Spectrum Handoff by Baum-Welch algorithm for services in Cognitive Radio Networks

Deepak Kumar. V, Gokulamaanickam. B, S. Nandakumar

Abstract: Cognitive Radio Networks (CRN) is the upcoming future prospect in 5G networks. Lack of available spectrum is a serious problem in the networking industry nowadays since, for each individual organization only a limited spectrum bandwidth is offered by National Telecommunications and Information Administration (NTIA). The problem arises due to the increase in the number of users who are supposed to use a limited amount of available bandwidth. Using spectrum handoff allows a cognitive user to access the available licensed spectrum in the absence of the primary user in that particular channel. Efficient spectrum sensing has to be done to check the availability of unused spectrum holes. Machine learning models such as Markov model and Hidden Markov model are used to predict the probabilities. In this paper we have presented a model for efficient sensing using Baum-Welch algorithm, a neural network algorithm which can train inner layer channel traits for given sequence of switching services to yield accurate results without huge datasets. Following emission probabilities are obtained for the channels that are trained from transition probabilities of channel services such as video, voice and data. From the obtained probability values each channel can be offered with best suited services.

Keywords: Baum-Welch algorithm, Cognitive Radio Networks (CNR), Emission Probability, Hidden Markov model (HMM), Markov model, Transition Probability.

I. INTRODUCTION

Cognitive Radio is set to become one of the major lynchpins of communication as the world moves over to a higher ratio of users to available spectrum bandwidth and spectrum handoff is becoming an important part of cognitive radio technologies and an important area of research going forward. This is due to the need for more accurate spectrum sensing and handoff. This is resulted in application of various algorithms and procedures to produce more accurate handoffs. These includes methods to reduce the errors in spectrum sensing in a dynamic spectrum environment, methods to reduce the number of handoffs and methods to reduce the delay caused as the result of spectrum sensing.

One of the methods to reduce the errors in spectrum sensing is Hidden Markov Model (HMM), HMM can be trained to predict the spectrum sensing sequence which can increase the number of available spectrums to the SU.

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A. *Cognitive Radio Technology*

The increasing spectrum demand has put a heavy burden on the efficiency of communication. The ratio of users to the available spectrum bandwidth has increased tremendously which has now led to new and alternative methods to reduce the burden on the available bandwidth without compromising the quality of the available service. One of such methods to be mentioned a lot is cognitive radio technology. The main aim of cognitive radio technology is to increase the usage of the available spectrum bandwidth to its maximum.

The basic architecture of cognitive radio network consists of a primary network, primary user, secondary network, and secondary user. Primary user is the licensed user of a primary network having exclusive right to use spectrum bands in the primary network under the coordination of the primary base stations. Secondary network or CR network consists of one or more secondary users with or without the presence of secondary base stations [1].

In any spectrum which has been assigned to a primary user, there exists a part of the spectrum which is unused. Cognitive Radio technology makes use of this unused spectrum also known as “Spectrum holes” by assigning it to an unlicensed secondary user who in turn varies his operating parameters to access and utilize the unused spectrum of the primary user [2].

The problem with cognitive radio networks arises when the primary user of that spectrum wants to make use of the spectrum which the secondary user has been used till then. The secondary user has to now not only vacate the current spectrum which he is using right now but also should find another spectrum which he can use to continue the service he is availing all the while without reducing the quality of service he’s providing. The other problem occurs when there is spatial movement of secondary user. This leads to overlap in the transmission coverage of SU with a PU using the same spectrum band [3].

Always remember though that in any spectrum the primary user has a higher priority over the secondary user. Here arises the need for efficient spectrum handoff without disruption in the quality of service that was being provided [3].

B. *Spectrum Handoff*

The main aim of spectrum handoff is to assign a suitable channel to the SU for the completion of his transmission. There are mainly two types of spectrum handoff based on channel selection [4]:

- Reactive Handoff: In this method of spectrum handoff, the secondary user goes for a reactive spectrum sensing and handoff procedure. When the need for handoff arises the SU performs spectrum sensing to find a suitable backup channel [3]. Communication link is than established with the backup channel. In this type of handoff, the spectrum sensing and handoff is only initiated when an event occurs which requires the SU to switch channel and the advantages of such a handoff method is that the spectrum sensing is done on the most relevant spectrum environment resulting in an accurate target channel to which spectrum handoff is done eliminating other unwanted handoffs in the process [4]. The disadvantage with this method is the time delay accompanying the sensing methods used to find the most accurate sensing methods [3]. This can be a source of concern because in this method of the sensing procedure is only initiated after the detection of the event leading to the initialization of the handoff procedure.

- Proactive Handoff: Just like in reactive handoff, proactive handoff uses proactive sensing and handoff methods. In this method the SU searches for an available channel by initiating spectrum sensing even before the PU arrives to start actual handoff procedure. The arrival of the PU can be predicted by analyzing the PU traffic model [3].

C. *Hidden Markov Model*

Hidden Markov model is a extended model of Markov model in which the system following the particular model is said to follow Markov Model with the states being unobservable or hidden. The HMM model uses transmission probability, emission probability and initial state probability to find the sequence of states followed by the process.

- Transmission probability: It is the probability of the next state being q_i given that the current state is q.
- Emission probability: It is the probability of the output state being P_o given that the currently present state is q.
- Initial state probability: It is the probability of a particular state being initial state of the system.

II. REVIEW OF RELATED WORKS

The ever-increasing problem of accommodating increasing number of users without compromising the quality of service given has led to increasing interest in CRN and specialized spectrum handoff. In [5], the authors have taken into account not only transmission coverage overlap between SU and PU but overlap between multiple SU using the same network. They do this by adopting a random sensing order policy. The authors propose a finite chain novel Markov model to model a SUs to find the inter-CRN, intra-CRN, average number of handoffs and successful transmission probabilities and other communication parameters [5].

In [6], the authors propose a improved spectrum sensing and access method to reduce the delay in handoffs as well as the number of handoffs in a CRN. Their work also resulted in decrease in the number of PU collision and higher spectrum efficiency. A spectrum handoff scheme for vehicular CRN keeping in mind network mobility using GRA and MADM is proposed in [7]. This method also takes into account mobile network velocity and its effect on spectrum handoff and was tested in a dynamic network environment. In [8], the authors propose a spectrum handoff method based on activity pattern of PU in the past while also acknowledging CR user movements. This data is used to design an HMM based spectrum handoff. In [9], the author uses HMM to correct the sensing sequence and predicts the channel status. The author also performs a heuristic sensing algorithm in proactive spectrum sensing and uses various filtering methods to improve the expected performance of their proposed system. In [10], the authors proposed a 2-tier CRN system which there is a single tier of PU and two tiers of SU. First tier of SU use the spectrum holes available in the network and indulge in VOIP and the second tier of SU use the silence period in the VOIP to send data.

III. SYSTEM MODEL

In this section we will discuss in detail about the following terms, Markov model, Hidden Markov model, Emission probability, Transition probability, Forward algorithm, Backward algorithm and finally Baum-Welch algorithm. We presented the sequential process for finding the probabilities.

A. *Markov Model*

Let A be a transition probability given by

$$A = (a_{ij})_{M*M}$$

a_{ij} =P [$x_{t+1} = s_j \mid x_t = s_i$], i, j=1, 2…., M, (1)

where a_{ij} is transition probability of the current state s_i, s_j is the next state with t=1,2, 3…, T which is time taken for sensing the spectrum, with M number of states (In our model M=3) each for video, voice and data.

$x_t \in \{s_1, s_2, \dots s_M\}$, $\{s_1, s_2, \dots s_M\}$ is the state sequence.

Hence A can be written as,

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}, \quad (2)$$

Let X=$\begin{bmatrix} x \\ y \\ z \end{bmatrix}$, be the unknown probabilities of respective video, voice and data services.

Let B=$\begin{bmatrix} b1 \\ b2 \\ b3 \end{bmatrix}$, be the initial service state of video, voice and data services respectively.

So probability of choosing a suitable service is found by the relation, X = AB (3)

The result of this is obtained for 5 channels as shown in the Fig.1 without taking into considerations of hidden layers.

B. *Hidden Markov Model*

Here the Hidden Markov model takes into consideration of the hidden states. In this model huge amount of data sets are not essential to predict the probability which differentiates the Markov model. Here we have considered the past 10 observation transitions that have been randomly generated.

The main parameters to be considered for the evaluation are:-

* Transition probabilities (A)
* Emission probabilities (€)
* Initial state probabilities (B)

Let the observation sequence be,

O = { o_k }, k=1, 2,…., K (K=10 for our model)

Let the hidden states be,

Q = { q_i }, i=1, 2…., N

Let the emission probabilities be,

ϵ = { $e_{ik} = P(o_k \mid q_i)$ }

Let the initial state probabilities be,

B = { $b_i = P(q_i \ at\ t = 1)$ }

By Markov chain rule,

P($s_t \mid s_{t-1}; s_{t-2}, s_{t-3}, \dots$) =

P($s_t \mid s_{t-1}$), t=2,3,4…

1. *Forward Algorithm*

For computing the probability of partial sequence of observations following iterations are made,

$\alpha_1(i) = (b_i * e_k(\text{o}(1)),\ 1 \leq \text{k} \leq 10$

Initialization:-

$$\alpha_t(i) = \text{P}[\ \text{o}(1),\text{o}(2),\ldots,\text{o}(t) \mid \text{q}(t) = q_i\ ] \qquad (4)$$

Recursion:-

$$\alpha_{t+1}(i) = [\ \sum_{j=1}^{10} \alpha_t(j)\ a_{ij}\ ]\ e_i(\text{o}(t+1)), \qquad (5)$$

where i=1,2…, N and t = 1, 2….., T-1

Termination:-

$$\text{P}(\text{o}(1)\text{o}(2)\ldots\text{o}(T)) = \sum_{j=1}^{10} \alpha_T(j) \qquad (6)$$

Here using forward algorithm the unconditional probability is obtained by summing the partial observation sequence. First the probability of single state sequence is obtained as product of initial 'i' hidden states and emission probability of o(1) in the i^{th} state. Then recursion is applied for finding next state sequence by multiplying emission probability by o(t+1) sequence with sum of probabilities of transition probabilities and partial probability sequence. By running number of iterations we can find the required probability.

2. *Backward Algorithm*

Here by considering conditional probability of partial observable sequence which is found by back tracing the observed sequence from o(t+1) to the state sequence starting with i^{th} state by taking a symmetrical backward variable

$$\beta_t(i) = \text{P}(\text{o}(t+1),\ldots,\text{o}(T) \mid \text{q}(t) = q_i) \qquad (7)$$

Initialization:-

$$\beta_T(i) = 1,\ \text{i}=1,2\ldots,\text{N} \qquad (8)$$

Recursion:-

$$\beta_t(i) = \sum_{j=1}^{N=10} a_{ij}\ b_j(\text{o}(t+1))\ \beta_{t+1}(j) \qquad (9)$$

where i = 1, 2…. N and t = T-1, T-2,….,1

Termination:-

$$\text{P}(\text{o}(1)\text{o}(2)\ldots\text{o}(T)) = \sum_{j=1}^{N=10} e_j\ b_j(\text{o}(1))\ \beta_1(j) \qquad (10)$$

Finally backward variables are found recursively from backward propagation of observation sequence. Similar to forward algorithm, backward algorithm is used to find optimum state sequence and weighing Hidden Markov parameters. Both Forward and Backward algorithms yields equivalent results for overall probabilities.

$$\text{P(O)} = \text{P}(\text{o}(1),\ \text{o}(2),\ldots\text{o}(T)) \qquad (11)$$

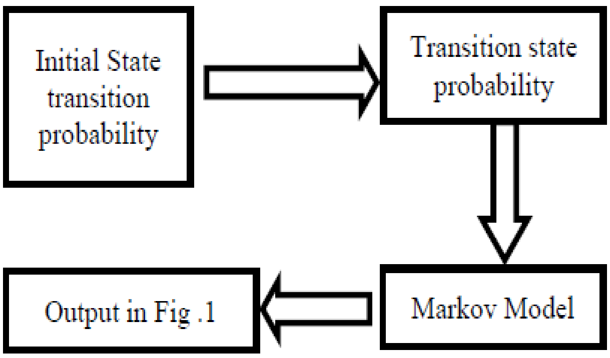

Fig. 1.Flow chart of Markov model

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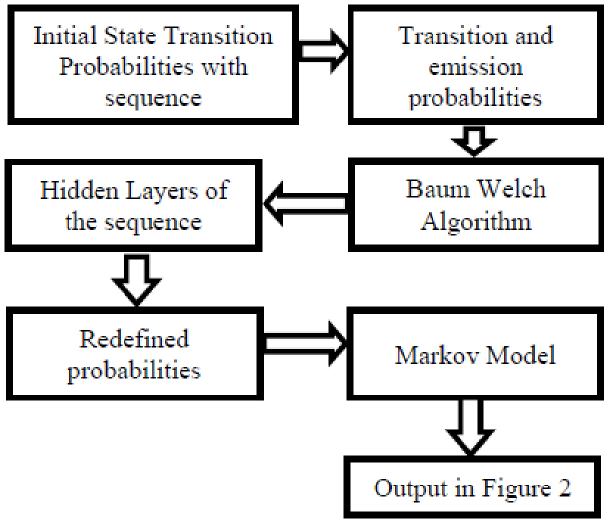

Fig. 2.Flow chart of Baum-Welch trained model

Table- I: Final State probabilities using Baum Welch algorithm

Probability	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5
Video	0.783	0.3522	0.4174	0.4707	0.3244
Voice	0.1008	0.2	0.309	0.1915	0.5844
Data	0.1162	0.4478	0.2736	0.3377	0.0912

3. *Baum-Welch Algorithm*

Generally Forward and Backward algorithm individually is more than enough for predicting the next sequence but in case of Spectrum Handoff noise interferences affects the entire channel switching results. Thereby choosing incorrect spectrum sensing and handoff may lead to collision of SU's and PU's. So to overcome this Baum-Welch algorithm is used to maximize the probability of observed sequence before switching. So that updated emission probabilities are obtained from running number of iterations until the obtained results were of maximum accurate. Then with this probability optimum channel for video, voice and data services was chosen from given past few sequences of services. It involves both forward and backward variables. From these two variables new parameters are obtained which redefines the transition and emission probabilities which has maximum accuracy as compared to normal Markov model as discussed earlier.

The first parameter found is,

$$\psi_t(i,j) = P\big(q(t) = q_i, q(t+1) = q_j \big| O, A, B, €\big) \qquad (12)$$

It's the joint probability of being in state q_i in time t and q_j in time t+1, in which few past observed sequence, Transition probability, Emission Probability and initial state probability are given.

We get the following conditional probability with available parameters as discussed above,

$$\psi_t(i,j) = \frac{[\alpha_t(i) \times a_{ij} \times b_j(\text{o}(t+1) \times \beta_{t+1}(j)]}{P(O|A,B,€)}$$

(13)

The probability of output sequence is expressed as, $P(O|A,B,€) = \sum_{i=1}^{N}\sum_{j=1}^{N}[\, \alpha_t(i) \times a_{ij} \times b_j(\mathrm{o}(\mathrm{t}+1) \times$ $\beta t+1j] = i=1N\alpha t(i)\beta t(i)$ (14)

The probability of being in state q_i at time t is given as,

$$¥_t(i) = \sum_{j=1}^{N} \psi_t(i,j) = \frac{\alpha_t(i)\beta_t(i)}{P(O|A,B,€)} \quad (15)$$

From the equations (12), (13), (14) and (15) the accurate probabilities are obtained as follows,

Updated initial probabilities,

$$b_i^{'} = ¥_1(i) \quad (16)$$

Transition probabilities,

$$a_{ij}^{'} = \frac{\sum_t^{T-1} \psi_t(i,j)}{\sum_t^{T-1} ¥_t(i)} \quad (17)$$

Emission probabilities,

$$b_{ij}^{'} = \frac{\sum_t^{R} ¥_t(j)}{\sum_{t=1}^{T} ¥_t(j)} \quad (18)$$

$\sum^R$ denotes summation over t such that o(t) = o_k .

The obtained probabilities from the equation (16), (17) and (18) are again fed into Markov model to obtain the corrected probabilities as shown in Fig.4.

IV. RESULT AND DISCUSSION

Here the past 10 observation sequence considered for training using the Baum Welch Algorithm are as follows,

{ video, voice, voice, data, data, video, video, data, voice, data }

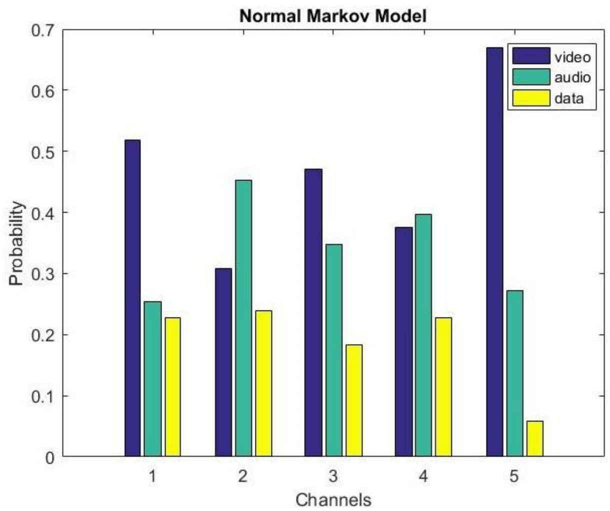

Fig. 3. Normal Markov model.

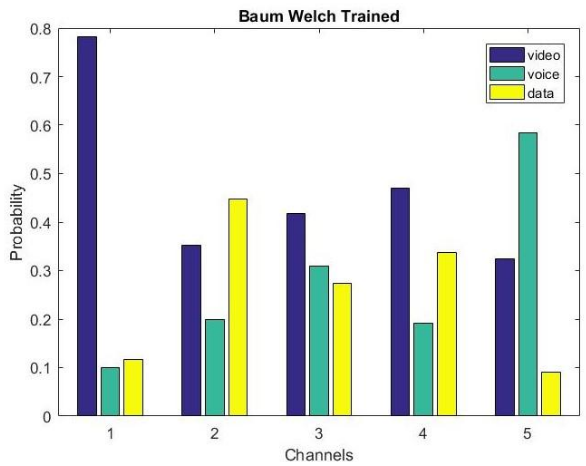

Fig. 4.Baum-Welch trained model.

The following results were simulated in the MATLAB environment. We just took 5 channels in our simulation and analyzed the best suitable channel for video, voice and data services with their different transition probabilities in all 5 channels. Fig. 3, shows the normal Markov model without Neural network trained by just considering the initial state probabilities and transition probabilities without considering inner layer probabilities. But in Fig. 4, we considered a neural network trained model by Baum-Welch algorithm by considering the hidden layer probabilities from given probabilities. Thereby we got corrected Emission probabilities, Transition probabilities and initial state probabilities which were again fed into Markov model for getting updated probabilities for choosing finest service.

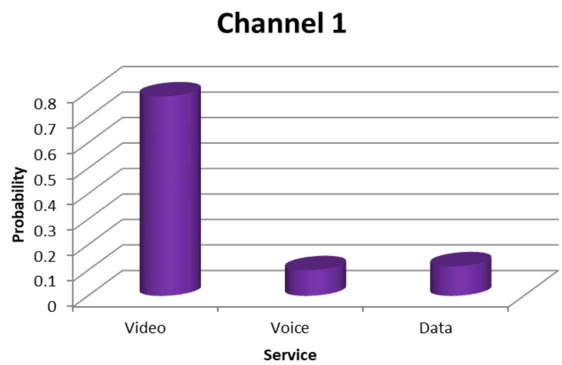

Fig. 5. Best channel for video.

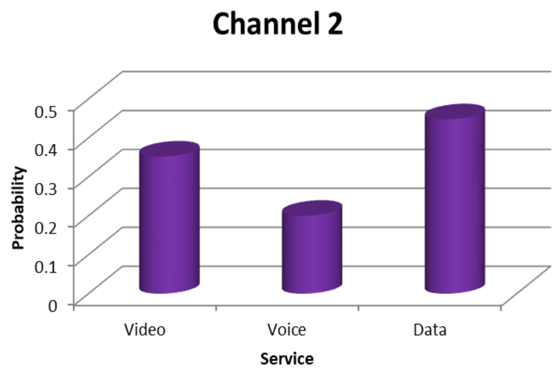

Fig. 6.Best channel for data.

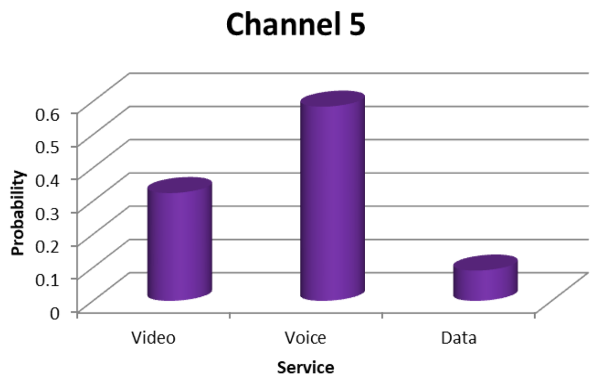

Fig. 7.Best channel for voice.

Here Fig.5, Fig.6, Fig.7 shows the best suitable channel for choosing video, data and voice services based on the hidden inner layer computations using Baum Welch model from Fig.2 and the following probabilities were obtained as shown in the Table- I.

V. CONCLUSION

In this paper we proposed Baum Welch model which yields very accurate results for spectrum handoff in Cognitive Radio networks. Here by using the neural network model we can reduce the latency amount of sensing time and efficiency is drastically increased. We just compared a Markov model without training. The results seemed to vary. Baum Welch algorithm is more accurate as it takes into considerations of layers in depth. It's mathematically proven that Baum Welch gives around 90% desirable outcome and has been verified with real time examples shown in [11],[12]. Here there would be tradeoff with the complexities for accuracy while using more than 10 channels. Future work can be done on reducing such complexities with prediction accuracy level unchanged.

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