Wireless Pers Commun (2018) 100:1499–1515
https://doi.org/10.1007/s11277-018-5650-4

A Novel Content Aware Channel Allocation Scheme for Video Applications over CRN

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Published online: 16 April 2018

Abstract Cognitive radio (CR) has emerged as an effective solution to spectrum scarcity problem which efficiently utilizes the unused spectrum of licensed primary user (PU). Video applications, as a bandwidth intensive and delay-sensitive application, will surely get benefitted from CR technology due to its ability to provide additional bandwidth to end users. In this article we investigate the challenges of quality of experience (QoE) driven video applications over CR networks due to the random behavior of PUs, dynamic characteristic of the primary channels, packet error rate etc. Generally, all video applications could be categorized into three groups like slight motion, gentle walking and rapid motion (RM) and each group has its own quality of service (QoS) requirements. The aim of this paper is to minimize QoE degradation by estimating the quality of the available channels based on our proposed Channel Quality Index metric and then allocating the channels depending on the QoS requirements of a particular video application. Extensive analysis validates that there is a performance enhancement of different video applications, especially RM type (nearly 66%) which is considered as most critical among all.

Keywords Cognitive radio · Quality of service · Quality of experience · MOS · Channel allocation · Channel Quality Index

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1 Introduction

The exponential growth of video applications like multimedia, video streaming, video conferencing and quality of experience (QoE) provisioning of different bandwidth extensive applications have created a major challenge for network operators due to limited spectrum availability. Demand for higher bandwidth to achieve desired quality of service (QoS) has made the spectrum very expensive resource which is depleting day by day. However, as per Federal Communication Commission (FCC), the actual spectrum utilization varies from 15 to 85% across different geographical areas [1] which shows the inefficiency of static spectrum allocation policy. Static spectrum allocation policy prohibits an unlicensed user to use the licensed spectrum even if the spectrum is underutilized which leads to poor spectrum efficiency. Cognitive radio (CR) is an efficient solution to the spectrum scarcity problem which utilizes dynamic spectrum access (DSA) technique. CR network (CRN) allows secondary user (SU) to use the available spectrum of primary user (PU) opportunistically without creating significant interference to PU. CR periodically senses the licensed spectrum to find out probable transmission opportunity and dynamically reconfigures it's operating parameters. In CRN, interest of PUs is protected by assigning highest priority to PUs and SU has to evacuate the licensed channel if PU reappears. This may lead to service interruption, transmission delay, spectrum handoff or in worst case service termination. Therefore, achieving a good QoS is a major challenge for CR designers specifically for band width hungry and delay sensitive real time applications like video.

In literature [2], challenges that arises for critical real time applications over CR are highlighted. To device a reliable CRN, several aspects of CR have been considered [2–4] and works have been performed. Spectrum management, spectrum sensing, spectrum access techniques, efficient scheduling for medium access control (MAC), cross-layer optimization and security aspects etc. are few such areas. However, all of the research works mentioned above mainly deals with lower layer issues like efficiency of physical layer or MAC layer in terms of spectrum efficiency, without focusing much of the quality issues of the upper layers.

In recent years, CISCO [5] has predicted that nearly 66% of mobile traffic would contain video applications. Video over CRN has attracted tremendous research interest in current years due to its ability to access more bandwidth to enhance QoE of video applications. Additionally, a PU can utilize cognitive technology to take the advantage of available licensed or unlicensed spectrum to support different video services, such as video-on-demand streaming, video conferencing, and online gaming. However, challenges for video applications over CRN are twofold: First, real time applications like videos are delay, error sensitive and bandwidth-hungry applications [6] which should be carried by channels having good condition like better signal to noise ratio (SNR) and lower delay etc. However, unpredictability and unreliability of wireless channels reduce the final video quality and also reduce the QoE of the end users. Several research works have been done to address the video quality issues over wireless channels which includes source and channel rate control [7], adaptive playback [8, 9] control, error concealment [10] and layered coding [11]. Layered coding and channel rate control are normally implemented at the transmitter end to overcome the effect of dynamic channel condition whereas error concealment and adaptive playback are two methods applied at the receiver end to improve the video quality. All methods discussed above mainly nullify the effect of adverse channel conditions to some extent, however it cannot perform well if the channel selection is very poor.

Further, for CRN the challenges increase due to the dynamic time varying nature of the available channels. Available licensed channels may significantly differ from each other in terms of frequency, gain and the rate of interruption due to primary activity which defines the channel condition. This channel condition plays a major role in perceived video quality and finally affects the QoE of the end user. QoE enhancement is considered as a major challenge for CRN operators and addressed in several research works in the literature. In [12], Fountain Code was envisaged to improve the reliability of multimedia transmission over CRN. In [13], the authors proposed an integrated cross-layer design approach using partially observable Markov decision process to optimize the application layer parameter along with access strategy and spectrum sensing. Maximizing scalable video quality with fairness is analyzed in [14] and a centralized channel allocation scheme is proposed in [15] to allow video services to the SUs. Channel allocations between cognitive video receivers are dealt in [16] to maximize the overall network throughput. Also, in [17], the authors formulated a stochastic programming model for relay-assisted downlink multiuser video streaming in a CR cellular network. In [18], sample division multiplexing is used to improve the spectrum utilization for multimedia applications. An efficient channel modelling is proposed in [19] and the impact of channel unavailability is addressed through source rate control and adaptive playback scheme. All these research works have treated different video applications uniformly without focusing much on their individual properties like content type and respective QoS requirements.

In [20], authors have used cluster analysis and grouped video applications into three categories: 'slow movement' (SM), 'gentle walking' (GW) and 'rapid movement' (RM) based on their spatial and temporal feature extraction. All these types have different QoS requirements, as an example RM type of videos are more sensitive to the channel conditions like channel data rate, packet error rate whereas SM type is less sensitive. All channels are not equally suitable for different video applications and it is observed that channels which are not suitable for RM type, could be assigned to SM type without compromising the quality. Therefore, channel estimation and content aware channel allocation is very crucial to improve overall QoE of the system. In this article, we have analyzed the requirements of different video applications separately and allocate the channels in such a way that it can satisfy the need of the applications. Here, we propose a novel content aware channel allocation scheme which optimally assigns network channels by considering the application requirements and improves the QoE of the overall CRN. To the best of our knowledge none of the above research articles have focused on content aware channel allocation policy which can match the channel condition with the application requirement to improve user's satisfaction. Specifically, it improves the QoE of most critical video applications like RM or GW in a CRN.

1.1 Our Contributions

Dynamic channel allocation increases service interruption and also reduces the service quality due to the latency and transmission failure. Hence, QoE enhancement of video application is more challenging because of its dependency on number of networks and non-network related parameters. To understand the effect of network related parameters on QoE of video applications, we have analyzed the mathematical model of mean opinion score (MOS) in Sect. 3 and studied the effect of different parameters on the performance in Sect. 4. We have derived a single metric called Channel Quality Index (CQI) which integrates all network related parameters of CRN and proposed a unique channel allocation scheme (CAS) to enhance the perceptual quality of the end users. The major contributions of this work are as follows:

1. Study the effect of different network parameters on the subjective quality of video applications. We have extended our analysis to identify the effect of different video types which provides a clear understanding about the QoS requirements of different video applications.
2. We derive the CQI of available licensed channels considering different aspects of CRN like probability of detection, probability of false alarm, idle channel probability, throughput and packet error rate. CQI is a single metric which combines all aspects of CRN and could be used for channel quality estimation. CQI is used by cognitive base station (CBS) for content aware channel allocation to SUs.
3. Classification and priority assignment of different video applications based on their QoS requirements. QoS requirement is mainly governed by the content type of different video applications.
4. Proposing a novel CQI based content aware channel allocation scheme which allocates suitable channels to the video users based on their QoS requirements.
5. Our proposed work is different from other related work by its unique features which can be outlined in three aspects.
   (a) Content awareness of video applications and prioritizing them based on their QoS requirements.
   (b) Due to non-uniformity, some video applications require high quality stable, reliable channels compared to others to achieve desired QoE. However, identifying such channels require prolonged sensing time which reduces the channel throughput. Due to channel quality awareness through CQI, our proposed scheme utilizes the cognitive cycle efficiently which improves the system performance.
   (c) Our proposed scheme contributes to all three major aspects of CRN, i.e., efficient channel utilization, QoS provisioning and QoE improvement.
6. We perform a comprehensive simulation to evaluate the performance of the proposed channel allocation scheme and compared our proposed CAS with traditional non-priority based random and uniform channel allocation policy to analyse the effectiveness of our proposed scheme.

The remainder of this paper is organized as follows. System model and SU access strategy is discussed briefly in Sect. 2. Section 3 deals with the mathematical modelling of video applications. Section 4 illustrates the effect of different network parameters on the QoE metric. In Sect. 5 we present CQI formulation, application priority scheduling and also proposed the content aware channel allocation scheme. Simulation results are shown and analyzed in Sect. 6. Finally, Sect. 7 concludes the paper.

2 System Model

In this section, we briefly discuss about the system model, its major components and SUs access policy to occupy available licensed channels.

2.1 Cognitive Radio Network Architecture

In general, CRN comprises of two major components: primary network (PN) and secondary network (SN). PN consists of primary base station (PBS) and licensed PUs who enjoys absolute priority over licensed channels. SN consists of one central unit called CBS and intelligent SUs. The objective of CRN is to improve the spectrum efficiency without creating significant interference for the PUs. Spectrum opportunity can be identified using spectrum sensing techniques [20] and decision can be made either individually or collectively by some centralized controller like CBS. In this article, it is assumed that CBS uses co-operative spectrum sensing [21] technique that improves the reliability of the decision and also eliminate the sensing error. In this paper, we deal with single hop video down streaming over infrastructure based overlay cognitive radio network. Figure 1 depicts the network architecture where CBS is connected to the application servers through core network (CN). The CBS senses and find out all available licensed channels and then runs the content aware CQI based CAS scheme which improves the overall QoE of the system.

2.2 SU Access Model

CRN consists of '*M*' number of SUs and '*N*' orthogonal licensed channels. We assume that there are '*K*' number of idle channels sensed by SUs at a particular instant of time which is designated as $CH = \{CH_1, CH_2, \ldots, CH_K\}$. The idle channels found by SUs may vary significantly in terms of frequency, channel SNR, and channel availability which defines the channel quality. In this article we analyse single hop multi-user video streaming scenario where channel quality estimation is performed through CQI and used it for channel allocation to improve the QoE of the overall system.

In order to detect the presence of the PU, SUs have to perform the sensing operation periodically. Let 'ΔT' represents the maximum interference duration which PU can tolerate. To keep the interference level within the tolerable range, the system time is discretized into 'ΔT' duration and each 'ΔT' is divided into micro-slots like sensing duration (ΔT_s), feedback slot (ΔT_f) and actual video transmission slot (ΔT_{data}). In this paper, we have considered channel allocation epoch time (T) [16] which represents the total time duration for which CBS allocates a particular channel to a SU. So, a particular SU can use the assigned channel for $L = T/\Delta T$ discrete time slots. Figure 2 represents the discrete time

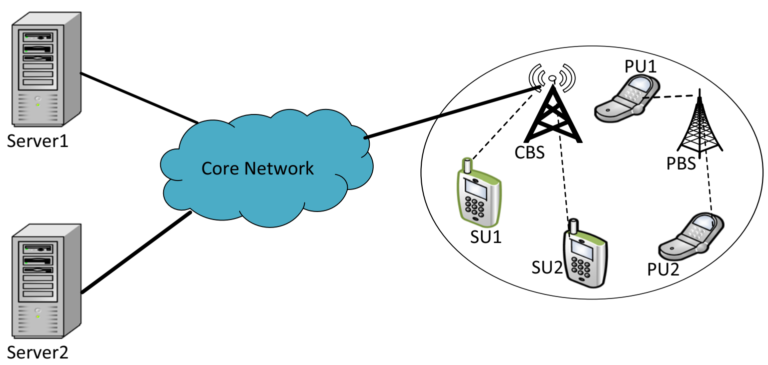


Fig. 1 System model for video streaming over CRN

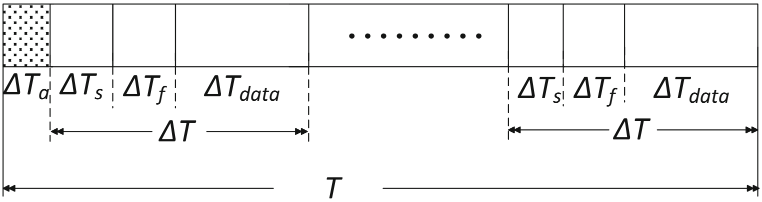


Fig. 2 Illustration of discrete time slot durations

slot and different fields of 'ΔT'. CBS execute the channel allocation algorithm at the beginning (ΔT_a) of each 'L' slots and assign suitable channels to SUs.

3 Application Layer Modelling

Quality assessment is an important parameter of video transmission and can be measured by objective or subjective approach. Objective approach incorporates different network parameters to evaluate end user satisfaction and does not involve actual human perception. On the other hand, subjective quality assessment is performed based on human perception and the Mean Opinion Score (MOS) is the metric used for video quality assessment recommended by the International Telecommunication Union (ITU). Based on the users' perception, MOS can be rated as follows: 5 (Excellent), 4 (Good), 3 (Fair), 2 (Poor), 1 (Bad). MOS for video applications can be represented as a function of transmission data rate, frame rate and packet error rate [20] as:

$$MOS = f(R, FR, P_l) \tag{1}$$

where 'R' is the data rate, 'FR' represents the frame rate and 'P_l' is the packet loss rate. From cluster analysis [20], it is observed that videos can be grouped into SM, GW and RM types based on the spatial and temporal features. SM group includes the video types having small moving region of interest (lips/face) on a static background like news casting. GW includes the video types where both the content and the background moves relatively at higher speed. Carphone and Foreman are typical example of this type of videos. In RM type, the entire sequence moves at higher speed. Sport clips like Football falls under this category. Generally, MOS for video applications can be represented by the following model [20] where the parametric coefficients are different for different video applications:

Table 1 Value of different parameters for different types of videos

Type	a1	a2	a3	a4	a5
SM	2.797	− 0.0065	0.2498	2.2073	7.1773
GW	2.273	− 0.0022	0.3322	2.4984	− 3.7433
RM	− 0.0228	− 0.0065	0.6582	10.0437	0.6865

$$MOS = \frac{a1 + a2 * FR + a3 * \ln(R)}{1 + a4 * P_l + a5 * (P_l)^2} \quad (2)$$

where $a1$, $a2$, $a3$, $a4$ and $a5$ are the coefficients and typical values of the coefficients are shown in Table 1 [20].

4 Effects of Channel Quality on Different Video Applications

In this section, we study the QoS requirements of different video applications and analyze their effects on end user perceptual quality. Channel data rate and packet error rate are two network parameters which have different impacts on SM, GW and RM type of videos. Figure 3 shows the relationship between channel data rate and MOS where the data rate is varied from 10 to 1000 kbps. Analysis shows that SM type of videos can achieve good quality even at lower data rate, however RM/GW type require relatively higher data rate to achieve acceptable quality. Effect of packet loss rate is studied in Fig. 4. The impact of packet loss rate is higher for RM/GW type of videos compared to SM type due to their rapid motion content which is highly sensitive to packet loss rate. The above analysis clearly shows that channel bit rate and packet error rate have higher influence on the perceptual quality of RM and GW type of videos compared to SM type. Although three types of video belong to the same application type, still there exists requirement diversity due to different motion content.

In CRN, primary channel characteristic is highly dynamic in nature due to number of factors like: ergodic behavior of PU, reappearance of PU during secondary transmission, different channel frequency, channel gain etc. Performance of different videos are highly influenced by channel characteristics. Here we present a scenario that clearly shows that same channel can perform differently for different video applications. To illustrate this, we have considered ten candidate channels, each of 1 MHz with different channel characteristics in terms of channel SNR, idle duration and PU arrival rate etc. Figure 5 demonstrates MOS achieved by three types of videos over ten available channels where

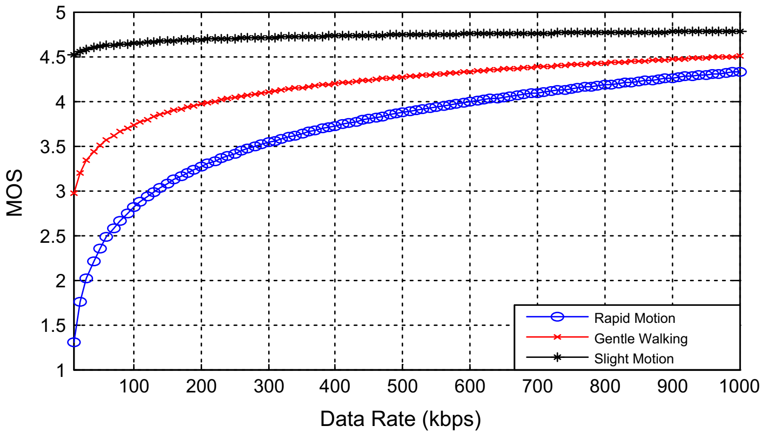


Fig. 3 Variation of MOS with channel data rate for different video applications

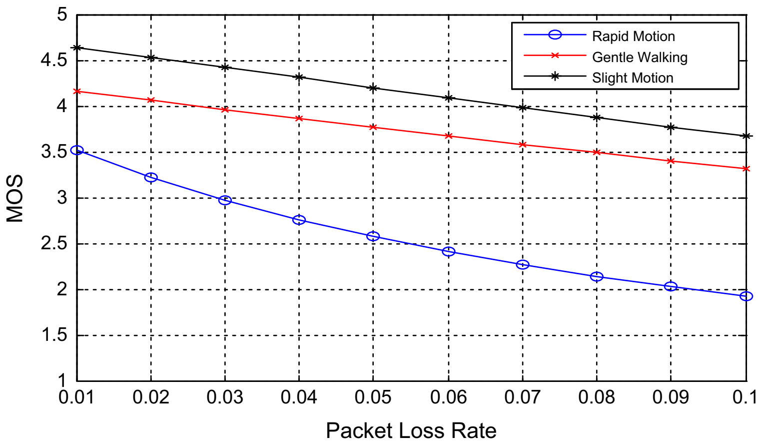


Fig. 4 Variation of MOS with packet loss rate for different video applications

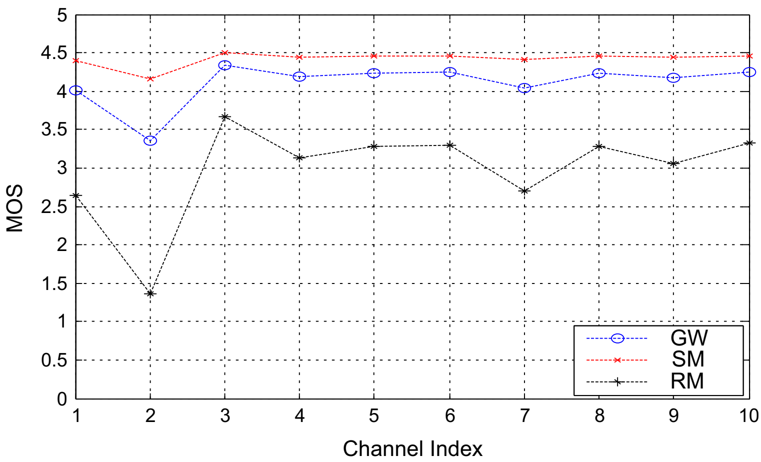


Fig. 5 Performance of different channels for different video applications

channel characteristics are different. Out of these ten available channels, channel no. 2 is the worst channel having very poor channel condition.

In Fig. 5, it is observed that the performance of SM type is acceptable over channel number 2, however the same channel is not suitable for RM type of videos as the MOS achieved by RM video in this channel is very low. This shows that channel allocation has a great influence over QoE of end user. Therefore, if the channel allocation is not done properly by considering the content type of different video applications the overall system performance may degrade sharply for RM/GW type of videos.

5 Proposed Content Aware CQI Based Channel Allocation Scheme

In this section, we briefly discuss about our proposed channel quality estimation method and CQI based channel allocation scheme. Here, we start with the statistical model of primary channel and gradually move towards the collection of necessary information for channel quality estimation. Necessary information which are required for CQI are: probability of false alarm, channel SNR, packet error probability etc. Finally, we discuss about our proposed content aware CQI based channel allocation procedure. CBS plays very important role in channel estimation and channel allocation scheme which we shall discuss in the following subsections.

5.1 Primary Channel Availability Model

PU can have different traffic patterns over licensed channels which could be deterministic or stochastic. Primary channel can be mathematically modelled as two states Markov process as shown in Fig. 6 where 'ON' state indicates the presence and 'OFF' state indicates the absence of a PU on channel number 'j'. Parameters 'α_j' and 'β_j' denotes the transition probability of PU from 'OFF' to 'ON' and 'ON' to 'OFF' states for 'jth' channel. This model is considered as a suitable model as it approximates the channel usages pattern at public safety band [22]. The busy and idle period of channel 'j' can be assumed to be exponentially distributed with probability density function $f_{off}(t,j) = \beta_j e^{-\beta_j t}$ and $f_{on}(t,j) = \alpha_j e^{-\alpha_j t}$. Both these '$\alpha_j$' and '$\beta_j$' can be estimated with statistical methods [23]. Average busy and idle periods are $1/\alpha_j$ and $1/\beta_j$ respectively and the stationary probability that the channel 'j' is idle can be represented as:

$$\Pr{}_{off_j} = \frac{\beta_j}{\alpha_j + \beta_j}, \quad \forall j \in K \tag{3}$$

CBS collects and stores all statistical information related to 'jth' channel in its data base and periodically updates the information according to the sensing results from SUs.

5.2 Channel Sensing and SNR Estimation

In a wireless environment, SUs are located at different geographical regions which lead to different sensing ability and varying performance. Cooperative sensing with proper set of SUs improves overall sensing performance [24]. Due to its simplicity, Energy Detection (ED) based sensing technique is widely used in CRN where SU does not require any prior information about the PU signal. In this model, we have used ED based periodic spectrum sensing technique which senses the channel periodically to avoid potential interference to the PU. SUs measure the channel SNR value and also calculate probability of false alarm

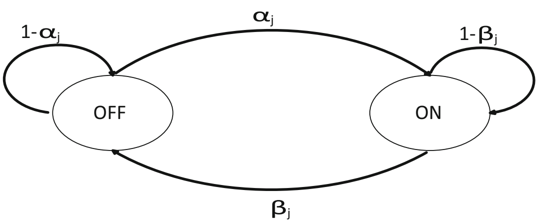


Fig. 6 Primary channel availability model

(P_f), probability of detection (P_d) [25] for a particular channel 'j' and send the information to CBS periodically. Pseudo code for spectrum sensing, SNR calculation and PU traffic estimation is shown in Algorithm 1.

Algorithm 1: Channel sensing and estimation

Input: ED threshold (λ), Input samples $Y_{ij}[n]$

Output: SNR (γ_{ij}) sensed by user 'i' on channel 'j'

Probability of false alarm ($P_{f\,ij}$)

if $\sum_{n=1}^{N} Y_{ij}[n] \geq \lambda$

    channel is not idle, measure γ_{ij}

else

    channel is idle, calculate $P_{f\,ij}$

    $P_{f\,ij} = 0.5 * erfc(\frac{\lambda - N}{2\sqrt{N}})$

    $P_{d\,ij} = 0.5 * erfc(\frac{\lambda - N*(1+\gamma_{ij})}{2\sqrt{N*(1+\gamma_{ij})}})$

end

$$P_{d_{ij}} = 0.5 * erfc\left(\frac{\lambda - N(1 + \gamma_{ij})}{2 * \sqrt{N(1 + \gamma_{ij})}}\right) \tag{4}$$

$$P_{f_{ij}} = 0.5 * erfc\left(\frac{\lambda - N}{2 * \sqrt{N}}\right) \tag{5}$$

5.3 Channel Quality Index (CQI) Calculation

In this subsection, we formulate CQI to estimate the channel quality of a CRN. Channel properties varies from each other based on the PU traffic pattern and channel SNR. Therefore, channel idle time, channel data rate and packet error probability are three main parameters that control the performance of a channel for video applications. Data collected during the spectrum sensing cycle discussed in the earlier subsection could be used by CBS to estimate the traffic pattern over different primary channels. Maximum-likelihood estimation method can be used to obtain the mean idle and busy time, hence 'Pr_{off}' of a particular licensed channel could be obtained. 'SNR_{ij}' and '$P_{f_{ij}}$' are obtained from Algorithm 1 during channel sensing and estimation cycle. Our proposed CQI estimates the quality index of a particular channel 'j' for a particular SU 'i' which helps CBS to allocate channels to different traffic classes based on their requirements.

(a) *Channel Data Rate Calculation*
Channel data rate for 'ith' SU on 'jth' channel can be derived as:

$$R_{ij} = \frac{\Delta T_{data}}{\Delta T} * B_j * \log_2(1 + SNR_{ij}) * (1 - P_{f_{ij}}) * \Pr_{off_j} \tag{6}$$

where B_j represents the channel band width of 'jth' channel, SNR_{ij} represents the channel SNR sensed by 'ith' SU over 'jth' channel. '$P_{f_{ij}}$' is the probability of false alarm estimated by 'ith' user on 'jth' channel. Pr_{on_j}, Pr_{off_j} are stationary probabilities for busy and idle period of 'jth' channel.

(b) *Calculation of Probability of Packet Error Rate*

In a CRN, total packet loss of SU consists of two parts: first the packet error which occurs due to random PU activity that interrupts SU transmission and second the packet loss which occurs due to channel noise. We need to consider both of them separately to estimate the channel quality. Let 'l_s' be the uniform packet length of all SUs and 'v_p' be the mean idle time of channel 'j'. Due to random arrival of PU, the average packet collision probability on 'jth' channel for 'ith' user is:

$$P_{c_{ij}} = \Pr_{on_j} * (1 - P_{d_{ij}}) + \left(1 - e^{-ls/R_{ij} * v_p}\right) * \Pr_{off_j} * (1 - P_{f_{ij}}) \tag{7}$$

Let, Λ_{ij} be the channel BER for 'ith' user on 'jth' channel which is a function of channel SNR_{ij}. Packet error rate of 'ith' user on 'jth' channel due to the channel noise can be calculated as:

$$P_{l_{ij}} = 1 - (1 - \Lambda_{ij}(SNR_{ij}))^{ls} \tag{8}$$

Therefore, end to end packet error rate (P_{eij}) of 'ith' user on 'jth' channel can be expressed as:

$$P_{e_{ij}} = 1 - \left(1 - P_{c_{ij}}\right)\left(1 - P_{l_{ij}}\right) \tag{9}$$

(c) *CQI Formulation*

We combine channel data rate and packet error for CRN and propose a single metric called CQI for channel quality estimation. CQI (Q_{ij}) of 'ith' user on 'jth' channel is calculated as:

$$Q_{ij} = \ln\left(R_{ij}\right) * \left(1 - P_{e_{ij}}\right) \tag{10}$$

5.4 Content Aware Application Priority Scheduling Scheme

Application priority scheduler (APS) is an integral part of CBS which prioritizes the user's applications based on the content information collected from the SUs. Highest priority is assigned to the RM type videos as they have higher motion content and more sensitivity to network parameters. In Sect. 4 we have observed that QoE of RM type video degrades more rapidly if the channel assignment is not done properly. Medium priority is assigned to GW type of videos as they are less sensitive compared with RM type and lowest priority is assigned to SM type of videos as they are least sensitive to network conditions. If two applications have same priority, then relative priority can be assigned based on First-In, First-Out (FIFO) rule.

5.5 Content Driven CQI Based Channel Allocation Scheme

CBS also contains another important sub-module called *channel scheduler* (CS) which performs channel allocation for different video applications. The main objective of the proposed channel allocation scheme is to improve the overall system performance by identifying the QoS expectation of different video applications and allocate the channels based on application's requirement. Analysis shows that RM types of videos have more stringent QoS requirements therefore, best set of channels should be assigned to them. Next priority will be given to GW and SM type of videos respectively. Figure 7 shows different elements of CBS involved in content aware CAS.

This proposed content aware channel quality index based CAS performs the following sets of activities: First, CBS identifies the content of different SUs, classify them into appropriate group, assign priority and arrange them in APS priority queue. Secondly, CBS estimates the channel quality based on CQI. Typical Channel Quality Index Matrix (***Q***) can be represented as:

$$Q = \begin{bmatrix} Q_{11} & Q_{12} & . & . & Q_{1K} \\ Q_{21} & Q_{22} & . & . & Q_{2K} \\ . & . & . & . & . \\ . & . & . & . & . \\ Q_{M1} & Q_{M2} & . & . & Q_{MK} \end{bmatrix} \tag{11}$$

Third, CBS serves different class of videos based on their relative position in the priority queue and allocates the best available channel form the list based on CQI matrix (CQIM) '***Q***'. The pseudo code for channel assignment scheme will run at Channel scheduler (CS) which is shown in Algorithm 2.

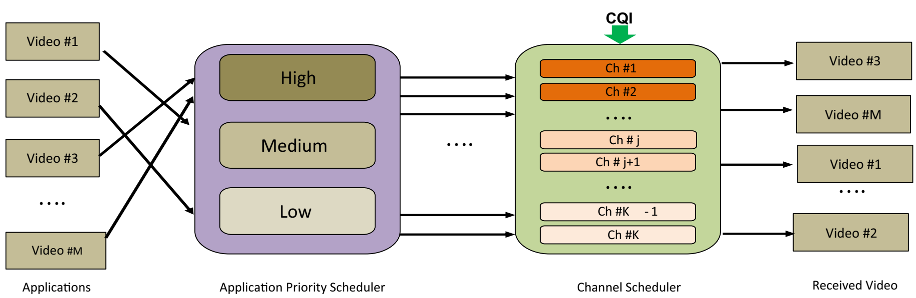


Fig. 7 Content aware CQI based CAS

Algorithm 2: Content aware CQI based CAS

Input: Assigned Priority, $P=\{P_1,P_2,\ldots,P_M\}$

Set of channels, $CH=\{CH_1, CH_2, \ldots CH_K\}$

CQIM, $Q=\{Q_{ij}\}$, where $i \in [1,M], j \in [1,K]$

Output: Channel Assignment $SU_i \leftarrow CH_j$

Initialize: rem_idle_ch=K

Arrange SU's in decending order based on P

SU^*=Reorder (SU)=$\{SU_1{}^*, SU_2{}^*, \ldots, SU_M{}^*\}$

for $i=1$ *to* M

Allocated best channel CH_j to $SU_i{}^*$ based on Qij

rem_idle_ch=rem_idle_ch-1;

if (rem_idle_ch==Ø)

break;

endif

endfor

6 Simulation Results

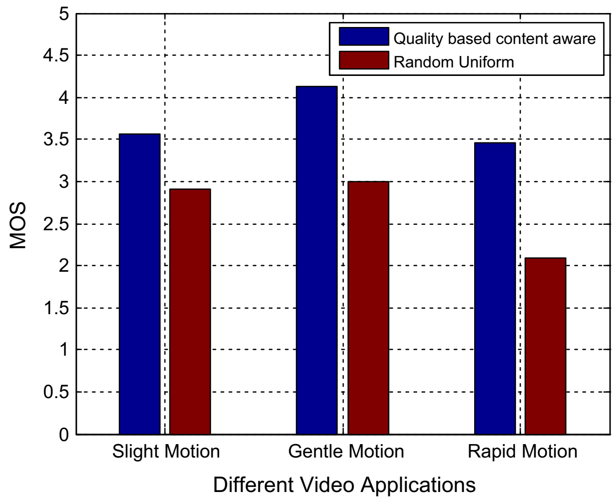
Different parameters used for performance analysis are summarized in Table 2. Here we have considered ten idle channels (K) each of 1 MHz and channel SNR randomly varies between 0 and 20 dB. We compare the performance of the proposed algorithm with traditional *random and uniform non-priority channel allocation scheme* where channel allocation is done randomly from the available channel list and applications are served on FIFO basis. Channel quality estimation and QoS requirements of different video applications are not considered for channel allocation. Extensive analysis is performed to compare the former scheme with our proposed CAS.

Figure 8 shows the QoE achieved by different video applications for two different channel assignment schemes. As we can see from Fig. 8, the outcomes of two CAS differ

Table 2 Simulation parameters for channel performance analysis

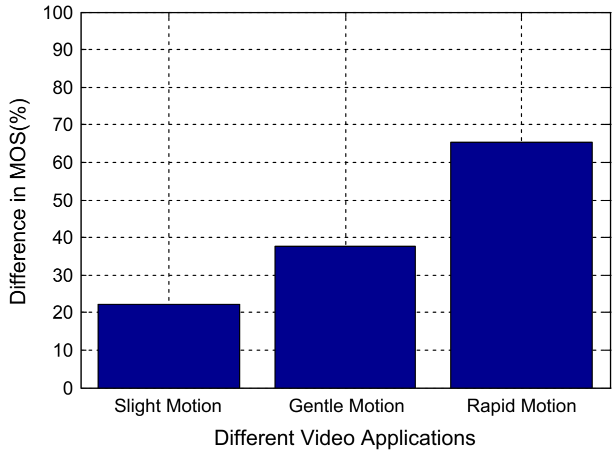
Symbol	Definition	Value
B	Channel band width	1 MHz
ΔT	Discrete time interval	1 ms
ΔT_s	Sensing time interval	100 µs
v_p	Average channel idle time	160 ms
P_f	Probability of false alarm (as per IEEE 802.22)	≤ 0.1
P_d	Probability of detection (as per IEEE 802.22)	≥ 0.9
Pr_{off}	Channel idle probability (randomly chosen)	$\left[\frac{1}{3}, \frac{2}{3}\right]$
SNR	Channel SNR (randomly chosen)	[0, 20 dB]
FR	Frame rate	30 frames/s
l_s	Packet size	256 bits

Fig. 8 Performance evaluation of proposed channel assignment policy



significantly from each other and our proposed content aware scheme gives better performance in terms of overall QoE. The improvement is more visible for RM type of video which is most critical among all video applications due to its high sensitivity to different network parameters. The improvement is due to the ability of our proposed scheme which emphasize on the content awareness and quality driven channel allocation that satisfy the need of various video applications. Figure 9 illustrates the percentage QoE improvement for different channel assignment schemes. Effect of channel allocation is not much noticeable for SM type as it has less motion content and it can achieve acceptable quality even at poor channel condition. However, for GW type of videos the proposed channel assignment scheme performs better and the improvement is nearly 38%. QoE improvement is maximum for RM type of videos where channel assignment plays critical role and the performance improvement is nearly 66%. This analysis illustrates that the proposed CAS improves the overall QoE of different video applications and thus improves the quality of different video transmission over CRN.

Fig. 9 Percentage improvement of QoE for proposed scheme assignment policy



7 Conclusion

This paper proposes a content aware CQI based channel allocation scheme for improved video quality over CRN. The proposed scheme identifies the QoS requirements of different video applications and also estimates the service quality offered by different channels and finally allocates a channel which optimally satisfies the requirement of the application. Analysis shows that RM type of videos are more sensitive to network parameters due to their higher motion content. During channel allocation, priority would be given to this type of applications, otherwise overall system performance would reduce. On the other hand, SM type of video does not require very high quality channels due to their low motion content and this gives additional flexibility to assign channels which are not suitable for RM or GW type of applications. To perform efficient channel allocation for different video applications we have proposed content aware CQI based channel allocation scheme. CQI is formulated for channel quality estimation which considers all relevant system parameters like channel bandwidth, channel SNR, packet error rate and other statistical information of PU activity. This Proposed algorithm runs on CBS at the beginning of channel assignment cycle where CBS estimates the channel quality based on CQI. APS module assigns the priority to different video applications based on their QoS requirements. Finally, CBS performs the channel allocation based on the channel quality and application demand. In this article, we have compared our proposed scheme with traditional random and uniform channel assignment schemes where the channel quality estimation and QoS requirements are not considered for channel allocation. Simulation results revealed that our proposed scheme outperforms the traditional schemes and nearly 38% QoE improvement is observed for GW type of videos, about 66% improvement is observed for RM type of videos. QoE enhancement of these two critical video applications leads to the overall performance enhancement of video applications over CRN.

Acknowledgements The authors deeply acknowledge the support from Visvesvaraya PhD Scheme, (DeitY), Govt. of India.

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Publisher's Note

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