The Use of Rateless Coding Technique in Cognitive Radio Networks Based on Primary User Channel Occupancy Modeling

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ABSTRACT:
In this paper, we investigate the channel selection technique in secondary user communication in cognitive radio network using rateless codes. In order to increase the tolerance of interference from the primary user appearance, also considering losses caused by collision between several secondary users, each secondary user uses rateless codes. We model the primary user occupancy and interference dynamics of a channel, which is used by a secondary user, using a Hidden Markov Model (HMM). The HMM is trained using Baum-Welch procedure and each secondary user uses a trained HMM to predict the primary user channel occupancy in future time slots and compute the Channel Availability Metric (CAM) for the channel. CAM is used by secondary user to select a preferable primary user channel for its communication. Simulation results, demonstrate the efficiency of the proposed channel selection technique in secondary user communication.
KEYWORDS: Cognitive Radio, Rateless Codes, HMM, Occupancy Modeling.

1. INTRODUCTION

Over the past decade, with a tremendous growth in use of wireless and application services, Radio Frequency (RF) spectrum is greatly scarce and expensive. The increasing demands for additional bandwidth have led to studies that indicate the spectrum assigned to primary users is underutilized.

Cognitive radio technology helps to improve the efficiency of spectrum utilization by introducing secondary usage of the spectrum licensed to primary users but with lower priority. An important constraint in cognitive radio is that the secondary users should not interfere with the primary users. Generally, only the secondary users are equipped with sensing devices, but not the primary users. The primary users are not aware of the existence of the secondary users. Therefore, once a primary user starts to transmit its signal through the channels where the secondary user is transmitting, the signal of the secondary user is then jammed by the strong interference from the primary user. However, since the secondary user vacates the primary user channel very fast, the primary transmission is not affected. Since the packet loss from jamming can be treated as erasures, the primary user channel can be modeled as an erasure channel. In order to recover lost packets, powerful erasure correcting codes can be used by secondary users. Individually, rateless codes have been suggested to be used for cognitive radio networks [1], [2]. Rateless codes [3] are a class of erasure correcting codes that have the ability of reconstruction the original data as long as total number of the correctly received coded packets exceeds a sufficient value. In the context of multiple access, rateless codes have the ability of distributing the data to different channels without any coordination among them. Also, they can struggle the effect of interference during the transmission over each channel. In this paper, we apply rateless codes in a cognitive radio network with multichannel multiuser capability for distributed spectrum access and investigate the problem of how to select appropriate channels to improve channel utilization of secondary users. We also suggest an effective channel selection technique that derives the preferable channels by secondary user to decrease the interference probability to primary user and improve the throughput and other performance metrics of secondary user communication such as decoding error probability.

The reminder of this paper is organized as follows. In section II, we describe the system model. In section III, we introduce the rateless coding technique and properties of rateless codes. The measure for investigating the performance of secondary users, throughput and decoding error probability and a detailed analysis of our channel selection algorithm are provided in section IV. In section V, we introduce The Hidden Markov Model (HMM) based channel occupancy model and propose the novel channel selection technique to improve the throughput and decoding error probability of secondary user communication. Simulation results are provided in section VI and section VII contains conclusion.

2. SYSTEM DESCRIPTION

We consider a cognitive radio network with total S_t Parallel channels, one primary user and K secondary user transmitter-receiver pairs, as shown in Fig.1. Each secondary user uses rateless codes to encode its finite data packets into an infinite number of coded packets. Through spectrum sensing, each secondary user specifies the presence or absence of primary user over each channel. Therefore, at the beginning of a transmission time slot with a duration τ, secondary user transmitter determines the set of channels without primary user activities so called "vacant channel set". In order to transmit coded packets, each secondary user selects N channels from "vacant channel set" independently at random to construct secondary user link (SUL). In future time slots, secondary user transmitter alternatively senses the selected channels and transmits one coded packet through each channel in each time slot. In a time slot, there is the probability of primary user reoccupancy over the selected channels by secondary user, also different secondary users in network may choose the same channel to transmit their coded packets, and thus there is interference during the transmission. At the each secondary user receiver, in order to correctly receiving the coded packet, the instant SINR should be greater than the given threshold so called decoding threshold. When the secondary user receiver has enough correct packets and successfully recovers the original data, it informs the transmitter that it can stop sending further packets.

In our system model, each channel is modeled as frequency flat, block fading channel. Also we assume that the gain of channels between different secondary user transmitters and receivers is independent and identically distributed (i.i.d), corresponding to Rayleigh fading of the amplitudes with variance $\sigma^2 = 1$. The gain of channel between the k_t'th ($k = 1,2,...,K$) secondary user transmitter and the k_r'th ($k = 1,2,...,K$) secondary user receiver over each channel ξ_{k_t,k_r}, is a random variable which has the χ^2 distribution with 2 degree of freedom. So we can define the probability density function of it as follows:

$$f_{\xi_{k_t,k_r}}(\xi) = e^{-\xi} \tag{1}$$

In the context of dynamic spectrum access, the Primary user activity is assumed to be independent with secondary users and channel occupancy by primary user is modeled by two states, namely busy and idle, where busy denotes the channel is occupied by primary user and idle denotes the channel is not use by primary user i.e. available for use by secondary user. We

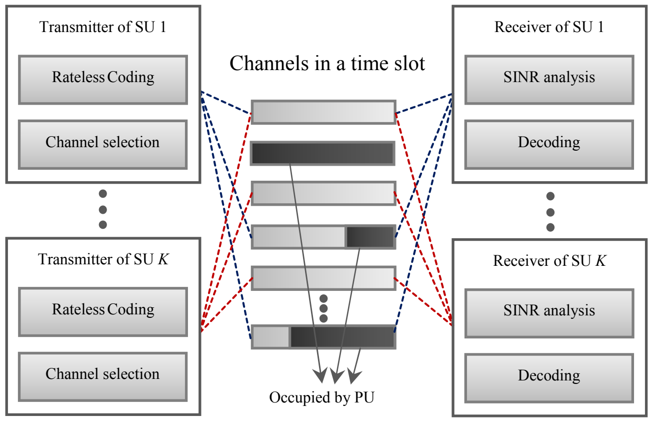

Fig.1. System model

describe the probability density function of the idle and busy of each channel as follows:

$$f_{idle}(t) = \gamma_1 e^{-\gamma_1 t} \tag{2}$$

and

$$f_{busy}(t) = \gamma_2 e^{-\gamma_2 t} \tag{3}$$

Where γ_1 denotes the transition rate from idle to busy and γ_2 denotes the transition rate from busy to idle. According to these definitions, the static probability of idle and busy for each channel can be expressed as:

$$P_{idle} = \frac{\gamma_2}{\gamma_1 + \gamma_2} \tag{4}$$

and

$$P_{busy} = \frac{\gamma_1}{\gamma_1 + \gamma_2} \tag{5}$$

3. RATELESS CODES

In this section, we discuss a new class of erasure correcting codes, called rateless codes that can be used to provide protection against erasures caused by primary user appearance over SUL. These codes are capable of providing protection from the effects of packet loss irrespective of the loss model of the SUL. By recovering lost data packets without requesting retransmission from the sender, these codes provide reliability in various network applications [4] such as multicast, parallel downloading, video streaming etc.

Rateless codes are absolutely different from the traditional erasure correcting codes. Unlike traditional erasure correcting codes, these codes don't have a fixed rate and have low encoding and decoding complexities. Instead of encoding the data packets into a pre-determined number of coded packets, the transmitter uses rateless codes to encode data packets into a potentially infinite number of coded packets. One of the most important properties of these codes is that the receiver does not care which coded packets are received or lost during the transmission, but only concern with the total number of the correctly received coded packets. As long as the receiver gathers a sufficient number of correctly coded packets, the coded data packets could be successfully decoded and the original data have been reconstructed. Other important property of rateless codes is that the transmitter does not require any feedback information for retransmission or coordination of any coded packets. Based on aforementioned exceptional properties of rateless codes, we suggest using these codes in our system model to deal with the interference among different secondary users.

The first practical realization of rateless codes which is designed for erasure channels invented by Luby, called LT code [5]. The other type of practical rateless codes is proposed by Shokrollahi, called Raptor code [6]. Raptor code extends the idea of LT code one important step further. This code consists of two-stage process with a linear block code, called pre-code, as the outer code and an LT code as the inner code. Common effective pre-codes include LDPC or Tornado codes. The property of Raptor code is that it works well over both erasure channels and noisy channels. According to the conclusion in [6], we can design a Raptor code with optimized degree distribution, which is able to recover M original data packets with $M\ (1\ +\ \varepsilon)$ correctly received coded packets through iterative message-passing decoding algorithm [7], where ε is called the overhead. In our system model, we apply Raptor code to each secondary user transmitter for the data transmission.

4. CHANNEL SELECTION ALGORITHM ANALYSIS

In this section, we study the effect of number of selected channels in SUL on the throughput and decoding error probability of secondary user. Also we derive the optimal number of selected channels to maximize these performance metrics while guaranteeing the constraint of interference to primary user communication.

At first, we define the throughput of secondary user k as follows:

$$\eta_k = \frac{M_k}{T_k} \tag{6}$$

Where M_k is the number of correctly received coded packets, and T_k is the number of time slots to receive these coded packets of secondary user k.

In the receiver of secondary user k, correspond to number of correctly received coded packets, decoding error probability (DEP) can be written as:

$$DEP_k = \frac{N_T - M_k}{N_T} \tag{7}$$

Where N_T denotes the number of correctly coded packets that the decoder needs to collect in order to recover the original data packets (for Raptor code, $N_T = M\ (1\ +\ \varepsilon)$), and M_k is the number correctly received coded packets over a period of T time slots for secondary user k.

As explained earlier, through spectrum sensing, each secondary user determines the "vacant channel set" and selects N channels for data transmission. But spectrum sensing process always suffers defects, and we should investigate the probabilities of "false alarm" and "miss detection" in spectrum sensing process. The probability of "false alarm" means that the channel is busy, while the secondary user estimates it as idle, and the probability of "miss detection" denotes the probability of estimating the channel is idle, while it is busy. We use the receiver operating characteristic (ROC) curve to determine the probabilities of "false alarm" and "miss detection", which the ROC curve is the system characteristics of an adopted spectrum sensing technique [8].

According to the probabilities of "false alarm" and "miss detection", also (4) and (5), the number of channels in the "vacant channel set" can be computed as follows:

$$S = \left\lfloor S_t.\left(\frac{\gamma_2}{\gamma_1+\gamma_2}.(1-\alpha)+\frac{\gamma_1}{\gamma_1+\gamma_2}.\beta\right)\right\rfloor \tag{8}$$

Where α denotes the probability of "false alarm", β denotes the probability of "miss detection" and $\lfloor . \rfloor$ is the floor function.

As explained earlier, in each time slot, due to probability of "miss detection", secondary user maybe select those channels which estimated as idle, while actually occupied by primary user. On the other hand, primary user maybe reappearance on the idle channels which selected by secondary user. In addition, there is the probability that a channel in the "vacant channel set" is selected by at least one secondary user. Therefore, according to these three cases, the probability of interference and collision can be expressed as:

$$p_I = \frac{\gamma_2}{\gamma_1+\gamma_2}.(1-\alpha).p_s.p_{idle\rightarrow busy} + \frac{\gamma_1}{\gamma_1+\gamma_2}.\beta.p_s \quad (9)$$

Where p_s denotes the probability of choosing a channel in the "vacant channel set" by at least one secondary user and can be expressed as:

$$p_s = 1-\binom{K}{0}\left(\frac{N}{S}\right)^0\left(1-\frac{N}{S}\right)^K = 1-\left(1-\frac{N}{S}\right)^K \quad (10)$$

and $p_{idle\rightarrow busy}$ denotes the transition probability from idle to busy on a channel during a time slot and can be written as follows:

$$p_{idle\rightarrow busy} = \int_0^\tau f_{idle}(t)dt = \int_0^\tau \gamma_1 e^{-\gamma_1 t}dt = 1-e^{-\gamma_1\tau} \quad (11)$$

Using (4), (5), (10) and (11) into (9), the probability of interference and collision can be expressed as:

$$p_I = \left(1-\left(1-\frac{N}{S}\right)^k\right).\Omega \quad (12)$$

Where

$$\Omega = \frac{\gamma_1\beta+\gamma_2(1-\alpha)(1-e^{-\gamma_2\tau})}{\gamma_1+\gamma_2} \quad (13)$$

The constant Ω specified by the system parameters.

Since the communication of primary user should be protected from the interference and collision, we define a threshold δ to restrict the probability of interference and collision:

$$p_I \le \delta \quad (14)$$

Using the above inequality, the upper bound of number of selected channels by secondary user from "vacant channel set", will be expressed as follows:

$$N \le N_{max} = \begin{cases} S, & if\ \delta \ge \Omega \\ \left\lfloor S\left(1-\sqrt[K]{1-\frac{\delta}{\Omega}}\right)\right\rfloor, & if\ \delta < \Omega \end{cases} \quad (15)$$

According to the above equation, it is important to select the appropriate number of channels that selected by secondary user to construct the SUL. Since the secondary user selects N channel from "vacant channel set" independently at random, if N is too large, the probability of collision between coded packets from different secondary users increases, so that the increasing of collision has led to reducing the throughput; if N is too small, secondary user cannot use the communication opportunities within the vacant channels. Therefore, we should derive the optimal number of selected channels by secondary user in order to maximize the throughput, while guaranteeing the constraint of interference to primary user.

We assume that secondary user k selects a channel from the "vacant channel set" for its communication and other i ($0 \le i \le K-1$) secondary users also select this channel for their transmission. In this case, we investigate the SINR of the secondary user k at the receiver, which can be considered by the packet of secondary user k as the desired signal and the packets of other secondary users as the interference:

$$\lambda_k(i) = \frac{P.\xi_{k,k}}{\sum_{k'=1,k'\ne k}^{i} P.\xi_{k',k}+\sigma} = \frac{\xi_{k,k}}{\sum_{k'=1,k'\ne k}^{i} \xi_{k',k}+1/\rho} \quad (16)$$

Where P is the power of secondary user transmission, ξ denotes the gain of channel which defined in section II, σ is the noise power caused by the channel noise, and $\rho = P_k / \sigma$ is the transmit SNR of secondary user k. Since the secondary user operates with a lower power profile compared with the primary user, therefore, once the primary user appears in a channel used by secondary user, the signal of secondary user either gets corrupted or lost completely. So, due to primary user channel occupancy in a time slot, the transmit SNR of secondary user is practically negligible.

The transmit SINR of secondary user k can be considered in two cases. In first case, we assume that only secondary user k selects the channel in order to transmit its coded packet (i = 0) and the SINR in (16) can be expressed as:

$$\lambda_k(0) = \frac{\xi_{k,k}}{1/\rho} \quad (17)$$

In second case, it is assumed that beside secondary user k, there are i ($1 \le i \le K-1$) other secondary users select the channel for transmit their coded packets. So, the SINR in (16) can be written as:

$$\lambda_k(i) = \frac{\xi_{k,k}}{\sum_{k'=1,k'\ne k}^{i} \xi_{k',k}+1/\rho} \quad (18)$$

The probability density function and cumulative distribution function (cdf) of (17) and (18) are presented in [9].

As explained earlier, in order to correctly received the coded packet and perform the decoding process, the SINR should be greater than the decoding threshold. According to the pdf and cdf of (18) [9], we can express the probability of correctly receiving the coded packet in a time slot as follows:

$$p_r = \sum_{i=0}^{K-1}\binom{K-1}{i}\left(\frac{N}{S}\right)^i\left(1-\frac{N}{S}\right)^{K-1-i}\cdot\int_z^{+\infty} f_{\lambda_k(i)}(x)dx$$
$$= \sum_{i=0}^{K-1}\binom{K-1}{i}\frac{N^i(S-N)^{K-1-i}}{S^{K-1}}\cdot\frac{e^{-z/\rho}}{(1+z)^i} \quad (19)$$

Where $f_{\lambda_k(i)}$ $(0 \le i \le K-1)$ denotes the pdf of SINR in (18) and z is the decoding threshold. According to the (19), the number of correctly received coded packets over a period of T time slots is:

$$M_k = N.p_r = N.\frac{e^{-z/\rho}}{S^{K-1}}.\left(S-\frac{z}{z+1}N\right)^{K-1} \quad (20)$$

In order to maximize the η_k, we should maximize the M_k. Therefore, we have an optimization problem so that by solving it, the optimal number of selected channels by secondary user to maximize the throughput is obtained. The optimization problem and an algorithm to derive the optimal N are provided in [9].

5. PRIMARY USER CHANNEL OCCUPANCY MODELING

In this section, we first introduce the HMM and its structure, then we discuss the channel occupancy model by primary user and introduce the channel selection technique to improve the performance metrics of secondary user communication, throughput and decoding error probability.

A. Hidden Markov Model

A HMM is comprised of a set Y of m possible states,

$$Y = \{y_1, y_2, ..., y_m\} \quad (21)$$

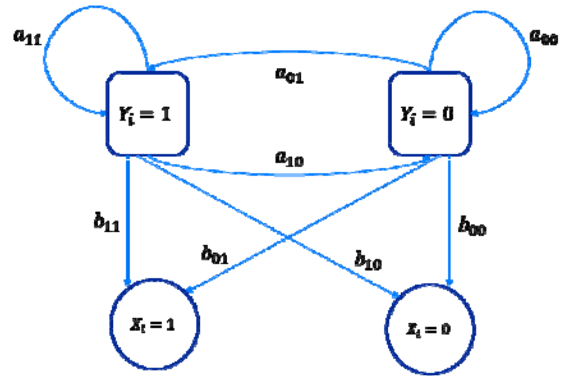

Fig. 2. Channel occupancy model by HMM

And a set X of n possible emissions,

$$X = \{x_1, x_2, ..., x_n\} \quad (22)$$

There are two statistical parameters that determine the performance of a HMM. The first parameter is the state transition probability matrix that represents the probabilities associated with changing from one state to another [10] and it can be express as follow:

$$A = (a_{ij})_{m\times m},\ i, j \in Y \quad (23)$$

Where the entries of (23) are denoted by,

$$a_{ij} = P_r(y_t = j \mid y_{t-1} = i),\ 2 \le t \le T \quad (24)$$

And T denotes the length of the observation period.

The second parameter is the emission probability matrix representing the probabilities associated with obtaining a special output given that the model is currently in a true state and we represent it as:

$$B = (b_{ij})_{m\times n},\ i, j \in X \quad (25)$$

Where the elements of (25) are defined by,

$$b_{ij} = P_r(x_t = k \mid y_t = i).\ 2 \le t \le T \quad (26)$$

We define the parameters of HMM by $\lambda = (A, B, \pi)$, where π is the initial state probability distribution vector.

B. Channel occupancy model

In order to model the primary user channel occupancy, the HMM has been suggested for modeling channel occupancy [11], [12]. In this situation, channel occupancy is modeled as a sequence of binary states. The binary model for channel occupancy is demonstrated in Fig. 2.

At each given time slot, the channel is said to be either occupied by primary user, $Y_i = 1$ or available for use by secondary user $Y_i = 0$. Our goal is to construct a HMM for modeling the channel occupancy by primary user and predict the occupancy model for future time slots. Then, in order to form the SUL, instead of choose the channels independently at random, we can choose preferable channels for data transmission.

C. The proposed HMM

In order to provide a prediction of channel occupancy by primary user, we model the channel as the hidden Markov chain, and train the model using an observation sequence $O = \{O_1, O_2, \ldots, O_T\}$ so called "training observation sequence". In this case, this sequence is comprised of two symbols, 1 and 0, as defined earlier, symbol 1 denotes the channel is occupied by primary user and symbol 0 denotes the channel is available for use by secondary user. For checking the accuracy and statistical stability of the trained HMM, we use the number of previously unseen "test observation sequence" that obtained for the same channel. Then a reliable trained HMM is obtained for the channel, and we use this trained HMM for generating the prediction sequence to compute the "channel availability metric". Therefore, a channel having the higher availability metric value is selected by secondary user for transmission its coded packets.

Based on our system model as described in section II, in order to train and test the HMM, we should obtain an observation sequence by secondary user k. In this manner, secondary user k periodically sense and observe the channel and simultaneously transmit one coded packet in each time slot. If the secondary user k observes the primary user appearance on the channel in a time slot, an observation symbol 1 is recorded, otherwise the recorded symbol is 0. Thus, we obtain the observation sequence $O = \{O_1, O_2, \ldots, O_T\}$ over a period of T time slots. The hidden Markov chain is trained with this obtained training sequence using Baum-Welch algorithm [13]. The Baum-Welch algorithm is an instance of a generalized Expectation-Maximization (EM) algorithm and makes use of both the forward and backward algorithms for HMM [14]. The trained HMM is used to predict the channel behavior with respect to primary user occupancy. As explained earlier, this model is represented as $\lambda = (A, B, \pi)$, along with symbols n and m, where n denotes the number of states in the model and m is the number of distinct observation symbols. Since the observation symbols are 1 and 0, in our model $m = 2$.

In order to construct the creditable HMM, we should validate the trained HMM over unseen observation sequences. The statistical stability of the trained HMM is validate by computing the log-likelihood parameter [15].

D. Channel selection technique

We consider a multichannel multiuser cognitive radio network with S_t Parallel channels as described in section II. Since each secondary user select N channels out of "vacant channel set". it is assumed that the training sequences for selected channels is obtained by secondary user k, through spectrum sensing and observation, which construct HMM for each selected channel using these training sequences, as described earlier. Therefore, the number of observation sequences for each secondary user is corresponding to the number of selected channels from "vacant channel set". Since the spectrum sensing mechanisms are not perfect, thus the impact of "false alarm" and "miss detection" have to be taken into consideration. Hence, the "vacant channel set" for each secondary user may be different.

Let H_s denotes the trained HMM for channel s, GS_{Hs} represent the binary sequence generated by H_s, $|GS_{Hs}|$ represent the length of sequence GS_{Hs}, GS^1_{Hs} denotes the number of 1's in the GS_{Hs}, and μ_s represent the average gap between each two 1's in the GS_{Hs}. According to these parameters, the Channel Availability Metric (CAM) for channel s is defined as follows:

$$CAM_s = \mu_s + \left(\frac{1}{GS^1_{Hs} / |GS_{Hi}|}\right) \tag{27}$$

According to (27), for a channel which trained HMM predicts lower number of time slots with symbol 1, the CAM is higher. In other words, the channel availability metric is higher for a channel which the trained HMM predicts lesser number of time slots in which the primary user occupies the channel i.e. large separation between symbol 1s in the generated sequences.

Secondary user k uses a trained HMM to obtain N generated sequences GS_{Hs} for N selected channels out of its "vacant channel set". Then, it computes the CAM for selected channels and selects the channel with highest value of CAM as the most preferable channel for data transmission and its communication. Other i ($0 \le i \le K - 1$) secondary users use a trained HMM to obtain generated sequences GS_{Hsi} for N selected channels out of their "vacant channel set" and construct their SUL according to the most preferable channels for their communication.

For instance, we consider a generated sequence GS_{Hs} generated by a trained HMM for s'th channel as follows:

$$GS_{Hs} = 0010110001100111 0 \tag{28}$$

In (28), the gap between symbol 1 appearing at position 3 and 5 is equal to 1, between positions 5 and 6 is 0, between positions 6 and 10 is 3, between positions 10 and 11 is 0, between positions 11 and 14 is 2, between positions 14 and 15 is 0, and between positions 15 and 16 is 0. The average gap between any two 1's in (28) is equal to, $\mu_s = \frac{(2+1+3+2+1)}{5} = 1.8$. In (28), $GS^1_{Hs} = 8$ and $\lceil GS_{Hs} \rceil = 17$. Thus, using (27), $CAM_s = 3.925$.

6. SIMULATION RESULTS

In order to examine the proposed channel selection technique, we consider a multichannel multiuser cognitive radio network with $S_t = 300$, $\tau = 2$ (ms), $\gamma_1 = 0.4$ $(1/s)$, $\gamma_2 = 0.6$ $(1/s)$, $\alpha = 0.2$, $\beta = 0.5$ and $\delta = 0.25$. According to (8), it is clear that $S = 200$. We apply a Raptor code with overhead $\varepsilon = 0.035$, which has a degree distribution [6]:

$$\Omega(x) = 0.007544x + 0.493610x^2 + 0.166458x^3 + 0.071243x^4 + 0.084913x^5 + 0.043365x^9 + 0.045231x^{19} + 0.010157x^{20} + 0.010479x^{66} + 0.017365x^{67}$$

In Fig. 3, the variation of throughput with N has been shown. It is assumed that the transmit power of secondary user k, $P = 0.001\,Watt$, and the noise power $\sigma = 0.000001$ $Watt$ and is same for all channels. At the receiver of secondary user k, the decoding threshold $z = 6$ dB. For each given K, there exists an optimal N that maximizes the throughput. According to the value of δ, and from (13), it is seen that $\delta \geq \Omega$, therefore $N_{max} = 200$. We note that N decreases as K increases, because each secondary user has to select less channels for data transmission to compensate the increasing interference caused by the increase of secondary users in network. We construct the two state HMM at the secondary user k for selected channels out of "vacant channel set" by training initial models with training sequence of 50 symbols, using Baum-Welch algorithm, also we initialize the model parameters of HMM i.e. A, B, and π using nearly uniformly distributed values [15]. In order to show the effect of proposed channel selection technique, secondary user k transmits its coded packets through N selected channels out of its "vacant channel set", and obtains a set of observation sequences correspond to N, over a period of $T = 50$ time slots. Secondary user k uses trained HMM to model primary user channel occupancy In future T time slots, and selects N channels based on preferable channels to transmit its coded packets, instead of randomly select N channels.

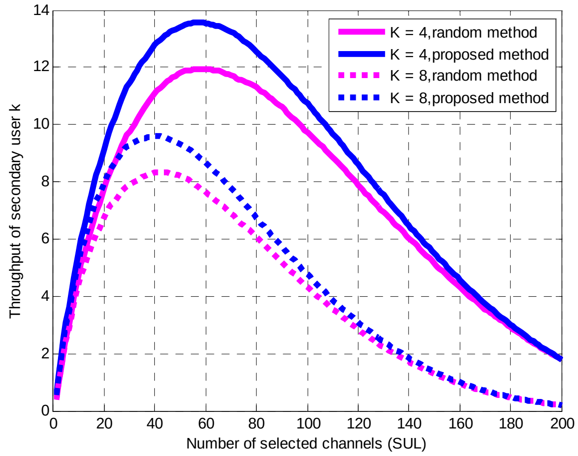

Fig. 3. Variation of throughput with N, $z = 6$ dB

In order to investigate the impact the decoding threshold z on the throughput, it is assumed that the transmit power of secondary user k, $P = 0.001$ $Watt$, and noise power $\sigma = 0.000001$ $Watt$ and is same for all channels. Secondary user k selects N channel from its "vacant channel set" for data transmission and transmits its coded packets over a period of $T = 50$ time slots and Then uses trained HMM to model the primary user channel occupancy in future T time slots and select N channels based on preferable channels to its communication, instead of select N channels randomly. In Fig.4, the variation of throughput with N, for $K = 6$ and two different values of decoding threshold $z = 5$ dB and $z = 8$ dB has been depicted. As it is observed, for larger value of the decoding threshold z, the throughput decreases. Because the probability of correctly receiving a coded packet for the receiver of secondary user k decreases.

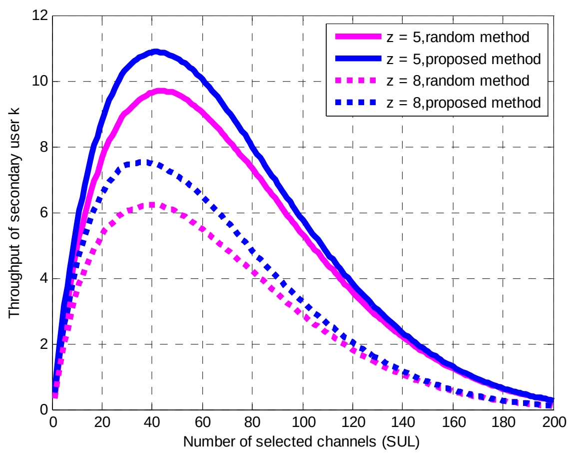

Fig. 4. Variation of throughput with N, $z = 5$ dB and $z = 8$ dB

Eventually, we study the effect of proposed channel selection technique on the decoding error probability in receiver of secondary user k. we assume that the number of data packets $M = 1000$ and secondary user k uses the considered Raptor code with overhead $\varepsilon = 0.035$. In this case, $P = 0.001$ $Watt$, $\sigma = 0.000001$ $Watt$, $K = 4$ and decoding threshold $z = 6$ dB. It is assumed that the secondary user k operates with the optimal N [9]. Secondary user k transmits its coded packets through N selected channels from its "vacant channel set" over a period of $T = 50$ time slots (secondary user k has M data packets to transmit over each period of T time slots), then uses the trained HMM to model the primary user channel occupancy in future T time slots, and selects N channels based on preferable channels, instead of randomly select N channels, to transmit the same number of coded packets over a period of T time slots. The decoding error probability and the effect of proposed channel selection technique have been shown in Fig.5.

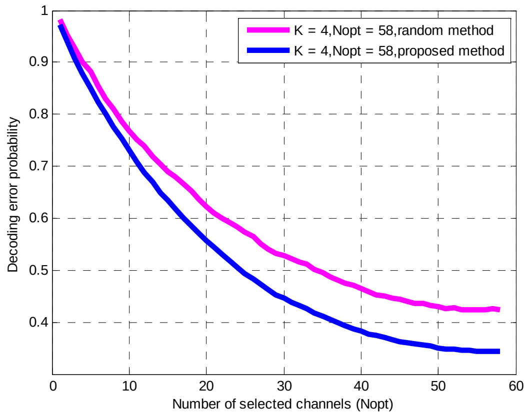

Fig. 5. Variation of decoding error probability with N, $z = 6$ dB

7. CONCLUSION

In this paper, we have used parallel channels for data transmission over a multichannel multiuser cognitive radio network with the help of rateless codes. We have shown that rateless codes have ability to increase the tolerance of interference from primary user appearance, also they can compensate for the loss incurred by collision between several secondary users. We have obtained the upper bound of the selected channels by secondary user with the goal of protecting the primary user transmission; also we have derived the optimal number of selected channels by secondary user to maximize the throughput of secondary user, considering the constraint interference of primary user communication. We have used the HMM to model the channel occupancy by primary user. The HMM has been trained by Baum-Welch procedure. We have proposed a channel selection technique to improve the spectral efficiency and decoding error probability of secondary user communication.

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