QoE Driven Video Streaming in Cognitive Radio Networks: The Case of Single Channel Access

Zhifeng He, Shiwen Mao
Department of Electrical and Computer Engineering
Auburn University
Auburn, AL 36849-5201 USA
Email: zzh0008@tigermail.auburn.edu, smao@ieee.org

Sastry Kompella
Information Technology Division
Naval Research Laboratory
Washington, DC 20375 USA
Email: sastry.kompella@nrl.navy.mil

***Abstract*—We consider the problem of streaming multi-user videos over the downlink of a Cognitive Radio Network (CRN), where each Cognitive User (CU) can access one channel at a time. Motivated by the prior work that establishes a separation principle for the joint design of spectrum sensor, sensing, and access polices, we first model cooperative spectrum sensing as an Integer Programming problem (IP) and develop a Greedy Poly-matching scheme to solve it for the optimal sensing strategies. We then formulate the problem of CU Quality of Experience (QoE) maximization as a maximum weight matching problem and solve it with the Hungarian Method for optimal channel assignments. The proposed spectrum sensing and channel assignment algorithms are compared with benchmark schemes in simulations, and are found to outperform the benchmark schemes in terms of available channels discovered and CU QoE achieved.**

***Index Terms*—Quality of Experience; cognitive radio networks; matching; multi-user video streaming; optimization.**

I. Introduction

A recent study by Cisco reveals a drastic increase in mobile data and that almost 66% of the mobile data will be video related by 2015 [1]. Such dramatic increase in wireless video traffic, coupled with the depleting spectrum resource, poses great challenges to today's wireless networks. It is of great importance to improve the wireless network capacity by promoting more efficient use of spectrum, which can be accomplished by the cognitive radio (CR) technology. CR is an evolutionary technology for more efficient and flexible access to the radio spectrum. In a cognitive radio network (CRN), Cognitive Users (CUs) search for the unoccupied licensed spectrum of the Primary User (PU) network and then opportunistically access detected spectrum holes in an unobtrusive manner. CR has been recognized as an effective approach to support bandwidth-demanding mobile services such as wireless video streaming [2], [3].

In the area of multimedia communications, subjective assessment methods have been studied intensively [4], which is shown to reflect viewers' perceptual quality more accurately than the traditional objective assessment method. The International Telecommunication Union (ITU) has proposed standards on subjective assessment methods for various application scenarios [5]. For video transmission, quality of experience (QoE) is an effective subjective quality assessment model for the perceptual visual quality of video sequences. One of the most widely used QoE metric is the Mean Opinion Score (MOS) [6]. In the MOS model, the visual quality of a video sequence is not only dependent on the network environment such as packet loss rate, network delay, but also dependent on the content type. For example, under the same network conditions, the visual quality of video contents of fast motions (e.g., sports) is generally worse than that of video contents of slow motions (e.g., news). Since the ultimate goal of most multimedia communication services is to achieve high perceptual quality for viewers, it is desirable to incorporate QoE models in such applications.

In this paper, we address the challenging problem of downlink multi-user video streaming in CRNs. We consider a CRN consisting of one cognitive base station (CBS) and multiple CUs. Without loss of generality, we assume each CU can sense and access one channel at a time. The CUs cooperatively sense the PU signals on licensed channels and the CBS infers the licensed channel states based on the CU sensing results with an OR fusion rule. Once the idle channels are detected, the CBS then assigns them to active CUs for downlink multi-user video streaming. We incorporate the video assessment model proposed in [6], [7], aiming to maximize the CU QoE by optimal designs of spectrum sensing and access policies.

It is obviously a challenging problem to jointly design the spectrum sensing and access polices for QoE-aware multi-user video streaming, due to the large number of design factors and the complex interactions that should be modeled in a cross-layer optimization framework. In [8], a separation principle is established for the joint design problem, which decouples the design of sensing from that of sensor and access policy. Motivated by this interesting work, we decouple the problem into two sub-problems: (i) discovering a sufficient amount of licensed channels reliably and quickly to meet the bandwidth demand of the CUs; and (ii) allocation of the available channels to the CUs according to their respective QoE requirements and network status. We propose a distributed Greedy Poly-matching algorithm that can compute optimal solutions to the channel sensing sub-problem, as well as a Hungarian method-based approach to achieve optimal solutions to the channel assignment sub-problem. Simulation results demonstrate the superior performance of the proposed methods in terms of the MOS that CUs can achieve under various network scenarios,

978-1-4799-3512-3/14/$31.00 ©2014 IEEE

with comparisons to the benchmark schemes.

The remainder of this paper is organized as follows. Section II reviews related work. The system model and problem formulation are presented in Section III. The optimal solution algorithms are proposed in Section IV and validated by simulations in Section V. Section VI concludes the paper.

II. Related Work

This paper is related to the prior work on Quality of Service (QoS) and QoE provisioning and video streaming over CRNs. We briefly review the related work in the following.

In [4], the quality of multimedia and audio-visual services is evaluated using a model that is based on subjective opinions, such as aesthetic feeling and activity feeling, and network parameters such as delay, packet loss rate, and frame rate. However, content type of the multimedia is not considered in this work. The video quality models proposed in [9] and [10] consider encoder based distortions only. The authors in [6] cluster video sequences into different content types according to the features of these sequences such as temporal (movement) and spatial (edges, brightness) characteristics by cluster analysis, and then a perceptual video quality metric in terms of MOS is derived based on the content type of the video sequence and some network parameters such as packet error rate, Sender BitRate (SBR), and frame rate. In [7], the authors develop a MOS prediction model as a function of the content type of the tested video sequence and some other parameters such as SBR, frame rate, and Block Error Rate, for video sequences streamed over UMTS (Universal Mobile Telecommunications System) network. As in [6], a content type classification framework is used in this paper. After all these, the author proposes an QoE Driven adaptation scheme which, for a given content type of tested video sequence, taking the distortion of the video sequence at the receiver side and the channel loss rate as the input, dynamically adjusts the SBR, which is the output, in order to maintain a certain level of MOS under changing network environment. However, the adaptation scheme may not be adequate for video streaming in CRN where channel availability is uncertain.

The problem of video streaming over CRNs has also been studied in a few prior works. The transmission of multimedia over CRN is first proposed by J. Mitola in [11]. Authors of [12] develop an auction game model to deliver content-aware multimedia. In [3] the quality optimization problem is formulated as an mixed integer nonlinear programming (MINLP) problem and solved with effective algorithms. The authors in [13] consider the scenario where multimedia transmission is scheduled in CRN and a QoE Driven channel allocation scheme is proposed to optimize the multimedia transmission of priority-based CUs, where the MOS model proposed in [7] is used. Specifically, each CU has different QoE requirements and thus has different priority in utilizing the idle channels of the PU system. Upon the re-appearance of an active PU on the idle licensed channel, each CU utilizing the idle licensed channels will evacuate from the current channel it is using to avoid conflict with the active PU.

Although some interesting works have been done on video streaming over CRNs, an important part of the challenging problem is how to discover a sufficient number of idle channels reliably and quickly, which is not well addressed in prior work but is essential for supporting the demand of large bandwidth for video applications. A holistic approach is necessary for supporting QoE-aware video streaming in CRNs, which integrates effective solutions to both the spectrum sensing problem and resource allocation problem for video sessions, considering their different characteristics related to MOS. We aim to develop such an approach in this paper.

III. System Model and Problem Statement

A. System Model

We consider a primary network operating on N_1 orthogonal licensed channels. There is a CR network co-located with the primary network, consisting of a CBS supporting M_1 CUs. The CUs sense the PUs' usage of the licensed channels and access the licensed channels in an opportunistic manner. As in priori work [14], [15], we assume the CUs, when they are not receiving data, measure the SNRs of the PU transmissions over all the licensed channels and report the measured SNRs to the CBS through some feedback mechanism. Based on such feedback, the CBS then assigns those CUs with good channel conditions to sense each licensed channel, so as to improve the sensing performance.

We consider the downlink multi-user video streaming scenario, where the CBS streams a video to each active CU using the license channels that are detected idle. We assume time is divided into a series of non-overlap GOP (Group of Pictures) windows, each consisting of T time slots. Each time slot can be further divided into the following four phases as in Algorithm 1 for spectrum sensing and access for multi-user video streaming.

Algorithm 1: Spectrum Sensing and Access for QoE-driven Multi-user Video Streaming

Phase 1: The CBS determines for each CU which channel to sense based on SNR feedback, and broadcasts the sensing schedule to the CUs ;

Phase 2: Each CU follows the sensing schedule to sense the channel, and then reports the sensing result to the CBS ;

Phase 3: The CBS makes two decisions: (i) the channel availability on the current time slot, based on the sensing results and fusion rule; and (ii) channel assignment to the CUs for multi-user video transmission on the current time slot, based on channel availability, channel condition, the Content Type (denoted as CT) of each CU, and other information. Then the CBS broadcasts the channel access schedule to the CUs ;

Phase 4: The CBS uses the assigned channels to transmit video data and each CU follows the channel access schedule to receive video data.

Note that at the very beginning of the first GOP window, the SNR information used in Phase 1 may not be available. However, such information can be obtained via estimation or learning techniques, or by letting CUs probing the channels when CUs are idle [16].

B. Problem Statement

1) Optimal Assignment Problem for Spectrum Sensing (OAPSS) : In a practical wireless network scenario, CUs are located at different geographical positions with different performance on detecting the primary signal on a particular licensed channel [14]. It has been proved that by selecting a suitable subset of CUs to sense a particular channel can improve the performance on detection of PU signal, thus reducing the probability of causing interference to the PU transmissions [15], [17]. A useful metric to evaluate the performance of detecting a PU signal is *probability of miss detection*, which is the probability that a CU fails to detect the existence of an existing PU signal.

Usually cooperative sensing is used to improve the detection performance by fusing the sensing results from multiple CUs, and a certain fusion rule is required to combine these results. In this paper the OR fusion rule is used at the CBS to decide the presence or absence of the PU signal on a particular channel. With the OR rule, if any of the CUs reports the presence of a PU signal then the CBS decides that the channel is busy; Otherwise, the CBS decides that the channel is idle. Here we use an $M_1 \times N_1$ matrix $\mathbf{X}$ to denote the sensing task assignment at time slot t, while the entry located in the i-th row and j-th column is defined as

$$x_{ij}^t = \begin{cases} 1, & \text{CU } i \text{ senses channel } j \text{ in time slot } t \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

Let $P_{d_{ij}}^t$ denote the probability of detection on channel j by CU i at time slot t. According to the OR fusion rule, the probability of detection on channel j at time slot t is

$$P_{d_j}^t = 1 - \prod_{i=1}^{M_1} \left(1 - P_{d_{ij}}^t\right)^{x_{ij}^t}. \quad (2)$$

For an energy detector, we have [17]

$$P_{d_{ij}}^t = \frac{1}{2}\text{erfc}\left(\left(\frac{\lambda_{ij}^t}{\sigma_n^2} - \varsigma_{ij}^t - 1\right)\sqrt{\frac{K}{2\left(2\varsigma_{ij}^t + 1\right)}}\right), \quad (3)$$

where λ_{ij}^t is the threshold of energy detection on channel j by CU i at time slot t, σ_n^2 is the power of the i.i.d. Additive White Gaussian Noise (AWGN) at the CU, ς_{ij}^t is the SNR of PU's signal on channel j at CU i, K is the number of samples on channel j by energy detection. In (3), $\text{erfc}(z) = \frac{2}{\sqrt{\pi}}\int_z^\infty \mathrm{e}^{-u^2}du$ is the complementary error function, and let $\text{erfc}^{-1}(\cdot)$ denote the inverse function of $\text{erfc}(\cdot)$. In order to guarantee the protection of the PUs, we set $P_{d_{ij}}^t = \bar{P}_d$ by tuning λ_{ij}^t for all i, j. Thus the probability of detection of the activity of a PU will be greater than $\bar{P}_d$ if the channel is sensed by some CUs. In the case that a channel is not sensed by any of the CUs, it will not be used for video streaming.

Under the assumptions that the PU signal is complex valued phase-shift keying (PSK) and the noise is circularly symmetric complex Gaussian (CSCG), then CU i's probability of false alarm on channel j, denoted by $P_{f_{ij}}^t$, can be expressed as [17]

$$P_{f_{ij}}^t = \frac{1}{2}\text{erfc}\left(\sqrt{2\varsigma_{ij}^t + 1}\,\text{erfc}^{-1}\left(2\bar{P}_d\right) + \sqrt{\frac{K}{2}}\varsigma_{ij}^t\right). \quad (4)$$

The objective of sensing task assignment is to maximize the probability of detecting all the idle channels at time slot t, while maintaining fairness among the probabilities of detection of the N_1 channels. It has been shown that proportional fairness can be achieved by maximizing the sum of logarithmic functions. The optimal sensing task assignment problem is to maximize the following objective function.

$$\begin{aligned} &\sum_{j=1}^{N_1} \log\left(1 - P_{f_j}^t\right) \\ &= \sum_{j=1}^{N_1} \log \prod_{i=1}^{M_1} \left(1 - P_{f_{ij}}^t\right)^{x_{ij}^t} \\ &= \sum_{j=1}^{N_1}\sum_{i=1}^{M_1} \log\left(1 - P_{f_{ij}}^t\right) x_{ij}^t \\ &= \sum_{j=1}^{N_1}\sum_{i=1}^{M_1} \varphi_{ij}^t x_{ij}^t, \end{aligned} \quad (5)$$

where $P_{f_j}^t$ is the probability of false alarm on channel j and $\varphi_{ij}^t \doteq \log\left(1 - P_{f_{ij}}^t\right)$.

We assume that each CU can sense one channel at each time slot, and the number of CUs that can be assigned to sense a channel i at each time slot is unrestricted. Therefore, the *optimal sensing task assignment problem* is formulated as

$$\max: \quad \sum_{j=1}^{N_1}\sum_{i=1}^{M_1} \varphi_{ij}^t \cdot x_{ij}^t \quad (6)$$

$$\text{s.t.} \quad \sum_{j=1}^{N_1} x_{ij}^t = 1, \text{ for all } i \quad (7)$$

$$x_{ij}^t \in \{0, 1\}, \text{ for all } i, j. \quad (8)$$

2) Optimal Assignment Problem for Video Transmission (OAPVT) : We consider the QoE model named Mean Score Opinion (MOS) proposed in [7]. The MOS of CU i during time slot t, denoted by Ψ_{ij}^t, can be expressed as

$$\begin{aligned} \Psi_{ij}^t &= \alpha + CT_i\gamma + (\beta + CT_i\delta)\ln\left(SBR_{ij}^t\right) \quad (9) \\ &= \alpha + CT_i\gamma + (\beta + CT_i\delta)\ln\left(B_j \log_2\left(1 + SNR_{ij}^t\right)\right), \end{aligned}$$

where $\alpha = 3.9860$, $\beta = 0.0919$, $\gamma = -5.8497$, and $\delta = 0.9844$ are constants, CT_i is the Content Type of the video sequences required by CU i, B_j is the bandwidth of channel j in kbps, and SNR_{ij}^t is the SNR of the video signal using channel j measured at CU i at time slot t [7].

We assume that N_2 channels are determined to be idle after the sensing phase, where $N_2 \leq N_1$. We consider a general case where not all the CUs have data to receive at all times. Instead, the probability of a CU has data to receive at each GOP window is $0 \leq \xi \leq 1$. The number of CUs that have data to receive in a GOP window (called active CUs) is denoted as M_2, where $M_2 \leq M_1$. An $M_2 \times N_2$ matrix $\mathbf{Y}$ is used to represent channel access assignment on time slot t, while the entry located in the i-th row and j-th column is

$$y_{ij}^t = \begin{cases} 1, \text{ assign channel } j \text{ to CU } i \text{ in time slot } t \\ 0, \text{ otherwise.} \end{cases} \tag{10}$$

We consider the case where each CU can use at most one channel at each time slot due to hardware constraints, and each channel can be used by at most one CU at each time slot. We aim to maximize the expected average MOS of all the CUs during a GOP window by assigning the available channels.

$$\max: \sum_{i=1}^{M_2} \mathrm{E}\left[\frac{1}{T}\sum_{t=1}^{T}\Psi_i^t\right] = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{M_2}\mathrm{E}\left[\Psi_i^t\right].$$

The above objective function can be maximized if we maximize the expected MOS increment of the M_2 CUs during each time slot [3], which can be written as

$$\begin{aligned} &\sum_{i=1}^{M_2}\mathrm{E}\left[\Psi_i^t\right] \\ = &\sum_{i=1}^{M_2}\sum_{j=1}^{N_2}\mathrm{E}\left[\Psi_{ij}^t\right]\cdot y_{ij}^t \\ = &\sum_{i=1}^{M_2}\sum_{j=1}^{N_2}\left[\Pr\left(H_{0j}^t|s_j=1\right)\phi_{ij}^t + \Pr\left(H_{1j}^t|s_j^t=1\right)\theta_{ij}^t\right]y_{ij}^t, \end{aligned}$$

where $s_j^t = 1$ indicates the channel is sensed idle; $\Pr(H_{0j}^t)$ and $\Pr(H_{1j}^t)$ are the probability of channel j to be idle or busy at time slot t, respectively; $\Pr(H_{0j}^t|s_j^t=1)$ and $\Pr(H_{1j}^t|s_j^t=1)$ are the conditional probability for channel j to be idle or busy conditioned on the sensing result, respectively; μ_{ij}^t and ν_{ij}^t are the received SNR at CU i using channel j which is indeed idle or busy at time slot t, respectively; and

$$\begin{cases} \Pr\left(H_{0j}^t|s_j^t=1\right) = \dfrac{\left(1-P_{f_j}^t\right)\Pr\left(H_{0j}^t\right)}{\left(1-P_{d_j}^t\right)\Pr\left(H_{1j}^t\right)+\left(1-P_{f_j}^t\right)\Pr\left(H_{0j}^t\right)} \\ \Pr\left(H_{1j}^t|s_j^t=1\right) = 1-\Pr\left(H_{0j}^t|s_j^t=1\right) \\ \phi_{ij}^t = \alpha + CT_i\gamma + (\beta + CT_i\delta)\ln\left(B_j\log_2\left(1+\mu_{ij}^t\right)\right) \\ \theta_{ij}^t = \alpha + CT_i\gamma + (\beta + CT_i\delta)\ln\left(B_j\log_2\left(1+\nu_{ij}^t\right)\right), \end{cases}$$

Define w_{ij}^t as

$$w_{ij}^t = \Pr\left(H_{0j}^t|s_j^t=1\right)\phi_{ij}^t + \Pr\left(H_{1j}^t|s_j^t=1\right)\theta_{ij}^t. \tag{11}$$

Algorithm 2: Greedy Poly-Matching Algorithm

1 **for** $i = 1 \to M_1$ **do**
2   **for** $j = 1 \to N_1$ **do**
3         $x_{ij}^t = 0$;
4   **end**
5     $j^* = \arg\max_{j\in\{1,\cdots,N_1\}}\{\varphi_{ij}^t\}$;
6     $x_{ij^*}^t = 1$;
7 **end**

The *optimal channel access problem* is formulated as

$$\max: \sum_{i=1}^{M_2}\sum_{j=1}^{N_2}\omega_{ij}^t \cdot y_{ij}^t \tag{12}$$

$$\text{s.t.} \sum_{j=1}^{N_2} y_{ij}^t \leq 1,\ i \in \{1,\cdots,M_2\}. \tag{13}$$

$$\sum_{i=1}^{M_2} y_{ij}^t \leq 1,\ j \in \{1,\cdots,N_2\} \tag{14}$$

$$y_{ij}^t \in \{0,1\},\ \text{for all } i,j. \tag{15}$$

IV. Solution Algorithms and Analysis

A. Poly-matching Based Solution to OAPSS

As can be seen from the above, after suitable substitutions, both the OAPSS and OAPVT problems are formulated as the well-known General Assignment Problem (GAP), in the form of Integer Programming (IP) problems, which has been proved to be NP-hard to solve.

However, we find that here OAPSS is a special case of the GAP. Since there is no constraint on how many CUs can be assigned to a channel, the problem is actually a Maximum Weight Poly-Matching (MWPM) problem on a bipartite graph that matches CUs to licensed channels with edge weights defined as φ_{ij}^t, while a channel can be matched to multiple CUs [18]. It can be solved by the following greedy strategy in Algorithm 2 [18].

This greedy strategy has a time complexity of $\mathcal{O}(M_1N_1)$. In fact this is a distributed algorithm, since each CU can choose its best channels to sense and there is no need to involve the CBS in this phase. Since the CUs can initialize their x_{ij}^t's and launch their searching procedures in Line 5 in parallel, this distributed strategy has a time complexity of $\mathcal{O}(N_1)$. We also show that the Greedy Poly-matching Algorithm is optimal.

Theorem 1. *The Greedy Poly-matching Algorithm 2 achieves the optimal solution to the OAPSS problem.*

Proof: Exchanging the summation order, the objective function of the OAPSS problem (6) becomes $\sum_{i=1}^{M_1}\left(\sum_{j=1}^{N_1}\varphi_{ij}^t x_{ij}^t\right)$, where $\sum_{i=1}^{N_1}\varphi_{ij}^t x_{ij}^t$ is the utility that CU i can achieve under the two constraints. Since each CU can have at most one channel, the maximum utility CU i can achieve is $\max_j\left\{\varphi_{ij}^t x_{ij}^t\right\}$, which is accomplished by in Line 5 of Algorithm 2. Since the optimal strategies of the CUs do

TABLE I
SIMULATION PARAMETERS

Parameters	*Value*
M_1	30
N_1	30
K	10^4
f_s	$10^6\ H_z$
T	100
B_j	$10^6\ H_z$
μ_{ij}^t	-25dB to -15dB
ν_{ij}^t	-80dB to -60dB
ς_{ij}^t	-30dB to -10dB
$\overline{P_d}$	0.95
$\max_j \left\{P\left(H_{0j}^t\right)\right\}$	0.9

not conflict with each other and thus are independent with other, the maximum utility of the CUs are also independent of each other. It follows that $\max \sum_{i=1}^{M_1} \left(\sum_{j=1}^{N_1} \varphi_{ij}^t x_{ij}^t\right) = \sum_{i=1}^{M_1} \left(\max_j \left\{\varphi_{ij}^t x_{ij}^t\right\}\right)$, and Algorithm 2 is optimal. ■

B. Hungarian Method Based Solution to OAPVT

In the OAPVT problem, since each CU can use at most one channel (see (13)) and each channel can be used by at most one CU (see (14)), it can be seen that the OAPVT problem becomes a maximum weight matching problem on a bipartite graph that matches active CUs to available channels, while only one edge is allowed for any CU and channel and the edge weights are defined as ω_{ij}^t. This maximum weight matching problem can be effectively solved in polynomial time using the Hungarian method, and the solution is optimal.

In our case, the time complexity of using Hungarian method to solve the OAPVT problem is $\mathcal{O}((M_2+N_2)(M_2N_2))$, where M_2+N_2 is the total number of vertices and M_2N_2 is the total number of possible edges in the bipartite graph representing the OAPVT problem.

V. SIMULATION RESULTS

In this section, the performance of the proposed algorithms is validated with Matlab simulations. We consider a scenario in which the PUs and CUs are randomly distributed around a CBS within the service radius of the CBS. Table II lists the values of the parameters used in the simulations, where f_s is the sampling frequency at the CUs with energy detection. The QoE video model related parameters are from [7]. We compare the proposed scheme with a benchmark scheme presented in [18], called Data Rate (DR) Driven scheme in the simulations, in which channels are assigned to end users to maximize the overall data rate of all the end users. The proposed channel sensing algorithm Algorithm 2 is also integrated with the DR Driven scheme for a fair comparison.

The effectiveness of the proposed sensing algorithm is presented in Fig. 1. We increase the minimum channel idle probability $\min_{i,j}\left\{\Pr\left(H_{0j}^t\right)\right\}$ from 0.1 to 0.47 and plot the number of channels that are really idle and the number of channels that are sensed idle. Here we compare with the random sensing scheme as in [19], where each CU randomly and independently selects one of the N_1 channels to sense with equal probability. As utilization of the channels decreases, the number of idle channels increases. The proposed sensing algorithm can discover more idle channels for CUs to use. Moreover, the number of channels that miss detection is less than 0.5 on average, which is less than $N_1 \times (1 - P_{d_j}^t) = 1.5$. Recall that N_1 is the total number of channels, $P_{d_j}^t$ is the probability of detection, so $N_1 \times (1 - P_{d_j}^t)$ is the expected number of channels missed detected. So the sensing algorithm offers an acceptable level of protection to the PUs, and is effective in detecting idle channels for the CUs.

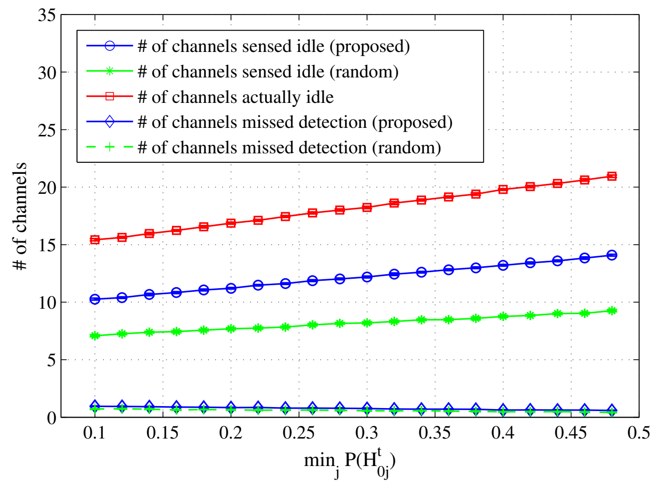

Fig. 1. Performance of channel sensing vs. the minimum channel idle probability (95% confidence intervals plotted as error bars).

We next compare the expected MOS of all the CUs at each time slot (denoted as Ψ_t) during an entire GOP window. In Fig. 2, we plot the achieved MOS sum of all the CUs achieved by the proposed scheme and the DR Driven scheme. We set $\min_j\left\{\Pr\left(H_{0j}^t\right)\right\} = 0.5$ and traffic load $\xi = 1$ in this simulation. Fig. 2 shows that the proposed QoE-aware scheme achieves a consistently high QoE sum than DR Driven does during the entire GOP window. This is because any solution derived by solving the data rate maximization problem in [18] yields a lower bound on the optimal objective value of the OAPVT problem, which aims at achieving the maximum expected average MOS by channel assignment.

Fig. 3 demonstrates how the CU video quality is affected by the traffic load of the CUs (i.e., ξ). Let avg_Ψ denote the average MOS sum of the CUs during an entire GOP window. The achieved average MOS sums by the proposed scheme and the DR Driven scheme are plotted, where 95% confidence intervals are plotted as error bars. As the CU traffic load is increased, more CUs need channels for video transmission. We can see that while the number of the really idle channels is greater than the number of active CUs, the average MOS sum of both schemes increases with ξ, and the performance gap between the two schemes grows larger. While the number of really idle channels is no greater than the number of active CUs, the average MOS sum of both schemes remain the same,

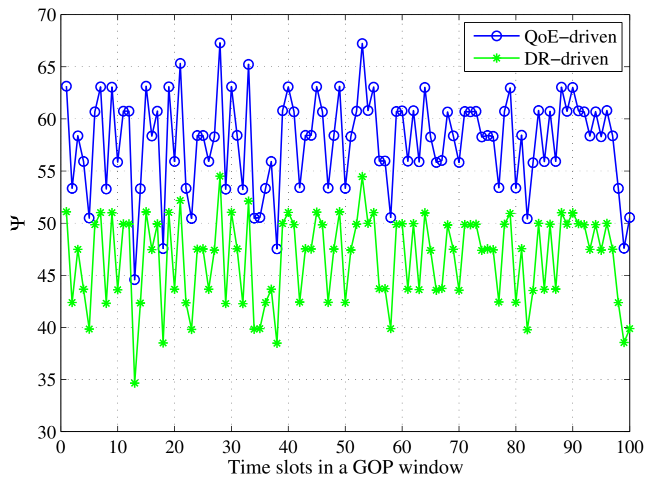

Fig. 2. MOS sum of all the CUs over time in an entire GOP window.

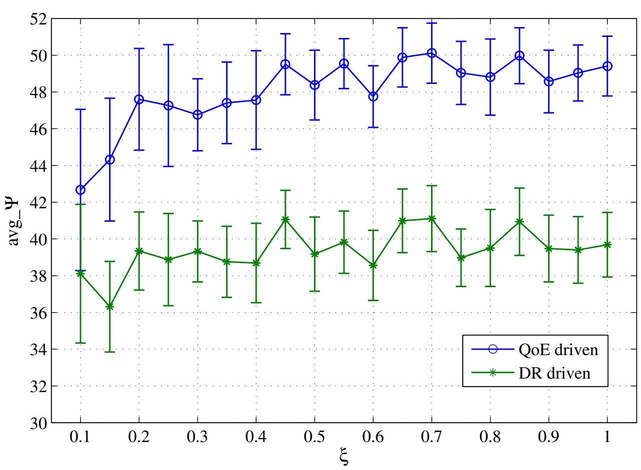

Fig. 3. Average MOS sum of the CUs over an entire GOP window, avg_Ψ, for different CU traffic loads ξ (with 95% confidence intervals).

since no more channel resource is available to satisfy the need of the extra CUs.

VI. Conclusion

In this paper, we investigated the problem of QoE-aware video streaming over CRNs. An IP problem on spectrum sensing was formulated and solved with a Greedy Poly-matching Algorithm. Then a channel assignment problem was formulated as an IP and solved with the Hungarian Method to derive the optimal channel assignment, where QoE is used as the performance metric. We showed that both proposed algorithms achieve optimal solutions for spectrum sensing and channel access, respectively. The proposed schemes were validated with simulations.

Acknowledgment

This work is supported in part by the US National Science Foundation (NSF) under Grant CNS-0953513, and through the NSF I/UCRC Broadband Wireless Access & Applications Center (BWAC) site at Auburn University. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the NSF.

References

[1] Cisco, "Visual Networking Index (VNI)," Feb. 2014. [Online]. Available: http://www.cisco.com/.

[2] D. Hu, S. Mao, Y. T. Hou, and J. H. Reed, "Scalable video multicast in cognitive radio networks," *IEEE J. Sel. Areas Commun.*, Special Issue on Wireless Video Transmission, vol.29, no.3, pp.334–344, Apr. 2010.

[3] D. Hu, and S. Mao, "Streaming scalable videos over multi-hop cognitive radio networks," *IEEE Trans. Wireless. Commun.*, vol.11, no.9, pp.3501–3511, Nov. 2011.

[4] K. Yamagishi and T. Hayashi, "Opinion model using psychological factors for interactive multimodal services," *IEICE Trans. Communication.*, E89-B(2):281–288, Feb. 2006.

[5] J. You, U. Reiter, M. Hannuksela, M, Gabbouj, and A. Perkis, "Perceptual-based quality assessment for audio-visual services: A survey," *Signal Processing: Image Communication.*, vol.25, no.7, pp.482–501, Aug. 2010.

[6] A. Khan, L. Sun, and E. Ifeachor, "Content clustering based video quality prediction model for MPEG4 video streaming over wireless networks," in *Proc. IEEE ICC'09.*, Dresden, Germany, June 2009, pp.1–5.

[7] A. Khan, L. Sun, and E. Ifeachor, "QoE prediction model and its application in video quality adaptation over UMTS networks," *IEEE Trans. Multimedia*, vol.14, no.2, pp.431–442, Apr. 2012.

[8] Y. Chen, Q. Zhao, and A. Swami, "Joint design and separation principle for opportunistic spectrum access in the presence of sensing errors," *IEEE Trans. Inf. Theory*, vol.54, no.5, pp.2053–2071, May 2008.

[9] A. Eden, "No-reference image quality analysis for compressed video sequences," *IEEE Trans. Broadcast.*, vol.54, no.3, pp.691–697, Sept. 2008.

[10] Q. Huynh-Thu and M. Ghanbari, "Temporal aspect of perceived quality in mobile video broadcasting," *IEEE Trans. Broadcast.*, vol.54, no.3, pp.641–651, Sept. 2008.

[11] J. Mitola III, "Cognitive radio for flexible mobile multimedia communications," in *Mobile Netw. Appl. J. (MONET)*, vol.6, no.5, pp.435–441, Sept. 2001.

[12] Y. Chen, Y. Wu, B. Wang, and K. J. R. Liu, "Spectrum auction games for multimedia streaming over cognitive radio networks," *IEEE Trans. Commun.*, vol.58, no.8, pp.2381–2390, Aug. 2010.

[13] T. Jiang, H. Wang, and A. Vasilakos, "QoE-Driven channel allocation schemes for multimedia transmission of priority-based secondary users over cognitive radio networks," *IEEE J. Sel. Areas Commun.*, vol.30, no.7, pp.1215–1224, Aug. 2012.

[14] W. Wang, B. Kasiri, J. Cai, and A.S. Alfa. "Channel Assignment of Cooperative Spectrum Sensing in Multi-Channel Cognitive Radio Networks," *Proc. IEEE ICC'11*, kyoto, Japan, June. 2011, pp.1–5.

[15] W. Wang, B. Kasiri, J. Cai, and A.S. Alfa. "Distributed cooperative multi-channel spectrum sensing based on dynamic coalitional game." *Proc. IEEE GLOBECOM'10*, Miami, FL, Dec. 2010, pp.1–5.

[16] Alexander W. Min, Kang G. Shin, "Joint Optimal Sensor Selection and Scheduling in Dynamic Spectrum Access Networks," *IEEE Trans. Mobile Computing*, vol.12, no.8, pp.1532–1545, Aug. 2013.

[17] B. Wang, K.J. Ray Liu, and T.Charles. Clancy. "Evolutionary cooperative spectrum sensing game: How to collaborate?" *IEEE Trans. Commun.*, vol.58, no,3, pp.890–900, Mar. 2010.

[18] K. Kar, L. Xiang, and S. Sarkar, "Throughput-optimal scheduling in multichannel access point networks under infrequent channel measurements," *IEEE Trans. Wireless. Commun.*, vol.7, no.7, pp.2619–2629, July 2008.

[19] H. Su, and X. Zhang, "Cross-layer based opportunistic MAC protocols for QoS provisionings over cognitive radio wireless networks," *IEEE J. Sel. Areas Commun.*, vol.26, no.1, pp.118–129, Jan. 2008.