deflection coefficient maximization (DCM) based optimal weight setting scheme can be realized by the normal DCM (NDCM).

To measure the effect of the PDFs on the detection performance at CHs under hypothesis $H_0$ and $H_1$, normal deflection coefficient (NDC) is introduced,

$$d_{n}^2 = \frac{|\mu_{i,1} - \mu_{i,0}|^2}{\sigma_{i,0}^2} = \frac{|w^T (\mu_{i,1} - \mu_{i,0})|^2}{w^T \Sigma_{0} w} = \frac{(w^T \Delta)^2}{w^T \Sigma_{0} w}$$

Normalizing each weighting co-efficient, the optimal weighting vector is obtained as

$$\omega_{opt,NDC,CH} = \omega_{opt,NDC} ||\omega_{opt,NDC}||^{-1}$$

For a given $P_f$, $P_d$ is maximized in the sense that the distance between the centres of two PDFs under hypotheses $H_0$ and $H_1$ is pushed apart from each other to the maximum by this weighting vector $\omega_{opt}$ hence, detection performance is optimized. The detection performance after performing linear energy fusion at CHs is thus given as:

$$P_{d,j,NDC} = Q\left(\frac{Q^{-1}(P_f)}{\sqrt{\sum_{i=1}^{M} \sum_{n=1}^{K} \omega_i (g_i \sigma_p^2 + \sigma_{s_i}^2)}}\right)$$

where, $\Delta = \frac{1}{M \Sigma_{n=1}^{K} \sum_{i=1}^{M} P_{f_i} h_i g_i \sigma_p^2}$
3.2 Selecting optimal number of SUs
The same CR network with a two-layer cluster is used, as described above, in implementing censored CSS. In such a system a SU will send a sensing result out of its cluster only if it is deemed informative, otherwise sensing results that are uninformative will be censored out. The problem, naturally, is to decide what is ‘informative’ and what is not.

In this case, a SU is allowed to transmit its sensing observation to FC if and only if its local normalized NDC value is larger than the average of that of all SUs at the CH. Therefore, the ‘censor before cooperation’ algorithm, as shown in Fig. 2, partitions total number of intra-cluster SUs, \( M \) into two sets: one active set and one passive set during intra-cluster CSS. The active set contains \( P \) number of SUs that will participate in CSS at a particular time, and the passive set contains the rest of the SUs, \( M-P \) at that particular time. Then, during inter-cluster CSS, only active set of SUs from each cluster are required to report to FC with their preliminary sensing data. Based on these information, FC will make a final decision according to linear energy fusion or OR logic rule.

This will significantly reduce the traffic overhead over reporting channel since apparently only \( P \) \((P<M)\) users are sending their observations to FC instead of \( M \). To reduce the power consumption of the individual SUs, the partitioning of the \( M \) users into the active set and the passive set is allowed to vary over time. Furthermore, if the spectrum range to sense is divided into sub-ranges, there can be a separate active set for each frequency sub-range.

The proposed ‘censor before cooperation’ algorithm can be regarded as a fair solution to find an optimal number and set of SUs. By using this, detection performance can be improved without any loss of reliability. However, hard combining is supposed to render slight degradation in performance compared to linear energy fusion OR-rule is used for hard combining in inter-cluster cooperation.

4 Performance Evaluation
In this section, the proposed ‘censor before cooperation’ algorithm performed at both CH (intra-cluster) and BS (inter-cluster) stages are first simulated in MATLAB and compared with other fusion rules like MRC, EGC and OR rule. 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 \( T_s = 25 \mu s \) and \( B = 6 \text{ MHz} \), respectively. The relay transmit power is set to 12 dBm. The simulation results are obtained from \(10^5\) realizations of channel gains and signal and noise variances and then the ROC curves are averaged.

4.1 Evaluation of intra-cluster CCSS at CHs
By plotting \( P_d \) vs. \( P_f \) according to (10) at the CH of single cluster containing 20 SUs, ROC curve is obtained as in Fig. 3 to observe and compare the overall effect of various weight-setting algorithms used in weighted energy 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 \( \omega_i \) assigned to the measurement of each SU at the CH. It does not require any channel state information, but still exhibits much better performance than the conventional OR-decision combining rule. Another widely used weight based on SNR (MRC) gives a better ROC compared to that of EGC using the formulas in [7] due to its adaptability. Comparing the effects of DC maximization, it is observed that optimal NDC weight setting is better than conventional EGC and
MRC, but the proposed NDC based on censoring outperforms all of the above weighting schemes, even for low probabilities of false alarm. This simulation shows that the optimum performance of SU network is achieved by cooperating a certain number of users with the higher NDC values rather than cooperating all the available SUs in the network.

Fig. 3. Comparison of fusion schemes of intra-cluster CCSS at CHs

Since censored optimal NDC gives superior optimization performance than any other schemes compared, comparison of ROC under censored NDCM will be considered onwards. Next, the effect of varying the number of cooperative SUs is investigated in 4 clusters containing 30, 20, 10 & 5 SUs as shown in Fig. 4.

Fig. 4. Effect of various no of users in intra-cluster CSS

Obviously, as \( M \) increases, separation between the signal and noise increases and detection performance improves as well in all clusters. At the same time, after deploying ‘censoring before cooperation’ algorithm number of SUs in active set, \( P \) becomes 7, 5, 2 & 1 respectively at an instance. A large number of SUs (\( M-P \)) from each cluster are put into passive sets and those are censored from taking part in cooperation in inter-cluster stage.

These are actually the users which contain only ‘uninformative’ sensing data and thus, even if these SUs were included to take part in CSS, these would have contributed to negative impact on detection performance, similar to the case of optimal NDC in Fig. 3, and would have given rise to a huge number of traffic overhead bits. This means by using the proposed censored CSS, the average transmitted sensing bits will be greatly reduced on top of boosting performance. This is because unreliable SUs are censored and excluded from the final decision.

4.2 Evaluation of inter-cluster CCSS at BS

Several fusion methods are employed for 3 CHs consisting of 5, 15 and 30 SUs in each cluster respectively in case of performance comparison in Fig. 5. Decision fusion based on OR rule results in worst performance among these. Our proposed algorithm based data fusion shows better result than conventional NDC, MRC & EGC in all \( Q_f \) regions.

Now 3 clusters are considered, \( N = 3 \), consisting of \( M_1=20, M_2=10 \) & \( M_3=5 \), bits per sample, \( u = 4 \), bandwidth, \( B = 6 \) MHz, sensing time, \( t_s = 0.025 \) ms, resulting in a sampling rate, \( k = 2 \times B \times t_s = 300 \). Transmission during inter-cluster CCSS using conventional OR rule fusion incurs only 3 bits (1 decision bit from each CH) whereas, energy fusion using optimal NDC, MRC & EGC result in \( u \times k \times (M_1 + M_2 + M_3) = 42,000 \) bits.

Fig. 5. Comparison of fusion schemes of inter-cluster CCSS at BS
At the same time, censored NDC causes \( u \times k \times (P1 + P2 + P3) = u \times k \times (6 + 2 + 1) = 10,800 \) bits. This means that it has the advantage of having \((M-P)\) or 75% lesser overhead bits (31,200 bits in this case) compared to other methods. To improve further, OR-rule followed by both optimal NDC & censored NDC based data fusion is deployed. It shows a slightly degraded performance than the optimized one, but greatly reduces bandwidth consumption.

![Fig. 6. Detection performance for different \( Pe \) at reporting channel](image)

Fig. 6 is simulated including different \( Pe \) in the reporting channel from 3 CHs to BS according to (12) for both conventional CSS and censored CSS (CCSS). As expected, the performance degrades since \( Pe \) increases. When \( Pe = 0 \), (12) reduces to (13) and thus, produces the best result, i.e. highest \( Qd \) due to error free reporting channel. If strictly observed, it is clear that performance difference between non-censored and censored fusion slowly diminished as \( Pe \) increases. Thus, it can be decided that censored fusion scheme is dominant over non-censored ones especially in reporting channels with low errors.

5 Conclusion
In this paper, an optimization scheme is presented to maximize the sensing performance by searching the optimal number and set of SUs in cooperation and controlling their weighting coefficients. The proposed ‘censoring before cooperation’ algorithm makes use of the channel information and chooses the part of SUs with better observations. Network performance significantly degrades if all the available users cooperate instead. It is an attractive scheme for users with limited power (such as nodes operating on battery) to take part in sensing since energy consumption is efficiently reduced considering the passive users. Besides, the total amount of sensing bits reported to the common receiver can be decreased to a great extent since most of the workload has been shared by the CHs, thereby facilitating a low-bandwidth reporting channel. Superiority of detection performance of the proposed weight setting and censoring algorithm has also been confirmed by monte carlo simulation in MATLAB and comparing with other conventional spectrum sensing schemes.

References: