Improving Spectral Efficiency Using Hidden Markov Models

T. Aswathy and R. Vadivelu

Abstract--- *Radio Frequency spectrum is a precious, natural resource for wireless communication. Insufficiency of the spectrum is one of the major problems we are facing today. Cognitive Radio is a promising technology used for the detection of the spectrum holes and to allocate these idle frequencies to Un Licensed User or Secondary User (SU) without causing much interference to Licensed User or Primary User (PU). In this paper, we present a novel approach for spectrum sensing using Hidden Markov Models (HMM). Existing research assumes the presence of a Markov chain for sub-band utilization by PU, but this assumption has not been validated. Here we validate the existence of a Markov chain for sub-band utilization and formulating the Hidden Markov Model (HMM) for spectrum sensing. The accuracy of the proposed method is substantiated using extensive simulations.*

Keywords--- *Cognitive Radio, Hidden Markov Models, Markov chain, Spectrum Sensing*

I. Introduction

THE RF spectrum is a natural resource for the current wireless communication system. As the number of wireless standards are increasing, spectrum scarcity also increases. Recent research shows that a large portion of the spectrum is not being occupied by PUs most of the time even in urban areas. These unoccupied frequency bands are called spectrum holes or white spaces [1]. Cognitive Radio (CR) is a promising technology used for the detection of spectrum holes and to allocate them to SUs without causing interference to PUs. The spectral efficiency and channel capacity can be improved using CR.

The sub-band utilization by PU at any time can be considered as a state, which can be either free (unoccupied) or busy (occupied). Existing research assume existence of a Markov chain for sub-band utilization by PUs. In this paper, we validate the existence of a Markov chain for this sub-band utilization.

Initially, the PU status is modeled as a uniformly random sequence for the sake of framework to start with. Since the true states of a sub-band are never known to the CR, instead of uniformly random sequence a Markov Model can be applied. Viterbi algorithm is used to find the hidden states of HMM. The effectiveness of this method can be assessed by performing extensive simulations.

The rest of the paper is organized as follows. Section II covers various issues in spectrum sensing and detection. Section III presents spectrum sensing engine based on energy detection. HMM concept is introduced in section IV and section V evaluates the system performance through simulations. Finally, section VI draws the conclusion.

II. System Model

The configuration [2] of the proposed spectrum sensing model using HMM is shown in Figure 1. Power measurements are collected for a sub-band at regular intervals of time, over the entire observation period. They are converted into binary data Y based on a preset threshold. CR performs a validation check on this data to ensure Markovian property. If it follows a Markov chain, then the Markovian parameters are estimated. CR simultaneously sense the spectrum for PU occupancy by energy detection and pass this data X to the HMM block. The predicted state X' is generated by Viterbi Algorithm. Original PU occupancy Y is compared with X and X' to find the accuracy of the proposed spectrum sensing mechanism.

The functions of each block are described as follows. The observation period is defined by $t = \{1, 2,. . . ,T\}$, where each i represents the i^{th} sensing duration. The binary sequence $Y = \{y_1, y_2,. . . , y_T\}$, represents the true state sequence. If $y_i = 1$ the sub-band is free otherwise it is occupied. The sensed output of CR is represented by $X = \{x_1,x_2, . . ., x_T\}$, the entity $x_i = 1$ if the state of the sub-band at the i^{th} sensing duration is sensed to be free. The sequence X represents the prediction of the true state sequence $Y = \{y_1,y_2,. .., y_T\}$.

Practically the true state sequence Y is unobservable. The only information available is the sensed data X provided by the appropriate sensing mechanism. Here we assume a Hidden Markov Model to find the hidden state Y.

The readings provided by the sensing mechanism can be prone to errors. Here we assume that Y is closer to X' than X, so Y is compared with X and X'. Our proposed work is to enhance the sensing accuracy of the sensed data X under the assumption that Y and X are governed by an HMM.

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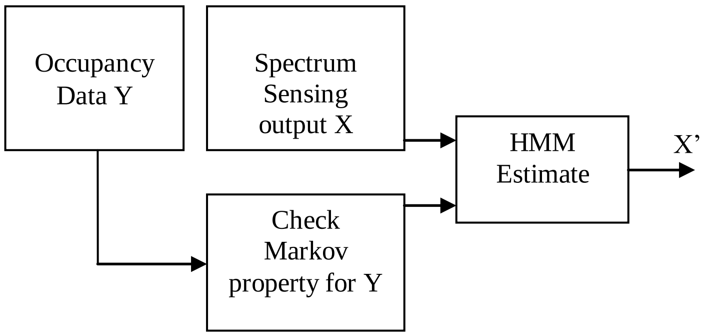

Figure 1: The System Model for Enhanced Spectrum Sensing

III. Proposed Method

Our work demonstrates a simulation model in MATLAB environment for the CR, with HMM as prediction of PU status. Our proposed work flow is as shown in Figure 2.

The PU status model will generate a sequence which implies the true status of the PU i.e., the true state Y. If $y_i = 0$ the channel is occupied otherwise it is free. Initially, the PU status is generated by the predefined Matlab function rand (). It will generate uniformly distributed random numbers from the interval (0, 1). This is applied as an input to the spectrum sensing engine block, which is based on energy detection.

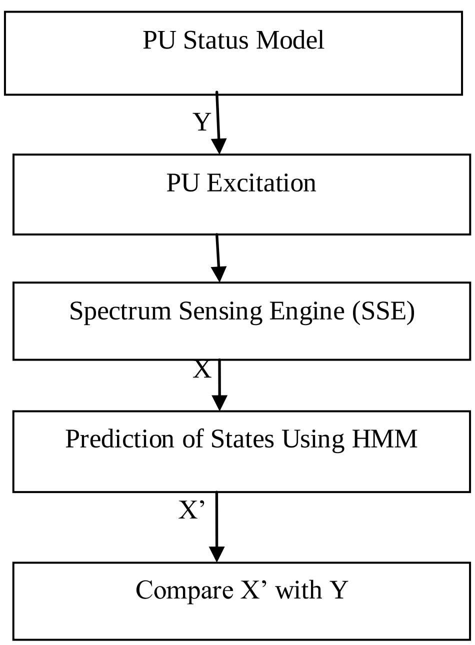

Figure 2: Proposed Work Flow

The PU excitation block will simulate air interface of CR. According to the status of PU signal, it may either transmit its signal (occupied by PU) or simply noise (free). Spectrum Sensing [3], [6] is the primary and challenging functionality of CR Here "energy detection" [4] method is used to detect the presence of the PU. The energy in the concerned sub band is measured and compared with a threshold. If the value is greater than the threshold, it will predict the presence of PU otherwise the channel is free to use by the SU. There may be error in the output of "Spectrum Sensing Engine (SSE)". Under the assumption that there is an existence of Markov chain in the PU usage, the output of SSE is modified into a more accurate model. The prediction of true state of PU from the output of SSE is aided by the HMM [8].

The predicted state X' and the true state Y are compared for more accurate prediction of proposed Spectrum Sensing Method. Instead of using uniformly random sequence for Y sequence generation, Markovian Model is applied with the assumption that the PU will follow a Markovian chain. Since the true states are hidden, Viterbi Algorithm (VA) can be used for predicting Hidden States, which will predict the most probable path for state Y to follow.

IV. Hidden Markov Model

The sequence Y is modeled as a Markov chain, which is characterized by an initial distribution $\pi = (p_0,p_1)$ and transition matrix $P = (p_{ij})$. State space $S = \{0,1\}$ and $P = Pr(y_n=j|y_{n-1}=i)$.

A HMM [7], [9] is a stochastic process created by two interrelated probabilistic functions. One of these functions is the Markov chain with a finite number of states. The other is a set of random functions, referred to as the *alphabet*, wherein each function generates a *symbol* related to a state in the Markov chain.

Here the states correspond to PU occupancy, i.e, it can be free or occupied. Given the initial probability π, transition probability P, emission probability $e_y(x_i)$, and the observation, we can find Y using VA.

- *Viterbi Algorithm Proceeds as Follows:*

Let v_i (t) be the probability of the most probable path ending in state i at time t.

- *Step I : Initialization*

  $v_i(1) = \pi\, e_y(x_1)$ i,j ϵ S.

- *Step II: Recursion*

  $v_j(t) = \max\,[v_i(t\text{-}1)\, p_{ij}\,]\, e_y(x_t)$ $1 \le i \le N$,

  N is the number of states

- *Step III. Termination and Back Tracking*

Let Y_n be the state in which the system is at time *n*. The process is assumed to be Markovian. The evolution of the sequence y_1, y_2,… y_n is hidden. However, the hidden sequence can be represented by a sequence of symbols from the alphabet **Ω** = {0, 1, 2,. . . , N}. A state k can produce a symbol b from a distribution over all possible symbols b = 0, 1, . . , N and its probability can be represented as:

$$e_k(b) = Pr\,(X_n = b|Y_n = k\,)$$

$$P^* = \max [v_i(T)] \qquad 1 \le i \le N$$

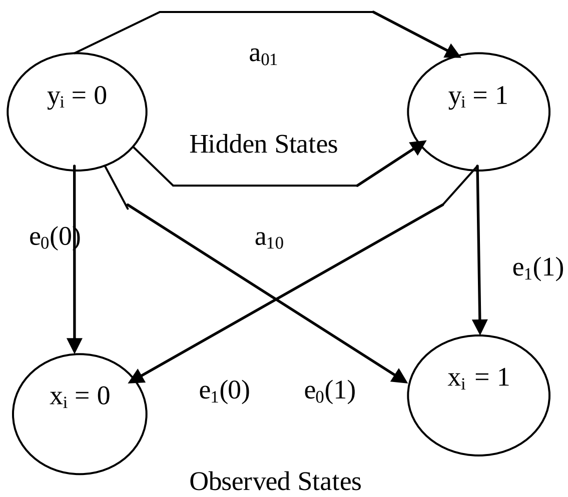

Figure 3: Representation of HMM in Spectrum Sensing

State Space : {0,1}
Hidden States : y_i , Observed States : x_i
Transition Matrix $P = p_{ij}$, i = 0,1 and j = 0,1
Initial Distribution : $p_0 = Pr(y_i = 0)$ and
$p_1 = Pr(y_i = 1)$
Emission probabilities, $e_y(x_i)$

These probabilities are known as *emission probabilities.*

At the end we choose the highest probability endpoint, and then we backtrack from there to find the highest probability path. Note that the maximally likely path is not the only possible optimality criterion, for example choosing the most likely state at any given time requires a different algorithm and can give a slightly modified result. But the overall most likely path provided by the VA provides an optimal state sequence.

V. Simulation Results

We have considered energy detection method for spectrum sensing with two PUs and the length of observation sequence is three. The measurements are collected in the band 10 - 12.5 MHz. Here FFT Averaging Ratio (FAR) Algorithm [10] is used for spectrum sensing. It works as follows, the base band signal is segmented into T frames and its t^{th} frame is denoted by $x_t(n)$, where N is the number of samples in a frame. Multiply $x_t(n)$ with a window function w(n) to get $x_{w,t}(n)$.

$$x_{w,t}(n) = x_t(n)\, w(n)$$

Then take its FFT to get $X_t(k)$.

$$X_t(k) = \sum x_{w,t}(n) \exp(-j2\pi nk/N) \qquad n = 0 \text{ to } N-1$$

$$K = 0,1,..,N-1,\ t = 0,1,..,T-1$$

Calculate its PSD as $|X_t(k)|^2$. The PSD of T frames are averaged to get $P_{avg}(k)$.

$$P_{avg}(k) = (1/T) \sum P_t(k)$$

The mean of $P_{avg}(k)$ is P_m , $P_m = (2/N+2) \sum P_{avg}(k)$

Form a decision variable r(k) as a ratio P_{avg}/P_m. Then thresholding is applied to r(k). If $r(k) > \alpha$, then it is occupied, otherwise it is free. α is a preset threshold. Decision results are shown in Figure 4 and 5. Here the threshold is set to be 1.0194.

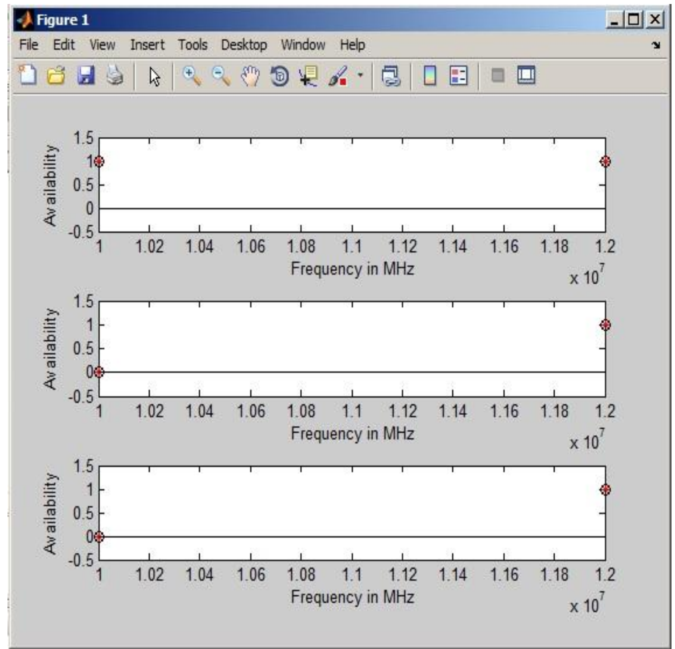

Figure 4: Status of the PU for Three Consecutive Observations

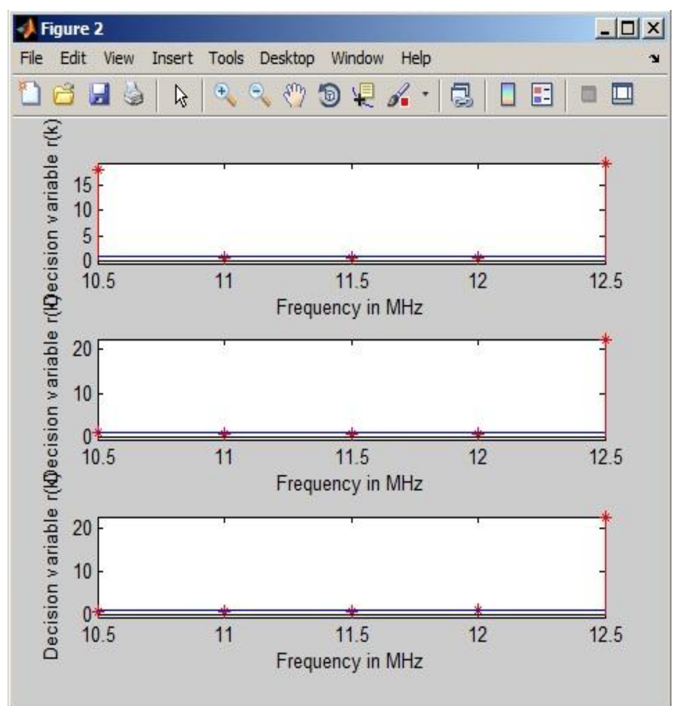

Figure 5: Decision Variable for Each Sub-Band

VI. CONCLUSION AND FUTURE WORK

Existing research assumes the existence [2] of a Markov chain in spectrum occupancy by PUs. In this paper, we used FAR Algorithm for sensing data. Initially used predefined function i.e, uniform random sequence is replaced by Markovian Model for PU status generation. Here a basic cognitive frame work is simulated. Energy Detection is used as the spectrum sensing method. Our assumption is that the output of sensed data is prone to errors.

Now we are working on VA which is a prediction algorithm for HMM. After completion, it will be added to the simulation model.

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