Hybrid SDF-HDF Cluster-Based Fusion Scheme for Cooperative Spectrum Sensing in Cognitive Radio Networks

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Abstract

In cognitive radio networks, cooperative spectrum sensing schemes are proposed to improve the performance of detecting licensees by secondary users. Commonly, the cooperative sensing can be realized by means of hard decision fusion (HDF) or soft decision fusion (SDF) schemes. The SDF schemes are superior to the HDF ones in terms of the detection performance whereas the HDF schemes are outperforming the SDF ones when the traffic overhead is taken into account. In this paper, a hybrid SFD-HDF cluster-based approach is developed to jointly exploit the advantages of SFD and HDF schemes. Different SDF schemes have been proposed and compared within a given cluster whereas the OR-rule base HDF scheme is applied to combine the decisions reported by cluster headers to a common receiver or base station. The computer simulations show promising results as the performance of the proposed scenario of hybridizing soft and hard fusion schemes is significantly outperforming other different combinations of conventional SDF and HDF schemes while it noticeably reduces the network traffic overhead.

Keywords: Cognitive radio, spectrum sensing, PU, SU, SDF, HDF, and clustering

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1. Introduction

Although the frequency allocation charts are very crowded in many countries around the world, wide segments of already-licensed spectrum are unfortunately still underutilized according to actual measurements such as, for instance, what was done by the Federal Communications Commission (FCC) [1]. To support the increasing demand for radio resources, the cognitive radio (CR) [2] is proposed as a key technology to dynamically allocate the spectrum bands based on certain criteria. The CR is visioned as an enabling technology for opportunistic access of spectrum holes that are temporarily and spatially available for radio transmission. The CR users are classified as secondary users (SUs) with lower priority than the primary users (PUs) who are obviously, licensees, or alternatively, users of existing technologies on unlicensed bands (e.g. IEEE802.11a). The crucial requirement of these SUs is to be armed with adequate spectrum sensing techniques that can reliably monitor the PUs' activities and quickly vacate the band once a PU has been detected. Many cooperative spectrum sensing schemes, where several SUs corporately decide on the presence or absence of a PU, have been proposed to tackle the hidden terminal problem that occurs when the PUs activities are shadowed from the local SU receiver by any existing intermediate objects such as in fading environments [3]. The decision on the presence of a PU is achieved by combining all individual decisions of local SUs at a central base station (BS) using various fusion schemes [4][5]. These schemes can be classified as hard decision fusion (HDF) [6][7][8], soft decision fusion (SDF) [9][10], or softened hard decision fusion (SHRD) [11]. In HDF, the local sensors, or SUs, make their own judgements on the presence of a PU and their corresponding resultant 1-bit decisions are sent to the BS for fusion. These hard fusion schemes have the advantage of reduced traffic overhead as only one single bit needs to be reported to the BS from each SU. In contrast, the SDF schemes require the local sensors to report their measurements as raw data to the BS at which, this data will be fused to construct a final decision on the presence of PU(s). These soft schemes show better detection performance than HDF schemes [12] but they own the negative feature of the increased overhead due to the huge amount of reported data from the SUs to the BS. The SHRD in [11] tried to relief SDF situation by softening the hard decisions but unfortunately, the detection performance was then sacrificed. Another way to improve the sensing performance is to group the SUs into clusters and instruct them to send their 1-bit hard decisions to clusters' headers which will then forward their evaluations to the BS [13][14]. These methods worked well in reporting channels experience Rayleigh fading and shadowing but there is still some performance loss due to hardening the decisions.

In this paper, a hybrid SDF-HDF cluster-based fusion cooperative spectrum sensing scheme is proposed to exploit the advantages of reduced overhead of HDF schemes and the superior detection performance of SDF ones. The SDF schemes use weighting coefficients vectors to control the contributions of different SUs into the global PU-availability decision taken by the fusion center. The proposed schemes of optimizing the weighting coefficients vector are based on maximizing the normal deflection coefficient (NDC) and modified deflection coefficient (MDC). These SDF schemes are implemented within the cluster and their detection performance is compared with the performance of other conventional SDF schemes such as the maximal-ratio combining (MRC) and equal gain combination (EGC) as well as the well-known OR-rule HDF scheme [11][12][14]. The 1-bit PU-availability decisions of several clusters will be then forwarded to a common receiver, or base station, at which an OR-rule based HDF scheme will be utilized to combine the clusters' decisions and come out with a global single decision on the existence or presence of a PU. The front-end detection performance of the proposed hybrid SDF-HDF cluster-based cooperative sensing scenario is evaluated and compared with various combinations of SDF and HDF schemes. Finally, the overhead traffic of the proposed SDF-HDF scenario is analyzed and compared with SDF-SDF and HDF-HDF scenarios.

The remaining part of this paper is organized as follows: Section 2 presents the system deployment, assumptions, and the corresponding mathematical modelling. Section 3 describes the procedures of optimizing the weighting coefficients vectors of the proposed SDF schemes. In section 4, the detection performance of the proposed hybrid SDF-HDF cluster based cooperative sensing is evaluated and the pertaining taffic overhead is compared with SDF-SDF and HDF-HDF scenarios. Finally, the conclusions are drawn in section 5.

2. Cognitive Radio Network (CRN) System Model

In CRNs, the detection performance might be severely degraded when the sensing observations are forwarded to a fusion centre through fading channels. A cluster-based cooperative spectrum sensing is proposed to improve the detection reliability and to realize some sort of space diversity to tackle possible hidden terminal and channel attenuation problems. **Fig. 1** shows the CRN deployment where each geographically-nearby M SUs are grouped into a cluster governed by a cluster header (CH) and the N CHs of the N clusters report their decisions to a common BS. The SUs of a cluster serve as relays in the sense that they receive different versions of a probable PU transmission and then forward them to the corresponding CH which will then perform linear weighted SDF on the test statistics of the individual SUs' received signals using energy detection. The use of a weighting vector in the linear soft fusion brings up the advantage of eliminating the need for finding optimal thresholds for the individual SU nodes and abstracting all into a single global threshold. Possible ways of optimizing the weighting vector are presented in section 3. A well-dedicated algorithm to choose the CH of each cluster can be found in [13] though the CH can be thought as a distinct/fixed BS. The individual 1-bit decisions of the N CHs are reported to the BS at which a HDF will be applied to obtain a final decision on the presence of the PU activities. It is also assumed that the instantaneous channel state information of the reporting channel is available at each CH. **Fig. 1** shows the proposed general deployment of the CRN with three main sequential links; the primary user-secondary user (PU-SU) link, the secondary user-cluster header (SU-CH) link, and finally the cluster header-fusion centre (CH-BS) link. The main operations performed within these three stages are, spectrum sensing, SDF, and HDF, respectively. For the simplicity of illustration, we assume that each cluster contains the same number of SUs, M.

2.1 Characterization of Primary User-Secondary User (PU-SU) Link

Multiple SUs are deployed over a certain geographical area of the CRN by some upper layer algorithms. The SUs perform local spectrum sensing independently to detect the PU's activities. The energy detector is used and it is known as a suboptimal detector of unknown signals [15]. The received demodulated signal is assumed to be confined in a priori known bandwidth, B, and sampled at a rate f_s, which is higher than Nyquist rate; $f_s > 2B$. The sensing task at any arbitrary SU is usually formulated as the binary hypothesis test

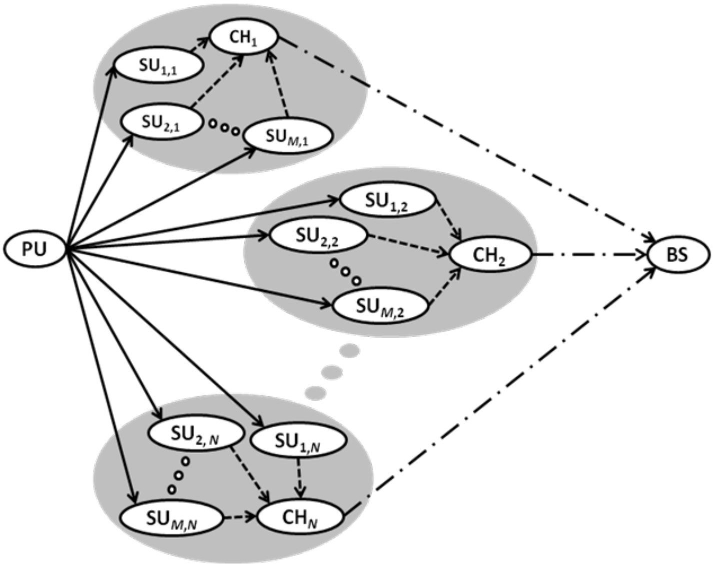

Fig. 1. Deployment of cluster based cooperative spectrum sensing in a CRN

$$\text{When PU is absent} \Rightarrow H_o\text{: } X_i[n] = W_i[n] \quad (1)$$

$$\text{When PU is present} \Rightarrow H_1\text{: } X_i[n] = g_i\, S[n] + W_i[n] \quad (2)$$

where $X_i[n]$ is the received sampled signal at the i^{th} SU receiver, $n = 1, 2, \ldots, K$, where K is the number of samples of the received signal and it is defined as $K = 2T_sB$ where T_s is the sensing time, $i = 1, 2, \ldots, M$, where M is the number of cooperative SUs per cluster, g_i is the sensing channel gain between the PU and the i^{th} SU which accommodates for any channel effects such as multipath fading, shadowing, and propagation path loss, $S[n]$ is the PU transmitted signal which is assumed to be independent and identically distributed (i.i.d.) Gaussian random process with zero mean and variance σ_S^2, i.e., $S[n] \sim \mathcal{N}(0, \sigma_S^2)$, and $W_i[n]$ is the i^{th} sensing channel noise which is assumed to be additive white Gaussian with zero mean and variance σ_{Wi}^2 experiencing i.i.d. fading effects, i.e., $W_i[n] \sim \mathcal{N}(0, \sigma_{Wi}^2)$. All these variances are collected into the vector $\vec{\sigma}_W = [\sigma_{W1}^2, \sigma_{W2}^2, \ldots, \sigma_{WM}^2]^T$ and the sampled signals received at the M SUs are collected into the vector $\vec{X} = [X_1, X_2, \ldots, X_M]^T$. The channel gains of the PU-SU and SU-CH links, g_i and h_i, respectively, are assumed to be constant over each sensing period; this can be justified by the slow-fading nature over these links where the delay requirement is short compared to the channel coherence time which is also called the quasi-static scenario [16]. A detailed system model for the proposed hybrid SDF-HDF cluster-based cooperative spectrum sensing is shown in **Fig. 2**.

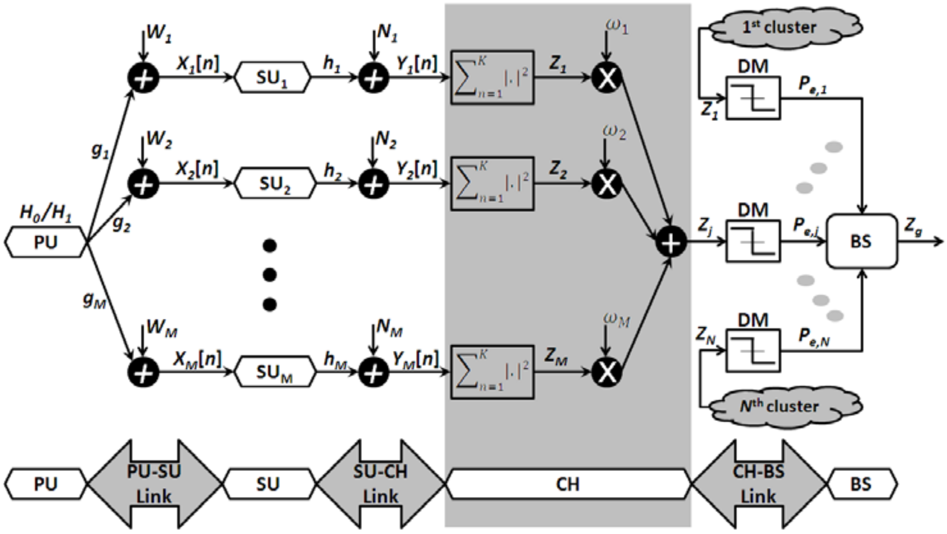

Fig. 2. Detailed system model of the proposed hybrid SDF-HDF cluster-based cooperative spectrum sensing.

2.2 Characterization of Secondary User-Cluster Header (SU-CH) Link

The SDF process is intialized by notifing the M SUs to relay their individual measurements of PUs' signal, $\boldsymbol{X}$, to the j^{th} corresponding CH through a dedicated control channel in an orthogonal manner. Each relay will simply act in an amplify-and-forward (AAF) manner. The justification of using AAF instead of the less complexity decode-and-forward (DAF) scheme is referred to its ability to improve the detection performance by employing some signal processing techniques at the CH. The channel noises $\{N_i\}$ of the SU-CH links are assumed to be zero mean and spatially uncorrelated additive white Gaussian with variances $\{\delta_i^2\}$ which are collected into the vector $\vec{\delta} = [\delta_1^2, \delta_2^2, ..., \delta_m^2]^T$. Then, the signal received by corresponding j^{th} CH from the i^{th} SU will be

$$Y_i\,[n] = \sqrt{P_{Ri}}\, h_i\, X_i[n] + N_i[n] \tag{3}$$

where P_{Ri} is the transmit power of the i^{th} relay and h_i is the amplitude channel gain of the i^{th} SU-CH link. The use of AWGN model here is justified by the slow-changing nature of the channels between the M SUs and their corresponding CH. Now, by considering the two hypotheses in (1) and (2), the received signal at the j^{th} CH can be expressed as

$$Y_i\,[n|H_o] = \sqrt{P_{Ri}}\, h_i\, W_i\,[n] + N_i[n] = u_{0i}[n] \tag{4}$$

$$Y_i\,[n|H_1] = \sqrt{P_{Ri}}\, h_i\, g_i\, S[n] + \sqrt{P_{Ri}}\, h_i\, W_i\,[n] + N_i[n] = \sqrt{P_{Ri}}\, h_i\, g_i\, S[n] + u_{0i}[n] \tag{5}$$

whose statistical properties are $Y_i[n|H_o] \sim \mathcal{N}(0,\ \sigma_{0,i}^2) \sim \mathcal{N}(0,\ P_{Ri}\,|h_i|^2\,\sigma_{Wi}^2 + \delta_i^2)$ and $Y_i[n|H_1] \sim \mathcal{N}(0,\ \sigma_{1,i}^2) \sim \mathcal{N}(0,\ P_{Ri}\,|g_i|^2 |h_i|^2\,\sigma_S^2 + \sigma_{0,i}^2)$. In a Matrix form, the received signals at the CH through the control channel under H_0 and H_1, respectively, can be written as

$$Y[n \mid H_0] = \begin{bmatrix} \sqrt{P_{R1}} h_1 & 0 & \cdots & 0 \\ 0 & \sqrt{P_{R2}} h_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \sqrt{P_{RM}} h_M \end{bmatrix} \times \begin{bmatrix} W_1[n] \\ \vdots \\ W_M[n] \end{bmatrix} + \begin{bmatrix} N_1[n] \\ \vdots \\ N_M[n] \end{bmatrix} \tag{6}$$

$$Y[n \mid H_1] = \begin{bmatrix} \sqrt{P_{R1}} g_1 h_1 & 0 & \cdots & 0 \\ 0 & \sqrt{P_{R2}} g_2 h_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \sqrt{P_{RM}} g_M h_M \end{bmatrix} \times \begin{bmatrix} S_1[n] \\ \vdots \\ S_M[n] \end{bmatrix} + \begin{bmatrix} u_{01}[n] \\ \vdots \\ u_{0M}[n] \end{bmatrix} \tag{7}$$

At the corresponding CH of M SUs, each received sequence $Y_i[n]$ will be individually averaged and squared using a separate energy detector to estimate its own energy as shown in **Fig. 2**. Thus, the estimated energy collected by the i^{th} SU all the way to the CH is

$$Z_i = \sum_{n=0}^{K-1} | Y_i[n] |^2 \ ; \qquad i = 1, 2, \ldots, M \tag{8}$$

By denoting $\{Z_{o,i}\} = \{Z_i | H_0\}$ and $\{Z_{1,i}\} = \{Z_i | H_1\}$, the two sets of test statistics can be written as $\vec{Z}_0 = [Z_{0,1}, Z_{0,2} \ldots Z_{0,M}]^T$ and $\vec{Z}_1 = [Z_{1,1}, Z_{1,2} \ldots Z_{1,M}]^T$. For a large number of samples, the central limit theorem (CLT) approximates each test statistic into the vectors $\vec{Z}_0$ and $\vec{Z}_1$ to be normally distributed with mean and variance given by

$$E(Z_i \mid H_0) = K\sigma_{0,i}^2 = K(P_{Ri} \mid h_i \mid^2 \ \sigma_{Wi}^2 + \delta_i^2) \tag{9}$$

$$\mathrm{var}(Z_i \mid H_0) = 2K\sigma_{0,i}^4 = 2K(P_{Ri} \mid h_i \mid^2 \ \sigma_{Wi}^2 + \delta_i^2)^2 \tag{10}$$

$$E(Z_i \mid H_1) = K\sigma_{1,i}^2 = K(P_{Ri} \mid g_i \mid^2 \mid h_i \mid^2 \ \sigma_S^2 + \sigma_{0,i}^2) \tag{11}$$

$$\mathrm{var}(Z_i \mid H_1) = 2K\sigma_{1,i}^4 = 2K(P_{Ri} \mid g_i \mid^2 \mid h_i \mid^2 \ \sigma_S^2 + \sigma_{0,i}^2)^2 \tag{12}$$

Next, all the individual test statistics $\{Z_i\}$ are used to linearly formulate the resultant test statistic of the j^{th} cluster, Z_j, which can be expressed as

$$Z_j = \sum_{i=1}^{M} \omega_i Z_i = \vec{\omega}^T \vec{Z} \tag{13}$$

where $j = 1, 2, \ldots, N$ and the weighting coefficients vector $\vec{\omega} = [\omega_1, \omega_2, \ldots, \omega_M]^T$; $\omega_i \geq 0$ satisfying the condition; $\| \vec{\omega} \| = 1$ which is used to optimize the detection performance. Different weight settings will be addressed later in section 3. Since $\{Z_i\}$ are all normal random variables, their linear combination, which represent the j^{th} cluster test statistic Z_j, will also be normally distributed with statistics given by

$$E(Z_j \mid H_0) = \vec{\omega}^T K\sigma_{0,i}^2 = \vec{\omega}^T K(P_{Ri} \mid h_i \mid^2 \sigma_{Wi}^2 + \delta_i^2) \tag{14}$$

$$E(Z_j \mid H_1) = \vec{\omega}^T K\sigma_{1,i}^2 = \vec{\omega}^T K(P_{Ri} \mid g_i \mid^2 \mid h_i \mid^2 \sigma_S^2 + \sigma_{0,i}^2) \tag{15}$$

$$\mathrm{var}(Z_j \mid H_0) = \sum_{i=1}^{M} \omega_i^2 (\sigma_{0,i}^2 + \delta_i^2) = \sum_{i=1}^{M} 2\omega_i^2 K(P_{Ri} \mid h_i \mid^2 \sigma_{Wi}^2 + \delta_i^2)^2 = \vec{\omega}^T \sum\nolimits_{H_0} \vec{\omega} \tag{16}$$

$$\mathrm{var}(Z_j \mid H_1) = \sum_{i=1}^{M} \omega_i^2 (\sigma_{1,i}^2 + \sigma_{0,i}^2) = \sum_{i=1}^{M} 2\omega_i^2 K(P_{Ri} \mid g_i \mid^2 \mid h_i \mid^2 \sigma_S^2 + \sigma_{0,i}^2)^2 = \vec{\omega}^T \sum\nolimits_{H_1} \vec{\omega} \tag{17}$$

where the covariance matrices $\sum_{H_0} = 2K\sigma_{0,i}^4$ & $\sum_{H_1} = 2K(P_{Ri} \mid g_i \mid^2 \mid h_i \mid^2 \sigma_S^2 + \sigma_{0,i}^2)^2$.

Considering that the global threshold at the j^{th} 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, and probability of false alarm, P_f, for the M SUs of the j^{th} cluster can be written as

$$P_{f,j} = P(Z_j > \beta_j \mid H_0) = Q\left(\frac{\beta_j - E(Z_j \mid H_0)}{\sqrt{\mathrm{var}(Z_j \mid H_0)}}\right) = Q\left(\frac{\beta_j - \vec{\omega}^T E(Z_i \mid H_0)}{\sqrt{\vec{\omega}^T \sum_{H_0} \vec{\omega}}}\right) \tag{18}$$

$$P_{d,j} = P(Z_j > \beta_j \mid H_1) = Q\left(\frac{\beta_j - E(Z_j \mid H_1)}{\sqrt{\mathrm{var}(Z_j \mid H_1)}}\right) = Q\left(\frac{\beta_j - \vec{\omega}^T E(Z_i \mid H_1)}{\sqrt{\vec{\omega}^T \sum_{H_1} \vec{\omega}}}\right) \tag{19}$$

In CRNs, the probabilities of false alarm and detection have unique indications. Specifically, (1-P_d) measures the probability of interference from SUs on the PUs. On the other hand, P_f determines an upper bound on the spectrum efficiency, where a large P_f usually results in low spectrum utilization. This is because the SU is allowed to perform transmissions if and only if the PU is undetected under either H_0 or H_1. In section 3, we will be maximizing P_d by controlling the weighting vector while meeting a certain requirement on the P_f and vice versa. Then, for a given P_f, P_d can be written as

$$P_{d,j} = Q\left(\frac{Q^{-1}(\overline{P}_{f,j})\sqrt{\vec{\omega}^T \sum_{H0} \vec{\omega}} - \vec{\omega}^T \theta}{\sqrt{\vec{\omega}^T \sum_{H_1} \vec{\omega}}}\right) \tag{20}$$

where $\vec{\theta} = [\theta_1, \theta_2, ..., \theta_M]^T$ and $\theta_i = K\, P_{Ri} \mid g_i \mid^2 \mid h_i \mid^2 \sigma_S^2$. Similarly, for a given $P_{d,j}$, $P_{f,j}$ can be expressed as

$$P_{f,j} = Q\left(\frac{Q^{-1}(\overline{P}_{d,j})\sqrt{\vec{\omega}^T \sum_{H_1} \vec{\omega}} + \vec{\omega}^T \theta}{\sqrt{\vec{\omega}^T \sum_{H_0} \vec{\omega}}}\right) \tag{21}$$

2.3 Characterization of Cluster Header–Fusion Centre (CH-BS) Link

In the CH-BS link, all CHs communicate with a common BS through a dedicated control channel in an orthogonal manner. The aggregated clusters decisions information will be forwarded from the N CHs to the BS at which a final global decision is made based on HDF. The HDF is used to reduce the reporting traffic overhead from the M SUs to the BS. In our proposed systen, it is assumed that the reporting channel of the j^{th} CH-BS link is a binary symmetric channel (BSC) with a probability of reporting error, $P_{e,j}$, and the conventional HDF OR-rule is employed at the BS. It was shown that the overall probability of false alarm, Q_f, and the probability of missed detection, Q_m, of the whole CRN are given by [14]

$$Q_f = 1 - \prod_{j=1}^{N} \left[(1 - P_{f,j})(1 - P_{e,j}) + P_{f,j} P_{e,j}\right] \tag{22}$$

$$Q_m = \prod_{j=1}^{N} \left[P_{m,j}(1 - P_{e,j}) + (1 - P_{m,j}) P_{e,j}\right] \tag{23}$$

where $P_{f,j}$ and $P_{m,j}$ are the probability of false alarm and probability of missed detection of the the j^{th} CH, respectively. Remember that $Q_d = 1 - Q_m$ and $P_{d,j} = 1 - P_{m,j}$.

For simplicity, assume that the BSCs of the CH-BS links are all identical and have the same probability of reporting error, i.e. $P_{e,j} = P_e$, then

$$Q_f = 1 - \prod_{j=1}^{N} \left[(1 - P_{f,j})(1 - P_e) + P_{f,j} P_e\right] \tag{24}$$

$$Q_m = \prod_{j=1}^{N} \left[P_{m,j}(1 - P_e) + (1 - P_{m,j}) P_e\right] \tag{25}$$

Furthermore, Q_f is bounded by the probability of reporting error as follows

$$Q_f \geq \overline{Q}_f = \lim_{Pf \to 0} Q_f = 1 - (1 - P_e)^N \approx NP_e \tag{26}$$

It will be seen that cooperative spectrum sensing with more CHs has a better performance in most cases. But when Q_f decreases to a threshold, namely, the lower bound $\overline{Q}_f$, the probability of missed detection Q_m will drastically increase to 1. Equivalently, the detection probability Q_d will quickly fall down to 0. Thus, cooperative spectrum sensing will be impractical when $Q_f \to \overline{Q}_f$. Moreover, $\overline{Q}_f$ increases with the increase of the number of CHs which is consistent with (26)

3. Detection Performance Optimization of SDF Schemes

3.1 Conventional SDF Cooperative Based Cooperative Spectrum Sensing Schemes

In this section, two conventional SDF optimization schemes for weighting vector setting at the CHs are presented, namely, equal gain combination (EGC) and maximal ratio combining (MRC). The proposed schemes in section 3.2 will be later compared with these two conventional weighting schemes.

3.1.1 Equal Gain Combination (EGC) Based Weighting Scheme

The EGC scheme is an existing weighting scheme that is similar to the one used in systems with multiple receive antennas. It does not require any channel state information (CSI), but still exhibits much better performance than the conventional HDF schemes. The individual weights assigned to the M SUs signals at the CH in (20) and (21) are all equal and expressed by

$$\omega_i = \sqrt{1/M} \tag{27}$$

This EGC weighting scheme will be used together with the MRC scheme for performing performance comparisons with the proposed optimal SDF schemes in section 3.2. The detection performance is evaluated using the so-called receiver operating characteristics (ROC) curve.

3.1.2 Maximal-Ratio Combining (MRC) Based Weighting Scheme

The weight coefficient assigned for a particular SU signal at a CH represents its contribution to the overall decision made. Thus, if a SU has a high PU signal-to-noise ratio (SNR) at its receiver that may lead to a correct detection on its own, it should be assigned a larger weighting coefficient. For those SUs experiencing deep fading or shadowing, their weights are decreased in order to reduce their negative contribution to the final decision. By maintaining $\|\boldsymbol{\omega}\| = 1$, we can derive the individual weight for the i^{th} SU's measurement as follows

$$\sum_{i=1}^{M} SNR_i = SNR_T \Rightarrow \sum_{i=1}^{M} \frac{SNR_i}{SNR_T} = 1 = \sum_{i=1}^{M} \omega_i^2 \Rightarrow \omega_i^2 = \frac{SNR_i}{SNR_T}$$
$$\omega_i = \sqrt{\frac{SNR_i}{SNR_T}} \tag{28}$$

where SNR_i is the signal-to-noise ratio at the CH receiver estimated for the i^{th} SU.

3.2 Deflection Coefficient (DC) Maximization Based Cooperative Spectrum Sensing Schemes

The deflection coefficient (DC) is a measure of the detection performance as it is formulated based on the distance between the centers of H_0 and H_1. The DC based weight setting scheme can be realized by maximizing the normal DC or the modified DC as shown below.

3.2.1 Normal Deflection Coefficient (NDC) Maximization

From (20) and (21), it is observable that the weighting vector $\boldsymbol{\omega}$ is playing an important role in determining the overall detection and false probabilities at the CH fusion stage. In addition, equations (14) to (17) show that $\boldsymbol{\omega}$ characterizes the PDFs of Z_j under H_0 and H_1. The statistical characterizations of these two PDFs can be used to mathematically define the detection performance objective, NDC mazimization, as follows

$$d_n^2 = \frac{\left[E(Z_j \mid H_1) - E(Z_j \mid H_0)\right]^2}{\operatorname{var}(Z_j \mid H_0)} = \frac{\left(\vec{\omega}^T K\, P_{Ri} \mid g_i \mid^2 \mid h_i \mid^2 \sigma_S^2\right)^2}{\vec{\omega}^T \sum_{H_0} \vec{\omega}} = \frac{\left(\vec{\omega}^T \vec{\theta}\right)^2}{\vec{\omega}^T \sum_{H_0} \vec{\omega}} \tag{29}$$

NDM provides a good measure of the detection performance because the $\sum_{H_0}$ covariance matrix under hypothesis H_0 is used to characterize the variance-normalized distance between the centers of the two conditional PDFs of Z_j under H_0 and H_1. Now, we set $d_n^2(\vec{\omega})$ as our optimization target, optimal weight vector $\vec{\omega}_{opt,NDC}$ that maximizes the distance is

$$\vec{\omega}_{opt,NDC} = \arg \max_{\vec{\omega}} d_n^2(\vec{\omega}) \tag{30}$$

By solving the equation $\frac{\partial d_n^2(\vec{\omega})}{\partial \vec{\omega}} = 0$, we obtain $\vec{\omega}_{opt,NDC} = \frac{\vec{\omega}^T \sum_{H_0} \vec{\omega}}{\vec{\omega}^T \vec{\theta}} \sum_{H0}^{-1} \vec{\theta}$,

let $\frac{\vec{\omega}^T \sum_{H_0} \vec{\omega}}{\vec{\omega}^T \vec{\theta}} = \alpha_{NDC}$ and by setting α_{NDC}, which is a scalar, to one and normalizing each weighting coefficient, we obtain the optimal weighting vector as

$$\vec{\omega}^*_{opt,NDC} = \vec{\omega}_{opt,NDC} / \| \vec{\omega}_{opt,NDC} \| = \sum_{H0}^{-1} \vec{\theta} \tag{31}$$

The justification of setting α_{NDC} to 1 is that α_{NDC} is a scalar value with no effect on d_n^2 in (29). This optimal weighting vector is the best that can push the centers of the two PDFs under H_0 and H_1 apart from each other and hence, maximizes the detection and false alarm probabilities in (20) and (21), respectively. For instance, consider a constant false alarm rate (CFAR) scenario where the probability of false alarm is set to $\overline{P}_{f,j}$. Then, by substituting the optimal weighting vector in (31) into (20) we obtain

$$P_{d,j} = Q\left(\frac{Q^{-1}(\overline{P}_{f,j})\sqrt{\theta^T \sum_{H0}^{-1} \theta} - \theta^T \sum_{H0}^{-1} \theta}{\sqrt{\theta^T \sum_{H0}^{-2} \sum_{H_1} \theta}} \right) \tag{32}$$

3.2.2 Modified Deflection Coefficient (MDC) Maximization

In this subsection, we investigate the maximization of DCM in order to find the optimal weights setting for the SDF at the CH. The MDC can be defined as

$$d_m^2 = \frac{\left[E(Z_j \mid H_1) - E(Z_j \mid H_0)\right]^2}{\operatorname{var}(Z_j \mid H_1)} = \frac{\left(\vec{\omega}^T K P_{Ri} \mid g_i \mid^2 \mid h_i \mid^2 \sigma_S^2\right)^2}{\vec{\omega}^T \sum_{H_1} \vec{\omega}} = \frac{\left(\vec{\omega}^T \vec{\theta}\right)^2}{\vec{\omega}^T \sum_{H_1} \vec{\omega}} \tag{33}$$

which employs the $\sum_{H1}$ covariance matrix under hypothesis H_1 to fulfill the task of variance-normalization. Obviously, d_m^2 can be obtained by simply replacing the $\sum_{H_0}$ covariance matrix in (29) with the $\sum_{H1}$ covariance matrix.

The optimal weight vector $\vec{\omega}_{opt,MDC}$ is then similarly defined as the one that maximizes the distance $d_m^2(\vec{\omega})$

$$\vec{\omega}_{opt,MDC} = \arg \max_{\vec{\omega}} d_m^2(\vec{\omega}) \tag{34}$$

By solving the equation $\frac{\partial d_m^2(\vec{\omega})}{\partial \vec{\omega}} = 0$, we obtain $\vec{\omega}_{opt,MDC} = \frac{\vec{\omega}^T \sum_{H_1} \vec{\omega}}{\vec{\omega}^T \vec{\theta}} \sum_{H1}^{-1} \vec{\theta}$,

let $\frac{\vec{\omega}^T \sum_{H_1} \vec{\omega}}{\vec{\omega}^T \vec{\theta}} = \alpha_{MDC}$ which is a scalar and again by setting $\alpha_{MDC} = 1$ to ensure $\| \vec{\omega} \| = 1$ and normalizing each weighting co-efficient, we obtain the optimal weighting vector

$$\vec{\omega}^*{}_{opt,MDC} = \vec{\omega}_{opt,MDC} / \| \vec{\omega}_{opt,MDC} \| = \sum_{H1}^{-1} \vec{\theta} \tag{35}$$

Again, this optimal weighting setting will be used to optimize the detection and false alarm probabilities in (20) and (21), respectively. Similar to NDCM, under a CFAR scenario, by substituting the optimal weighting vector in (35) into (20) we obtain

$$P_{d,j} = Q\left(\frac{Q^{-1}(\overline{P}_{f,j}) \sqrt{\theta^T \sum_{H1}^{-2} \sum_{H0}^{-1} \theta} - \theta^T \sum_{H1}^{-1} \theta}{\sqrt{\theta^T \sum_{H1}^{-1} \theta}} \right) \tag{36}$$

4. Numerical Results and Discussions

In this section, the proposed NDC- and MDC-based SDF schemes at the CH stage are compared with the conventional MRC- and EGC-based SDF schemes as well as the OR-rule based HDF. Then, the detection performance and traffic overhead for various combinations of hybrid SDF-HDF, SDF-SDF, and HDF-HDF cluster-based cooperative sensing schemes are simulated and numerically studied. The default sensing time and sensed bandwidth are set as T_s = 25 us and B = 6 MHz, respectively. The relay transmit power is set to 12 dBm and the channel gains of the PU-SU and SU-CH links, $\{g_i\}$ and $\{h_i\}$, respectively, are normally distributed but remain constant within each sensing interval T_s, as T_s is sufficiently small. $\{g_i\}$ and $\{h_i\}$ are randomly-generated so that a low SNR environment at SU, CH, and BS stages is realized (SNR < -10 dB). The simulation results are obtained from 10^5 realizations of channel gains and noise variances.

4.1 Detection Performance and Overhead Analysis of SDF at CH stage

In this section, the detection performance as well as the traffic overhead at the CH stage is studied. Within a cluster, there will be a data fusion process to be done at the CH if SDF is used whereas decisions fusion will be carried on if HDF is used. In SDF, the SUs relay their sensing measurement data to the CH for fusion. HDF uses a different concept where the sensing measurement data will be locally processed at SUs and 1-bit decisions will be then sent to the CH. **Fig. 3** presents a comparison between the proposed NDC- and MDC-based SDF schemes versus the conventional MRC- and EGC-based SDF schemes as well as the OR-rule based HDF. The detection performance is characterized by the ROC curve which is obtained by plotting the probability of detection (P_d) for a given probability of false alarm (P_f) as given in (20) but based on the corresponding weighting setting vector of each SDF scheme. The number of SUs in the cluster is set to 20. It is clear that the proposed NDC scheme shows the best detection performance comparing to MDC and the other conventional MRC and EGC SDF schemes as well as the OR-rule based HDF scheme. The OR-rule scheme, as expected, is inferior to all other methods as it suffers from a significant loss of information content being a HDF process. The EGC SDF scheme shows better performance than the OR-rule HDF scheme but it is inferior to all other SDF schemes due to its fixed and equal weighting coefficients assigned to the energy measurements of the M SUs at the corresponding CH. The MRC-based scheme shows better performance than the EGC one due to its adaptability. The MRC scheme assigns larger weights for the SUs with high SNRs and smaller weights for those with low SNRs and therefore, it controls the contributions of each SU in the overall decision taken at the CH stage. The NDC scheme outperforms the MDC one with non-trivial difference. The detection performance of NDC is slightly better than that of MDC because the MDC scheme introduces estimates of the PU signal strength and test statistics into the estimated covariance matrix $\sum_{H_1}$ simultaneously in opposite to the covariance matrix $\sum_{H_0}$ in NDC which is exclusively defined by the test statistics only. Obviously, the elements of $\sum_{H_0}$ are smaller than those of $\sum_{H_1}$ in magnitude, and therefore, $d_n^2 \rangle d_m^2$ based on (29) and (32), and $\vec{\omega}^*{}_{opt,NDC} > \vec{\omega}^*{}_{opt,MDC}$ as can be concluded from (31) and (35). By substituting these optimal vectors separately into (20) we obtained (32) and (36) which are the probability of detection for a given false alarm probability under NDC and MDC, respectively. By performing some mathematical analysis on these two equations we can observe that detection probability under NDC is a bit higher than that under MDC. Therefore, from now onwards, the NDC will be our default proposed SDF scheme for the subsequent simulation unless another is mentioned.

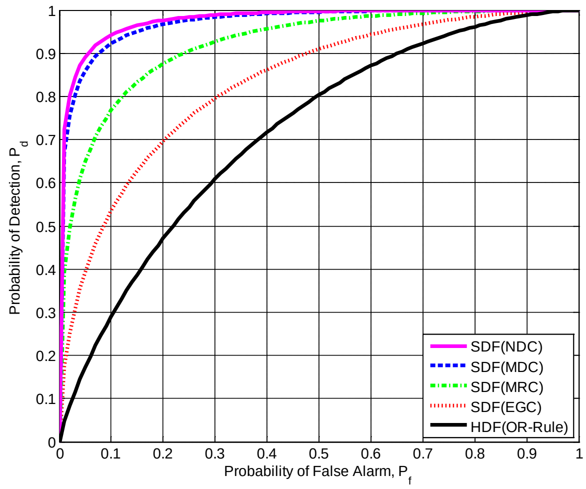

Fig. 3. ROC performance comparison of cooperative spectrum sensing SDF and HDF schemes within a cluster.

Next, we investigate the effect of varying the number of cooperative SUs in a cluster. The proposed NDC scheme is considered as it shows the best performance as has been presented above. **Fig. 4** shows the performance of the CRN at the CH stage represented by the ROC curve for different number of SUs; M = 5, 10, 15, and 20. Obviously, the performance improves well when the number of cooperative users in the cluster increases. In fact, when M = 5, the ROC curve becomes closer to the line of no-discrimination (where there is no difference between the PU signal and noise) than that when M = 20. Thus, as M increases, the separation between the hypotheses H_0 and H_1 increases and the performance of the ROC curve improves accordingly.

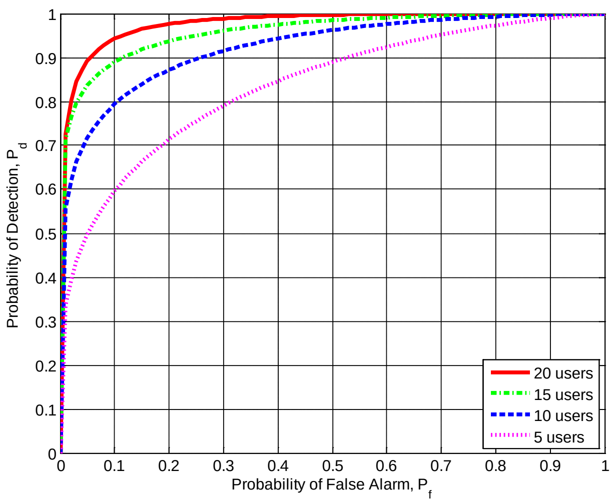

Fig. 4. ROC performance comparison of NDC-based SDF cooperative spectrum sensing at CH with different number of SUs per cluster.

Fig. 5 depicts some existing tradeoffs in the proposed SDF schemes within the individual clusters. Consider that during every sensing interval, T_s, there are K samples at each SU to be relayed to the CH over the SU-CH link. Suppose that all SUs relay their observations to the CH in an orthogonal manner and each SU quantizes the received signal samples with u bits per sample, thus, the total number of relayed bits by each SU is then uK. Assume that the SUs cooperate with the corresponding CH using a potential multiple-ary QAM, say 16QAM, 32QAM, 64QAM, 128QAM, or 256QAM. Then, the channel bandwidth of the SU-CH link can be written as

$$BW_{SU-CH\ link} = \frac{R_b}{\xi} = \frac{uK}{\xi T_r} = \frac{2T_S Bu}{\xi T_r} \tag{37}$$

where R_b is the bit rate, ξ is the spectral efficiency of the modulation scheme used (assume Nyquiest minimum bandwidth), T_r is the time required by each SU to relay its observation to the CH. The three surfaces sketched in **Fig. 5** show the estimated $BW_{SU\text{-}CH\ link}$ for different number of bits per QAM symbol (v) and number of bits per quantized sample (u) at different sensing times. The relay time, T_r, is set to 1 ms. It is clear that for a fixed sensing time, the minimum $BW_{SU\text{-}CH\ link}$ is achieved when high-order modulation scheme and low number of quantization levels are jointly used. Thus, the first tradeoff appears here is that the good achievement of minimizing the bandwidth is disturbed by sacrificing the detection performance because of the poor signal representation when lesser number of quantization level is used. Morever, $BW_{SU\text{-}CH\ link}$ can also be minimized by reducing the sensing time, say from 30us to 10 us, but then, the detection performance will be again degraded because of decreasing the sensing time. Thus, a wise compromise between the performance and resources should be carefully considered.

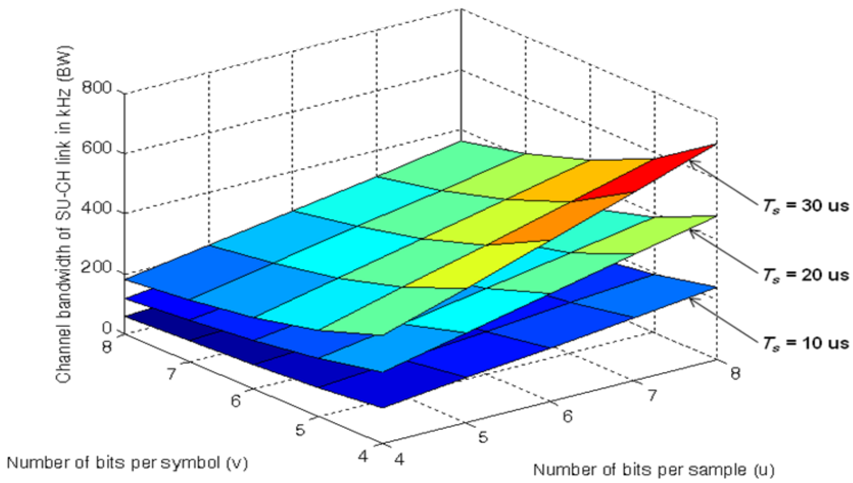

Fig. 5. The channel bandwidth of the SU-CH link as a function of number of bit per symbol and number of bits per sample with different sesning times.

4.2 Detection Performance and Overhead Analysis of Hybrid SDF-HDF Cluster-based Cooperative Spectrum Sensing

In this section, the front-end detection performance of our proposed Hybrid SDF-HDF cluster-based scenario is evaluated and compared with other different combinations of SDF and HDF schemes. The three possible system-level scenarios are SDF-SDF, SDF-HDF, and HDF-HDF. The HDF-SDF is unrealizable because once the detection information content is lost by hard fusion, this content cannot be retrieved or softened anymore. The SDF schemes used in this section are NDC, MRC, and EGC whereas the OR-rule is used as a HDF scheme. The MDC scheme has been excluded as it almost has the same detection performance as NDC. As expected, the SDF-SDF (NDC-NDC) cooperative sensing scenario shows the best detection performance among all other scenarios as demonstrated in **Fig. 6**. This finding is supported by the simaulation results of **Fig. 3** which has revealed that NDC has the best detection performance ever when used within a cluster and therefore, applying NDC in both SU-CH and CH-BS links will distinctly enhance the performance. However, being an SDF-SDF scenario, the NDC-NDC has the drawback of increased traffic overhead. On the other hand, the proposed hybrid SDF-HDF (NDC-OR) cluster-based cooperative sensing scenario has a superior detection performance comparing to all other SDF-SDF (except NDC-NDC scenario), HDF-HDF, and SDF-HDF combinations. The interesting finding here is that, although the SDF-SDF combinations of MRC-MRC and EGC-EGC use soft fusion in both SU-CH and CH-BS stages, these two combinations still unable to outperform the proposed SDF-HDF (NDC-OR) scenario which uses hard fusion in the CH-BS stage. It was shown in **Fig. 3** that all SDF schemes outperform the OR-rule HDF and therefore, one may intuitively say that applying SDF in two successive links will result in better performance than applying SDF followed by HDF in these two links. However, the improved performance of SDF-HDF (NDC-OR) over the two SDF-SDF scenarios, MRC-MRC and EGC-EGC, is justified by stating that the degradation occurred in SDF-HDF (NDC-OR), due to the utilization of OR-rule fusion scheme in the CH-BS link, is compensated by the superior performance of NDC so that the overall performance of the NDC-OR scenario is outperforming MRC-MRC and EGC-EGC combinations. The advantage of using HDF instead of SDF at the CH-BS link is the reduced traffic overhead especially when the number of clusters is comparable. The MRC-MRC and EGC-EGC have better performance than MRC-OR and EGC-OR, respectively, which is again due to using the OR-rule HDF in the CH-BS stage. Finally, the HDF-HDF (OR-OR) has the worst detection performance as comparing to all other combinations but it has the unique advantage of minimum traffic overhead. Thus, our proposed SDF-HDF can be said to be a good compromise between improving the detection performance by using SDF and reducing the traffic overhead by using HDF. In fact, the observations found in **Fig. 6** are very convincing as they are perfectly correlated to those obtained from **Fig. 3**.

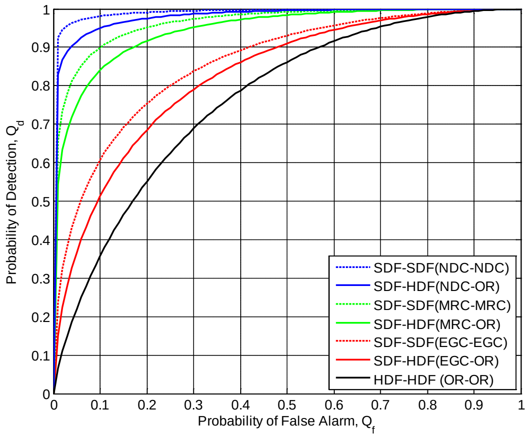

Fig. 6. ROC performance of the proposed SDF-HDF cluster-based cooperative spectrun sensing scheme with different SDF and HDF combinations.

In **Fig. 7**, the proposed hybrid SDF-HDF (NDC-OR) cluster-based cooperative spectrum sensing scheme is considered since it shows the best detection performance as shown in **Fig. 6**. The ROC curves are plotted with different reporting error, P_e, from the CHs to the common BS, i.e. $P_e = 0$ (no error), 0.05, 0.10 and 0.15. The number of clusters used is three clusters contain 5, 15, and 30 SUs. The simulation is run with different channel gain and noise realizations and the ROC curves are then averaged. As expected, the performance degrades as the reporting error increases. However, it is clear that the performance still within acceptable margins and of course the performance can be further improved by increasing the number of SUs per cluster and/or increase the number of clusters. The great winning of using the HDF between the CHs and the BS is the reduced traffic overhead whereas the use of SDF results in an improved detection performance. One can say, why not using HDF first followed by SDF. As mentioned earlier, the justification is that once the sensing measurements of the SUs are combined using HDF, the sensing information content will be lost and the measurements cannot be softened anymore.

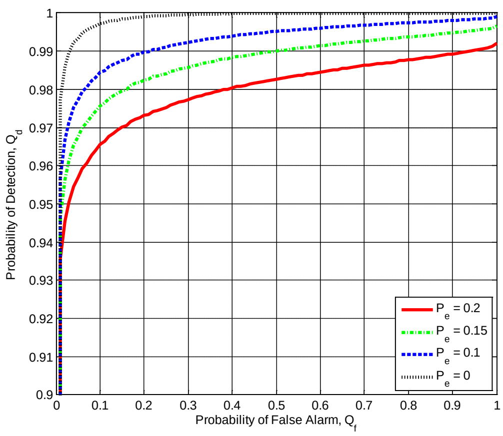

Fig. 7. ROC performance of the proposed SDF-HDF cluster-based cooperative spectrun sensing scheme with different probabilities of reporting error.

Table 1 presents a traffic overhead analysis for the three general possible scenarios;

SDF-SDF, SDF-HDF, and HDF-HDF. SDF might be NDC, MRC, or even EGC whereas OR- rule is used as HDF. Assuming that a quantization process, similar to the one used in **Fig. 5**, is applied whenever an SDF scheme is used in order to reduce the transmission bandwidth. Each SU in a particular cluster needs to transmit $u\times k$ bits with SDF and only one single bit with HDF to the corresponding CH. Now, let's simply define the overhead traffic by the total number of bits that need to be reported from each SU all the way to the BS. The overhead ratio in the SU-CH links is $(u\times k)$:$(u\times k)$:1 for SDF-SDF, SDF-HDF, and HDF-HDF scenarios, respectively, whereas in the CH-BS links, it is $(u\times k\times M)$:1:1 for SDF-SDF, SDF-HDF, and HDF-HDF scenarios, respectively. Considering our proposed SDF-HDF scenario, there is an increment of $(u\times k)$ times comparing to HDF-HDF in the SU-CH links and a reduction of $(u\times k\times M)$ times comparing to SDF-SDF in the CH-BS links. It is clear that the amount of overhead reduction when comparing to SDF-SDF is M times greater than the amount of overhead increment when comparing to HDF-HDF. In addition, when the number of clusters N is large, using SDF-SDF will lead to increase this number $u\times k\times M$ times greater than N. Strictly speaking, the HDF-HDF scenario offers the lowest ever overhead traffic, but unfortunately, the detection performance of HDF scheme is not as good as the SDF one as was shown in **Fig. 3**. Thus, the SDF-HDF scenario presents an excellent compromise to balance between these two conflicting objectives; maximizing the detection performance and minimizing the overhead traffic.

Table 1. Traffic overhead analysis for different SDF and HDF combinations.

Hybrid Scenario	Number of bits transmitted over $M\times N$ SU-CH links	Number of bits transmitted over N CH-BS links
SDF-SDF Scenario	$u \times k \times M \times N$	$u \times k \times M \times N$
SDF-HDF Scenario	$u \times k \times M \times N$	N
HDF-HDF Scenario	$M \times N$	N

5. Conclusions

The cooperative spectrum sensing is widely used to combat the potential destructive channel effects between existing PU(s) and SU nodes. The SDF-based cooperation schemes show superior detection performance to the HDF-based ones. On the other hand, the HDF-based schemes have the advantage of reduced traffic overhead over the SDF ones as only 1-bit hard decisions need to be reported to the fusion center(s). In this paper, the advantages of SDF- and HDF-based cooperative spectrum sensing schemes are jointly exploited by implementing a hybrid SDF-HDF cooperative spectrum sensing scheme. The simulation results show that the NDC-based SDF cooperative spectrum sensing scheme is superior to all other SDF and HDF schemes within a given cluster. Considering NDC, it has been shown that the detection performance can be significantly improved by cooperating of more users per cluster. It was also shown that the channel bandwidth when using SDF can be reduced by quantization but then there will be some performance degradation due to information loss. The front-end performance of the proposed hybrid HDF-SDF cluster-based spectrum sensing has been evaluated and the simulation results show that the proposed scenario outperforms different combinations of conventional SDF and HDF schemes. The proposed scenario has shown an acceptable performance under different reporting error of the CH-BS link. Finally, the traffic overhead of SDF-HDF has been compared with the SDF-SDF and HDF-HDF scenarios and the analysis concludes that the proposed SDF-HDF can be considered as an acceptable and good compromise between the detection performance and radio resources.

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