International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

Data Rate Prediction in Cognitive Radio by using Self Organizing Maps

Prachi Sankpal[1], Mithrav Venkatesan[2], Dr. A. V. Kulkarni[3]

[1]Department of Electronics & Telecommunication, Savitribai Phule, Pune University, D.Y.P.I.E.T., Pimpri, Pune, India

[2]Research Scholar, JSPM's RSCOE, Pune

[3]Dean R&D PG/Phd, Dept. of Electronics & Telecommunication, Savitribai Phule, Pune University D.Y.P.I.E.T., Pimpri, Pune, India

Abstract: ***This article presents the Learning Algorithm for increasing speed in cognitive radio system. In today's modern world wireless communications are an effective and efficient way for data transmission. Success of this communication depends on limited radio spectrum. Cognitive radio systems (CRs) are more flexible and used for intelligent spectrum management. However, the processes of a CRs are time consuming. Accordingly, a learning mechanism can increase speed of whole cognition process. This paper introduces a mechanism which is based on the well-known unsupervised learning technique, called Self-Organizing Maps (SOM's), and is used for assisting a CRs to predict the data rate that can be obtained, when it senses specific input data from its environment.***

Keywords: Cognition cycle, Learning Algorithm, SOM Training Algorithms Data rate, Simulation Scenario.

1. Introduction

Radio spectrum is the limited natural source. Cognitive Radio (CR) is an adaptive, intelligent radio and network technology that can automatically detect available channels in a wireless spectrum and change transmission parameters enabling more communications to run concurrently and also improve radio operating behavior. Cognitive radio manages the radio spectrum dynamically.CRS can further enhance techniques by adding past experience and knowledge to be taken into account during spectrum assignment.

CRs have ability to adapt the radio environments intelligently. CRs can adjust their operation according to the Environmental condition, user requirements, external parameters (frequency of carrier, type of modulation etc) [1]-[2] The cognitive radio is the iterative process which is called as the 'cognition cycle'. The whole cognition cycle consist of three phases which are shown in fig 1.[2,3] In the first phase which is known as "Sensing the radio Environment", the system collects information/measurements or data from the environment. In the second phase "Estimation and Prediction" the output of first phase is used for discovering the capabilities of each candidate configuration, and in that past experience of the system may also be used. In the last phase known as "Adaption", the system decides best configuration and accordingly adapts its behavior.[7]

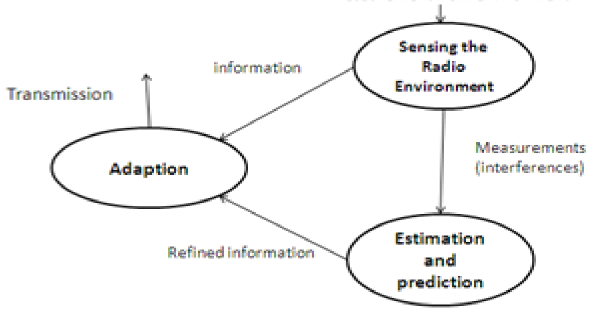

Figure 1: Representation of cognitive cycle

Cognition cycle is proven to be time consuming process so the different learning algorithms are used to speed up the cognition process. This paper introduces the learning technique which is based on unsupervised learning called as "Self Organizing Map" which is based on the Neural Network (nn) learning technique. SOMs are used to classify and represent the multidimensional data into 2 Dimensional (2D) maps. Here the SOM is used to predict the data rate when CRs operates in specific radio configuration. There are multiple inputs which are applied to system which includes Received signal strength Indicator (RSSI), input and output packets, input and output bytes and Labels. And the outputs are predicted values of data rate; finally the predicted values are compared with measured data rate. This paper is structured as follows. Section 2 contains Overview of SOM. Section 3 contains training of self organizing maps. Section 4 presents the simulation model used for proposed approach. Finally the paper is concluded in section 5

2. SOM Overview

Learning can be defined as process of updating the network architecture and connection weights so that network can efficiently perform a specific task. SOM is the unsupervised learning technique. Unsupervised learning does not require correct answers associated with each input pattern while training the network. It gives the correlations between the data and from these correlations it organizes data into various categories.

SOM were introduced by Kohonen in 1982 [4]. SOM is one of the class of neural network algorithms in unsupervised learning category. SOM visualizes high dimensional data sets on 2 dimensional regular grids of neurons. These maps having a rectangular or hexagonal shape which consist of cells [5]. According to techniques correlations of data samples mapped on SOM is done with cell/neuron of the map whose vector having weights as equal as possible to the values of the observed parameter. This cell/neuron is called as Best Matching Unit (BMU). After correlation of data samples with its BMU the latter and neighborhood around it stretch towards the represented on the SOM data sample. The above process is called as SOM training and result in an ordered SOM map. In the SOM map similar data samples are mapped to adjacent neurons and according to similarities the latter is adjusted to modify their distance. (More similar comes closest to each other). In this way the map is created and resulting map represents the classification and similarities of the data. This process is shown in fig 2.

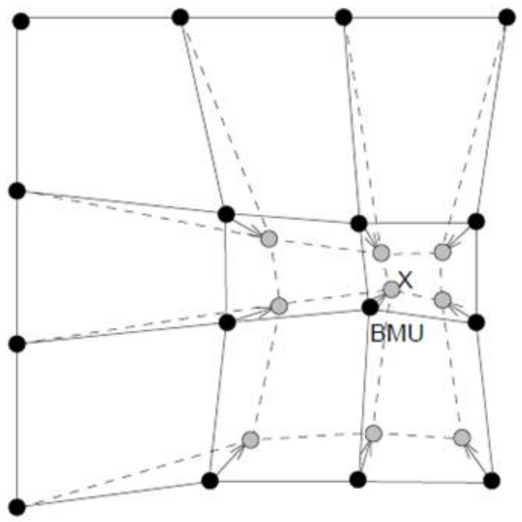

Figure 2: x is the inserted data sample affects its BMU and neighborhood. The solid line indicates situation before and dash line indicates situation after input of data sample [5].

Self-organizing maps learn to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors. Self-organizing maps do not have target vectors, since their purpose is to divide the input vectors into clusters of similar vectors. For these type of networks there is no desired output. There are two training algorithms used for SOM training. a) Sequential training b) Batch training

In sequential training algorithm, one by one each data sample is inserted to the training process, thus it only affects its own BMU and neighborhood around it. In batch training all data samples enters at once in the training process and eventually affects their BMU's and neighbors in parallel. These algorithms are described in detail in following section.

3. Training of SOM

a) Sequential Training Algorithm:

This algorithm is executed in the iterative manner as x is the data sample which is inserted into the training process by itself. When the CRs operates in the radio configuration mode the variables of each data sample x correspond to radio parameter are observed. This process is expressed as follows. First the random data sample is selected. Consider here x is the random data sample and its distance from each neuron is calculated. Consider m_i is the distance. The BMU of the data sample is nothing but the neuron which is closest to the selected data sample, and it is denoted by c. As the result of configuration cell is finally associated with data sample or combination of the parameter. Cell is denoted by m_c. c can be defined from following condition;

$$\|x(t) - mc(t)\| \le \|x(t) - mi(t)\| \qquad (1)$$

Where, $\|.\|$ denotes the metric and it is known as Euclidean distance, according to this distance is calculated. t indicates the iteration.

Once the data sample correlates with its BMU the weights of the vector of the BMU and vectors of its neighbor change in order to resemble more variables of data sample. This process is expressed in following equation:

$$m_i(t+1) = m_i(t) + \propto(t) h_{ci}(t)[x(t) - m_i(t)] \qquad (2)$$

Where c indicates the neuron, m_i indicates weight which can be updated, x(t) is the data sample and t is the index of iteration.
The learning rate factor $\propto(t)$ can be model from the any one of the following function:

- Linear function:

$$a(t) = a_o(1 - t/T) \qquad (3)$$

- Power function:

$$a(t) = a_o(0.005/a_o)^{t/T} \qquad (4)$$

- Inv function:

$$a(t) = a_o(1 + 100t/T) \qquad (5)$$

Where a_o is the initial learning rate and T is training length, both are the constant variables.

In contrast with the learning rate $h_{ci}(t)$ is the neighborhood function which is not depends on time. Also it doesn't depend on distance between neuron m_c and c (BMU).in this case following functions are used.

- Bubble:

$$h_{ci}(t) = l(\sigma(t) - d_{ci}) \qquad (6)$$

- Gaussian:

$$h_{ci}(t) = e^{-d_{ci}^2/2\sigma^2(t)} \qquad (7)$$

- Cutgauss:

$$h_{ci}(t) = e^{-d_{ci}^2/2\sigma^2(t)}.l(\sigma(t) - d_{ci}) \qquad (8)$$

- Ep:

$$h_{ci}(t) = \max\{0, 1 - (\sigma(t) - d_{ci})^2\} \qquad (9)$$

Where $\sigma(t)$ a neighborhood radius, dci denotes distance between cells m_c and m_i and l(x) is step function.
$l(x) = 0$ if $x < 0$ and $l(x) = 1$ if $x \ge 0$.

b) Batch Training Algorithm

This algorithm also executes in iterative manner. In this algorithm instead of inserting single data sample all available data samples are inserted simultaneously to the map so the specification of the learning rate is not required. As mentioned above all data samples are presented at a time, so it is faster than sequential training algorithm. In the training step the data set is classified according "Voronoi regions" [6] of the map weight vectors. This means that each data sample belongs to the data set of the map to which is closest. Following relation is used to calculate the weight of each cell m:

$$m_i(t+1) = \frac{\sum_{j=1}^{n} h_{ci}(t) x_j}{\sum_{j=1}^{n} h_{ci}(t)} \tag{10}$$

Where $c = \arg\min_k \{\|x_j - m_k\|\}$ indicates BMU cell of x_j, h_{ic} (t) indicates neighborhood function of BMU.

Following function is used to calculate the Voronoi regions of the map:

$$s_i(t) = \sum_{j-1}^{n_{vi}} x_j \tag{11}$$

N_{vi} indicates the no of data samples of call i, and following equation is used to calculate the weights of the vectors

$$m_i(t+1) = \frac{\sum_{j=1}^{m} h_{ij}(t) s_j(t)}{\sum_{j=1}^{m} n_{vi} h_{ij}(t)} \tag{12}$$

4. SOM Model

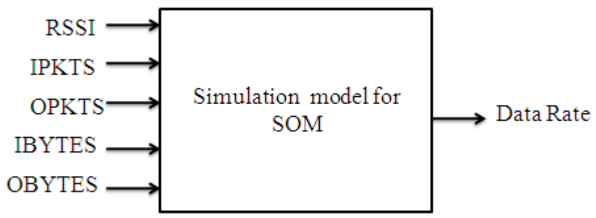

Figure 3: Simulation model for SOM

The simulation model which is used to predict the data rate by using SOM is shown in above figure. As SOM requires multiple inputs such as RSSI, Input packets, Output packets, Input Bytes, Output Bytes, and the objective is to obtain data rate. By implementing the SOM toolbox in Matlab this model will predict the bit rate. SOM training is necessary so above algorithms are used for training. The final output is in the form of clusters. Finally, obtained data rate is compared with measured value.

5. Conclusions

In this article we have presented an overview of Self organizing map (SOM) algorithm for assisting CRs to predict the data rate when it senses specific input data from its environment. Finally the achieved data rate is compared with measured values.

References

[1] Mitola III, Jr J, Maguire G. Cognitive radio: making software radios more personal. IEEE Pers Commun 1999;6(4):13–8.
[2] Haykin S. Cognitive radio: brain-empowered wireless communications. IEEE J Sel Areas Commun 2005;23(2):201–20.
[3] Demestichas P, Katidiotis A, Tsagkaris K, Adamopoulou E, Demestichas K. Enhancing channel estimation in cognitive radio systems by means of bayesian networks. Wirel Pers Commun 2009;49(1):87–105.
[4] Kohonen T. Self-organizing maps series in information sciences, second ed., vol. 30. Heidelberg: Springer; 1997.
[5] Vesanto J, Himberg J, Alhoniemi E, Parhankangas J. SOM toolbox for matlab 5 technical report A57. Helsinki, Finland: Neural Networks Research Centre, Helsinki University of Technology; 2000.
[6] S. Arya, T. Malamatos, D.M. Mount, Space-efficient approximate voronoi diagrams, in: Proc. 34th ACM Symp. on Theory of Computing (STOC 2002), pp. 721–730.
[7] Kostas Tsagkaris, Aimilia Bantouna, Panagiotis Demestichas in 19 march 2012, Elsevier
[8] Clancy C, Hecker J, Stuntebeck E, O'Shea T. Applications of machine learning to cognitive radio networks. IEEE Wirel Commun 2007;14(4):47–52.

Author Profile

Prachi Sankpal received the B.E degree in Electronics and Telecommunications Engineering from Savitribai Phule Pune University, Maharashtra, India in 2011. She is now pursuing Master degree in communication Network from D.Y.P.I.E.T. Pimpri, Pune, India

Mithra Venkatesan received BE from Madras University in the year 2002. Subsequently she pursued Master of Technology (M.Tech) in Power Electronics from Vellore Institute of Technology, Tamil Nadu in the period 2002-2004. Currently she is Research Scholar at JSPM's RSCOE, Pune, India.

Dr. A. V. Kulkarni Currently working as Professor of E&TC and Dean – R & D, PG& Ph.D. Overall teaching experience: 25years (with DYP Pratishthan). Presently working as Dean–R&D,PG&Ph.D,2011 and IUCEE Coordinator, 2010.