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Research Article

An Efficient Channel Sensing Algorithm Based on Hidden Semi Markov Model and Channel Quality Predicition

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Abstract: In recent years, Cognitive radio has become one of the most important emerging technologies to handle the primary user channel utilization in next generation cellular networks. The major issues in the future generation cellular networks are channel sensing and allocation for secondary user. Several optimization algorithms have been proposed in the literature for sensing the channel in future generation networks. Although, the existing algorithms provide good results, it has certain limitations such as high computational complexity in real time implementation. In order to overcome the limitation in existing algorithms and to obtain the efficient results, this study proposed a probability based channel sensing algorithm. Hidden Markov model is used as the probability calculation of primary user state and the predicted channel is validated using the proposed quality estimation method. The estimated channel is predicted using the probability of detection and probability of false alarm is used for validating the algorithms. The performance metrics used to evaluate the proposed algorithm is mean square error value and the channel is estimated using different estimators. The comparison of the proposed algorithm with the existing algorithms and performance of the proposed algorithm is better than the other algorithms.

Keywords: Hidden semi Markov model, primary user, secondary user, spectrum sensing

INTRODUCTION

In recent years, rapid growth of wireless communication fields leads to huge demand of channel resources. To overcome the shortage of the resources in communication field, researchers introduced a Cognitive Radio (CR) as solution to the resource scarcity (Haykin, 2005). The resources are utilized efficiently by allocating the channel to Secondary Users (SU) whenever Primary Users (PU) are absent. In other words CR provide strategies to use the transmission spectrum more efficiently by enabling the cognitive Secondary Users (SUs) to use the transmission bands allocated to the licensed Primary Users (PUs) while causing only limited (or tolerable) interference to them. In order to achieve an efficient communication, the secondary users must detect the presence of primary users (Gursoy and Gezici, 2011; Zhao and Sadler, 2007). The presence of the primary user is one of the important processes in communication and many methods are introduced for detecting the primary users over the last couple of years.

The different channel sensing techniques are surveyed by Letaief and Zhang (2009) for cognitive radio networks. The methods such as matched filter, energy detection and cyclostationary detection are used for channel sensing in cognitive radio networks. A practical scenario occurs when the primary spectrum utilization is such that the secondary user should search over a wide band to identify the locations of vacant frequency bands (also referred to as spectrum holes). For example consider a scenario where a Secondary User (SU) sequentially searches a number of wideband primary channels in order to identify a transmission opportunity. When the channel or spectrum hole is identified as a free then the secondary user predicts the quality of the selected channel and then utilize the selected channel for efficient transmission. The performance metrics used to evaluate the cognitive radio networks is throughput maximization, operational reliability and SNR estimation. The main disadvantages of the existing system are also explained in (Letaief and Zhang, 2009). The matched filter required an efficient receiver detects each and every primary user. The complexity is increased during the real time implementation of the matched filter. Energy detector is very sensitive to the noise variance and it affects the overall performance of the channel sensing algorithm. This is the main disadvantage of the energy detection.

Many researchers introduced the channel sensing algorithm for efficient transmission of data between the secondary users using the primary channel. Kim and Shin (2008) sorted the channel sensing time, channel availability probability using the optimal sensing

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sequence in homogenous channel capacity in an ascending order. Chang and Liu (2007) investigated optimal channel selection problem using error-free sensing. The difference between the transmission reward and probing cost is used to choose the strategy of the transmitter's objective. Shu and Krunz (2009) extended the work of (Chang and Liu, 2007) in (Shu and Krunz, 2009) by considering sensing error. The author considered a channel sensing order is random, channel probing is perfect and most importantly impact channel sensing order is not considered in this research work. This is the main disadvantage in this research. The authors in (Jiang *et al*., 2009; Ewaisha *et al*., 2011) used adaptive rate transmission and secondary utility function for obtaining the sensing order.

In this research, to overcome the problems in the existing methods, a new method called Hidden Semi Markov Model is proposed for channel sensing and the predicted channel quality is estimated. The selected channel is used for data transmission between the secondary channels. The proposed method is explained briefly in the following sections.

LITERATURE REVIEW

Cheng and Zhuang (2011) introduced a channel sensing order without previous knowledge of primary user activities for secondary users. The channels are sensed using this method in descending order using the achievable rates with optimal stopping. The performance of the method used in this approach is evaluated using the metrics such as throughput and resource utilization.

Eslami and Sadough (2010) investigated the problems of wideband spectrum sensing. The detecting vacant frequency subbands is considered as a major issue in cognitive radio networks. The mathematical framework is used in this system for detecting the frequent subbands. In order to achieve the efficient spectrum sensing the author used parameters of the phase-field functional, threshold value. The author compared the conventional sensing algorithms with the method used in this approach.

The sensing order problem for multi-user and multi-channel in cognitive radio networks is discussed by (Zhao and Wang, 2012). In this study, author mainly focused on the multiuser problem while other studies focus on a single user and access the channel according to their individual sensing orders. The major issue related in this study is channel access collisions among the secondary users. In order to overcome the problems the author used dynamic programming for the calculation of channel availability, transmission rate and collision probability and improve the sensing efficiency and transmission throughput.

The sensing-order problem in two-user multichannel cognitive medium access control is discussed by Fan and Jiang (2009). The brute force algorithm is used for finding the optimal sensing order for two users have some problems such as high computation complexity. The author used two algorithms for finding optimal sensing order. They are greedy algorithm and incremental algorithm. The algorithms were compared with existing algorithm brute force and the author proved that the algorithms have less computational complexity. Although the algorithms have less computational complexity, the results are not obtained efficiently.

System model: The system model of cognitive radio networks for sensing the channel is considered in this research in (Bulla, 2006). The scenario considered in this research consist of single primary transmitter, single cognitive radio are used for operating on single narrowband channel. The primary transmitter is active only when it has data to transmit. The primary transmitter state is identified using the cognitive radio which acts as a sensor. The primary transmitter is located in the transmission range of the cognitive radio and their locations are fixed. The licensed channel does not properly utilize by the primary user as a result the channel fluctuate between idle and active states. The channel state is represented using the finite set $X = \{1; \dots; d\}$.

METHODOLOGY

Hidden semi Markov model: A hidden semi Markov model is an extension of hidden Markov model using the semi Markov chain process with parameters such as variable duration or sojourn time for each state. In HSMM number of observation for each state is high than the number of observations present in the HMM (Sadough and Jaffrot, 2005; Sadough *et al*., 2009). This is the main dissimilarity between the HMM and HSMM. In this research, hidden semi Markov model is used for channel sensing. The HSMM consist of pair of discrete-time stochastic processes $\{S_t\}$ and $\{X_t\}, t \in \{0, \dots, \tau - 1\}$. The observed process $\{X_t\}$ is linked to the hidden, i.e., unobserved state process $\{S_t\}$ by the conditional distribution depending on the state process:

$$b_j(x_t) = P(X_t = x_t | S_t = j) \text{ with } \sum_{x_t} b_j(x_t) = 1$$

Semi-Markov chains: The semi Markov chain process is constructed using the embedded first order Markov chain and the parameters is defined by the initial probabilities $\pi_i := P(S_0 = i)$ with $\sum_i \pi_i = 1$ and the transition probabilities for the state i. For each $j \neq 1$:

$$p_{ij} := P(S_{t+1} = j | S_{t+1} \neq i, S_t = i) \text{ with } \sum_{i \neq 1} p_{ij} = 1 \text{ and pij=0}$$

The dwell time distributions are allotted to the states in the model in order to construct the semi-Markov chain model. It is explained as follows:

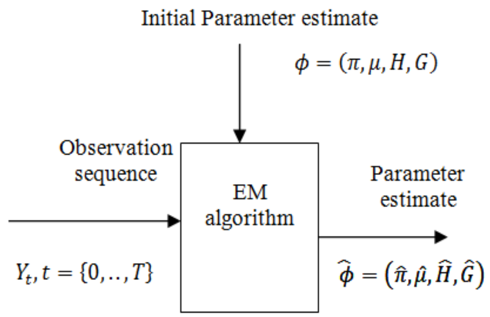

Fig. 1: Parameter estimation using Baum algorithm

$$d_j(u) := P\left(\begin{matrix} S_{t+u+1} \neq j, S_{t+u-v} = j, v \\ = 0, \ldots, u-2 | S_{t+1} = j, S_t \neq j \end{matrix}\right)$$

where, $d_j(u)$ is dwell time or sojourn time distribution for $u \in \{1, \ldots, M_j\}$ from $t+1$ to $t+u$. u is represented as unobserved process of length, M_j is upper bound of the time spent in state j. For the calculation of sojourn time, by assuming that the state occupancy distribution is used the finite set of points $\{1 \ldots, M_j\}$ and the point M_j is increased up to entire length of observed sequence. If it is last state means then the sojourn time is calculated for that particular state is:

$$D_j(u) := \sum_{v \geq u} d_j(v)$$

It is also called as survivor function of the sojourn time in state j. The survivor function is defined as a mean of individual probability masses of all possible sojourns of length $v \geq u$. The combination of first order markov chain and state occupancy distribution is used for the construction a semi-Markov chain. If the process starts in state j at time $t = 0$, the following relation can be verified:

$$P(S_t \neq j, S_{t-v} = j, v = 1, \ldots, t) = d_j(t)\pi_j$$

Parameter estimation: The HSMM based on HDP denoted by $\phi = (\pi, \mu, H, G)$ where π is an initial probability, a vector of mean observed signal strengths μ, a transition matrix H, a vector of observed signal strength variances G. The parameter estimation of hidden semi Markov model is more complicated than the hidden Markov model (Sadough, 2008). The EM algorithm is used for calculating the unknown parameters of the hidden semi Markov model from real data in the maximum likelihood sense. Given an initial parameter estimate ϕ and a sequence of signal strength observations $Y_t, t = \{0,..,T\}$ a parameter estimate $\hat{\phi}$ with higher likelihood is computed. The steps used to calculate the parameter estimation is explained as in Fig. 1.

The E-step involves estimating two terms:

- The probability of the current state is calculated using the below formula:

$$p(z_{t-1}, z_t | y_0^T; \phi), t = 1, \ldots, T$$

which can be efficiently calculated as follows:

$$p(z_{t-1}, z_t | y_0^T; \phi) = \frac{\bar{\alpha}(z_{t-1} y_0^{t-1}) \bar{\beta}(y_{t+1}^T | z_t) [H]_{z_{t-1}, z_t} p(y_t | x_t)}{\sum_{z_{t-1}, z_t} \bar{\alpha}(z_{t-1} y_0^{t-1}) \bar{\beta}(y_{t+1}^T | z_t) [H]_{z_{t-1}, z_t} p(y_t | x_t)}$$

where $[H]_{z_{t-1}, z_t}$ denotes the (z_{t-1}, z_t) entry of the transition matrix H.

- The probability of the process left state and entered state is calculated given below:

$$\xi_t(i, j) = P(z_t = i, z_{t+1} = j | X = x; \theta)$$

- The expected number of times a process spends u time steps in state j:

$$\eta_{iu} = P(z_u \neq i, z_{u-v} = i, v = 1, \ldots, u | X = x; \theta) + \sum_{t=1}^{T} P(z_{t+u+1} \neq i, z_{t+u-v} = i, v = 0, .., u-1, S_t \neq i | X = x; \theta)$$

M steps:

- The initial transition probabilities are estimated as:

$$\hat{\pi}_{j,i} = p(z_0 = (a, i) | y_0^T; \phi)$$

$$\hat{h}_{ab}(ij) = \frac{\sum_{t=1}^{T} p(z_{t-1} = (a,i), z_t = (b,j) | y_0^T; \phi)}{\sum_{(b,j) \in \mathbb{Z}} \sum_{t=1}^{T} p(z_{t-1} = (a,i), z_t = (b,j) | y_0^T; \phi)}$$

The aforementioned equation is mainly used for the calculation of parameters and if X_t is considered as normally distributed i.e., $X_t | S_t = i \sim N(\mu_i, \sigma_i^2)$ then parameters μ_i and σ_i^2 can be estimated as:

$$\hat{\mu}_i = \frac{\sum_{t=1}^{T} \sum_{i=1}^{r} p(z_t = (,i) | y_0^T; \phi) y_t}{\sum_{t=1}^{T} \sum_{i=1}^{r} p(z_t = (,i) | y_0^T; \phi)}$$

and,

$$\hat{\sigma}_i = \frac{\sum_{t=1}^{T} \sum_{i=1}^{r} p(z_t = (,i) | y_0^T; \phi)(y_t - \hat{\mu}_i)}{\sum_{t=1}^{T} \sum_{i=1}^{r} p(z_t = (,i) | y_0^T; \phi)}$$

- The state duration density is estimated using the following the equation based on the non probability mass function:

$$d_i(u) = \frac{\eta_{iu}}{\sum_v \eta_{iu}}$$

The cognitive radio systems performance is evaluated using the aforementioned parameter evaluation by generating the simulated data. The evaluation of transition matrix $\widehat{H}$ using the parameter estimate $\widehat{\phi}$ is a complex process and it is used to obtain the dynamics of the primary transmitter state process. Different propagation models and shadowing variance can be represented by adjusting $\widehat{\mu}$ and $\widehat{G}$ as appropriate, while retaining the same $\widehat{H}$.

State estimation and prediction: Let us consider the parameter estimation of HSMM as ϕ like aforementioned. The primary user state is represented as X_t and here two states are considered 0 and 1 (Tian and Giannakis, 2006). $X_t = 0$ represents the idle state and $X_t = 1$ represents active state. Then the state is estimated using the parameter of HSMM as:

$$p(z_{t+m}|y_0^T;\phi) = \sum_{z_t} p(z_t|y_0^T;\phi)p(z_{t+m}|z_t;\phi)$$
$$= \sum_{z_t} \bar{\alpha}(z_t, y_0^T)[H^m]_{z_{t-1},z_t}$$

For $m \geq 0$ and $t \geq 0$. As mentioned above, the complexity of the forward recursion for computing $\bar{\alpha}\,(z_t, y_0^t)$ is $O\,(d^2r^2)$ per step. Since H^m can be pre-computed, the computational complexity of the forward recursion is also $O\,(d^2r^2)$, or $O\,(r^2)$ when $d = 2$. A detection scheme for the state process of the semi Markov chain at time $t + m$, given y_0^t, is obtained from:

$$\widehat{X}_{t+m|t} = \begin{cases} 0, \text{if } p(x_{t+m} = 1|y_0^T;\phi) \geq \gamma \\ 1, \text{otherwise} \end{cases}$$

where, using (22) we can calculate:

$$p(x_{t+m} = 1|y_0^T;\phi) = \sum_{s_{t+m}} p(z_{t+m} =$$
$$1{,}st{+}m|y0T;\phi$$

And $0 < \gamma < 1$ is a decision threshold. The computational complexity of the detector given by (23) consists of $O\,(r^2)$ multiplications.

Based on the above the calculation the primary user state is estimated using the hidden semi Markov model probability and if the channel is idle state then the channel is selected for further data transmission. After the channel is selected it is verified using the channel quality prediction based on the mathematical formulation mentioned below. Selected channel is given as a input to the channel quality prediction.

Sensed channel quality prediction: The selected channel based on the state prediction of primary user is given as input to the quality prediction and it is evaluated using two metrics. The first parameter for channel quality prediction used here is primary channel sensing accuracy of the secondary user and the second parameter is duration of the channel availability. In this research, the channel is sensed using the probability of HSMM. The first parameter channel sensing accuracy can be calculated using the higher detection probability P_d and false alarm probability P_f. The general formula for the calculation of:

$$C_{sa} = P_d(1 - P_f)$$

The second parameter is calculated using formula given below:

$$C_{id} = 1/\lambda$$

where, λ is estimated duration of the primary state. The channel quality is calculated by combining the two parameters and the formula for the channel quality prediction is given below:

$$C_q = (1 + \log_\epsilon C_{sa})C_{id}$$

where, ϵ is used to represent the preference of the secondary channel and it can be derived as follows:

$$\frac{\partial C_Q}{\partial C_{id}\,\partial\epsilon} = -\ln C_{sa}\left(\frac{1}{\ln\epsilon}\right)^2 > 0$$

$$\frac{\partial C_Q}{\partial C_{id}\,\partial\epsilon} = -\frac{C_{sa}}{C_{id}\epsilon}\left(\frac{1}{\ln\epsilon}\right)^2 < 0$$

For the second parameter the channel idle duration ϵ value should be high and for first parameter the channel sensing accuracy ϵ value should be low.

EXPERIMENTAL RESULTS

The simulation results of proposed sensing algorithm are present in this section. The selected channel is validated using the estimators such as minimum MSE, Mismatched MMSE and proposed channel quality prediction in order to measure errors. It is assumed that primary users are present in the environment with a probability of 0.25; the parameter used for experimental results comparison is false alarm probability, detection probability and it is shown in the Table 1.

Mean square error: Mean Square Error (MSE) is defined as the difference between predicted values of the proposed algorithm and the true values of the quantity being estimated using the estimator. The proposed sensing algorithm errors are measured using estimators such MMSE, Mismatched MMSE and proposed channel quality prediction:

Table 1: Parameter used in experimental results

Parameter	Value
Length of the state/observation sequence (T)	100
False alarm probability	(0.01, 0.10)
Detection probability	(0.09, 0.99)

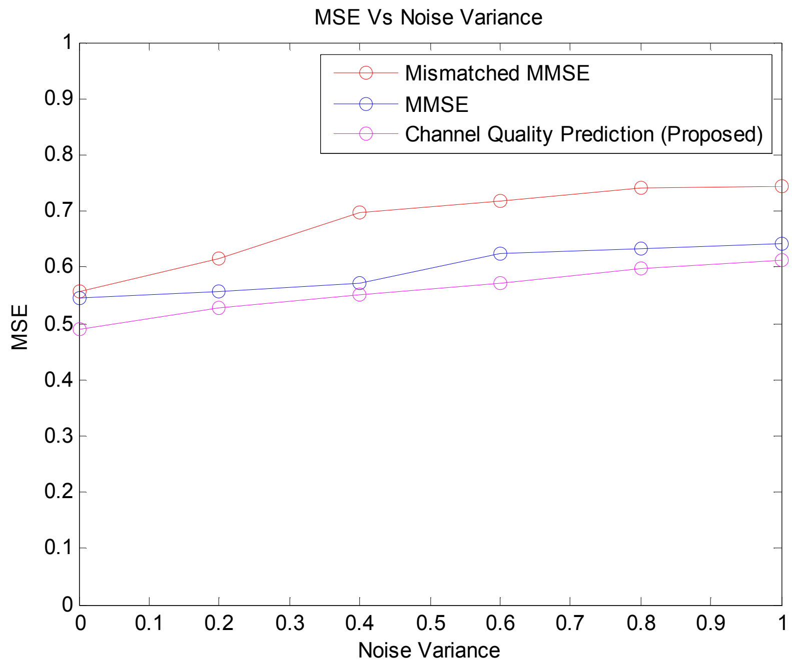

Fig. 2: MSE vs. average noise power

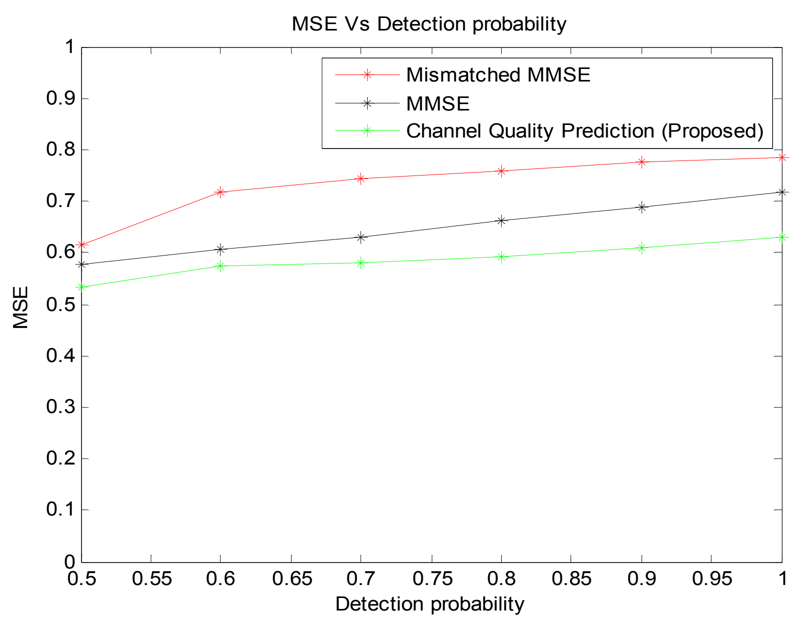

Fig. 3: Comparison of detection probability

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

Noise variance: The Figure 2 shows that the graphical representation of the measure of noise variance and MSE of the proposed algorithm using different estimators such as MMSE, Mismatches MMSE and proposed channel quality estimator. It shows that the proposed algorithm obtains the lowest values of the MSE and other two algorithms shows the worst performance. If the noise variance is increased then the MSE values are also increased which leads to the close performance. The experimental results are shown in the Table 2.

Detection probability: The Figure 3 shows that the graphical representation of the measure of noise variance and MSE of the proposed algorithm using different estimators such as MMSE, Mismatches MMSE and proposed channel quality estimator. It shows that the proposed algorithm obtains the lowest

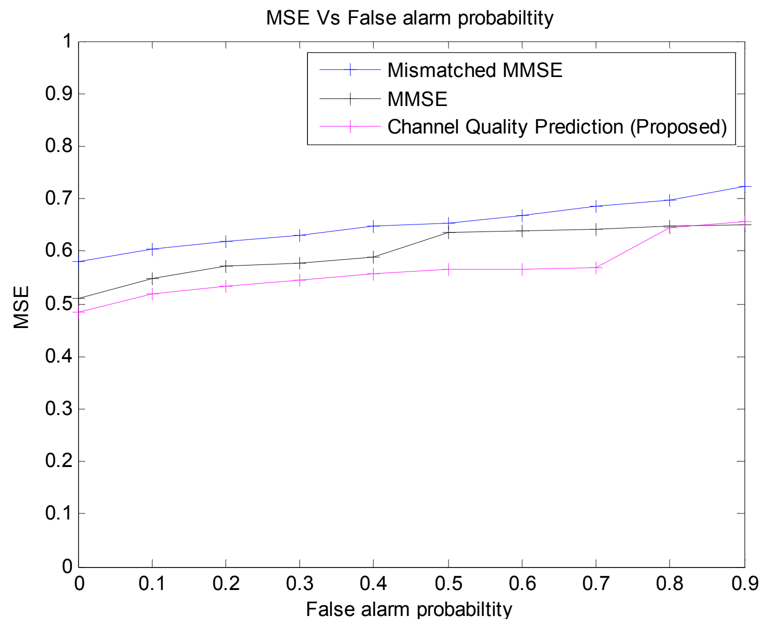

Fig. 4: Comparison of false alarm probability

Table 2: Comparison of MSE vs. average noise power

	Channel quality prediction (proposed)	MMSE	Mismatched MMSE
0.0	0.25	0.34	0.37
0.2	0.43	0.45	0.47
0.4	0.52	0.53	0.54
0.6	0.58	0.59	0.60
0.8	0.63	0.64	0.65
1.0	0.66	0.66	0.68

Table 3: Comparison of detection probability

	Channel quality prediction (proposed)	MMSE	Mismatched MMSE
0.5	0.420	0.433	0.458
0.6	0.425	0.445	0.457
0.7	0.430	0.448	0.458
0.8	0.435	0.452	0.459
0.9	0.443	0.456	0.460
1.0	0.450	0.459	0.462

Table 4: Comparison of false alarm probability

	Channel quality prediction (proposed)	MMSE	Mismatched MMSE
0.0	0.35	0.36	0.37
0.1	0.39	0.40	0.42
0.2	0.43	0.45	0.50
0.3	0.47	0.50	0.55
0.4	0.52	0.55	0.60
0.5	0.55	0.60	0.65
0.6	0.59	0.65	0.70
0.7	0.64	0.70	0.75
0.8	0.68	0.75	0.80
0.9	0.70	0.80	0.85

values of the MSE and other two algorithms shows the worst performance. If the detection probability is increased then the MSE values are also increased (Table 3).

False alarm probability: The Figure 4 shows that the graphical representation of the measure of noise variance and MSE of the proposed algorithm using different estimators such as MMSE, Mismatches MMSE and proposed channel quality estimator. It shows that the proposed algorithm obtains the lowest values of the MSE and other two algorithms shows the worst performance. The false alarm probability is indirectly proportional to the MSE value. If the false probability increases then the MSE value will be decreased. The false alarm value probability is measured using the different estimators and MSE value is calculated based the false alarm probability (Table 4).

CONCLUSION

The demand of the channel sensing approaches for secondary user in wireless communication has become an active research area. A large number of channel sensing algorithms are available in the literature. In this study, the channel estimation has been investigated using the channel sensing errors and the channel is sensed using the probability calculation of primary users using Hidden semi Markov model. Once the channel is sensed then the channel quality is estimated using the proposed mathematical formulation. The performance of the selected channel is measured using the proposed estimator and different estimator such as MMSE, Mismatched MSE. The experimental results show that the proposed algorithm and estimator is better than the other algorithms in all ways.

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