Spectrum Sensing using USRP SDRs and Convolutional Neural Networks

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Abstract - *Current allocation of the spectral bands to only licensed users leads to inefficiencies in spectrum utilization. Designing realistic cognitive radios that are capable of sensing spectrum holes is the key to solve this problem and to increase the capacity of next-generation wireless networks. In this paper, we propose convolutional neural networks for predicting the spectrum holes from a data set obtained via USRP software-defined radios [1]. Preliminary results show performance improvements over the previously proposed methods.*

Keywords: Cognitive radios, convolutional neural networks, spectrum sensing, software-defined radios.

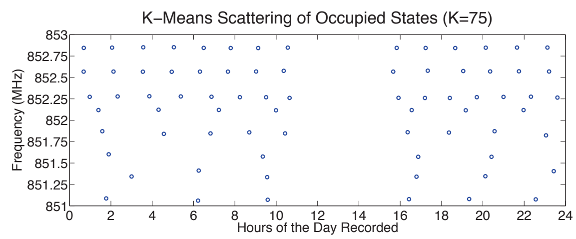
1 Introduction

Radio spectrum is a resource that is licensed by the governments all over the world. The current system of spectrum allocation is based on the outdated methodology of static allocation, which leads to inefficiencies and spectrum under-utilization [2]-[4]. Cognitive radio is a new technology that aims to utilize the licensed bands in a dynamic manner when licensed (primary) users are not using it. As opposed to traditional radios, which are hardware-based, cognitive radios are software-based and furthermore have the capability of sensing the wireless environment and adjusting to it. In order not to harm the primary user of the licensed spectrum, the cognitive radio should detect the existence of primary and also sense their spectrum-usage patterns.

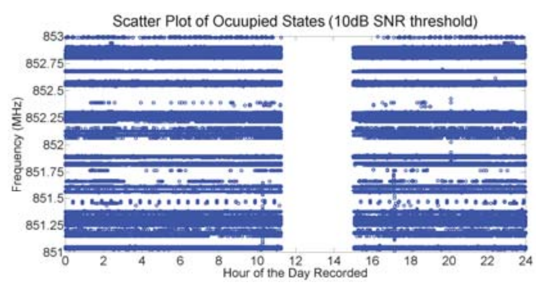
Our goal in this work is to study a neural network-based learning technique for cognitive radio networks. This includes both design of neural networks and practical implementation of the designs on real spectral data. The spectrum data is collected by Universal Software Radio Peripheral (USRP), which is built by Ettus Research [1]. Previous works in literature use simulated data as opposed to the approach taken in this work [6]-[8].

2 Design and Analysis

Data was collected on a Dell Vostro 3500 running Ubuntu 12.04 LTS with GNU Radio v3.6.2 installed. The radios used were Ettus Research USRP2 and USRP N210 software defined radios (SDRs) attached over Gigabit Ethernet. The daughterboards used in these radios were Ettus model SBX-40. We used Ettus VERT900 antennas for each measurement. We use the default native (non-decimated) sample rate of 1MHz, and an FFT size of ¾ MHz. This was automatically trimmed by the usrp_spectrum_sense.py script (GNU Radio) to remove distortion at the edges of the FFT range. The script was modified so that the artificial DC components introduced by the USRP SDRs are automatically removed. We store the current time, frequency of the current FFT bin, detected noise floor level, and bin signal level in a comma separated value (CSV) file.



(a) Scatter plot of actual occupied states



(b) K-means clustering

Fig. 1: Twenty hour period of data collection and its clustering using K-means where K=75

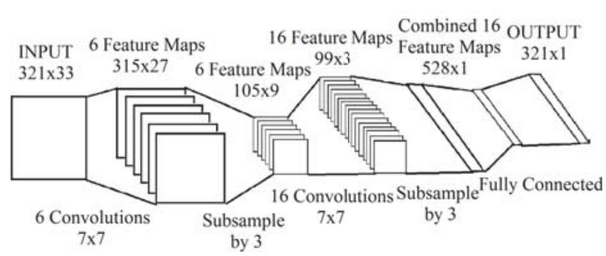
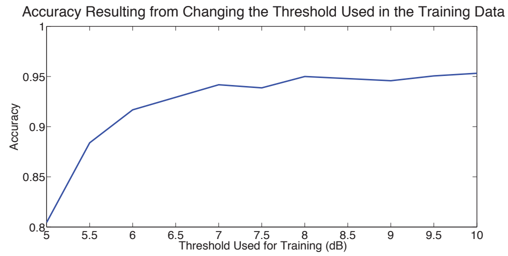


Fig 2: Convolutional neural network structure

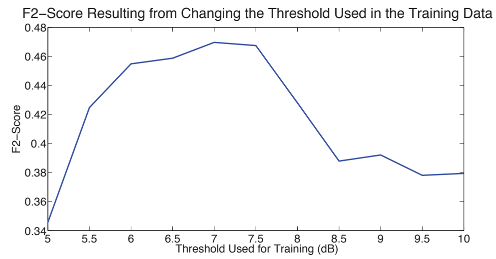
We used an energy detector with an SNR threshold τ_{tr} = 10dB for the training data in order to determine if a state is occupied or not. In order to characterize the data initially, we used unsupervised learning methods to cluster the occupied bins. The data was recorded for 20 hours and K-means clustering was used to in order to identify the density of the occupied states (see Fig. 1). In addition, PCA (Principal Component Analysis) was performed on the signal strength in each frequency over the same measuring period. PCA leads to two conclusions: (i) following Kaiser's rule 33 Principal Components (PCs) remain; (ii) 127 PCs are enough to account for 80% of the variance of this data.

One of the novelties of this work is interpreting the spectrum-hole data as a 2-dimensional image where one axis represents time and the other represents frequency. This interpretation motivates the use of Convolutional Neural Networks (CNNs) for predicting the primary users' spectrum usage pattern. In Fig. 2, we display the utilized CNN structure composed of convolutional, subsampling, and MLP (multilayer perceptron) layers. The input layer is 321x33 nodes.The first hidden layer performs convolution with 6 feature maps with each feature map consisting of 315x27 neurons. The second layer performs subsampling and local averaging. It consists of 6 feature maps with 105x9 neurons in each feature map. The second convolution layer has 16 feature maps, and is followed by another subsampling layer. Then, 16 feature maps with 33 length outputs (total 528 outputs) are passed through a MLP network to reach 321 outputs that predict the occupancy of each frequency bin during the next time interval.The final MLP has an input layer size of 528, a hidden layer of 127 and an output layer of 321. This hidden layer was chosen to reduce the number of weights. Training was performed with over 50,000 data images recorded over two 24-hour periods. A test set of 20,000 data images was recorded on a separate day, as well as a smaller 500 sample validation set for visual interpretation.

We use not only *accurac*y but also F_2 score as performance metrics since the cost of incorrectly identifying an occupied state is much higher than incorrectly identifying a free frequency. Note that F_2= (5 x Precision x Recall) / (4 x Precision + Recall). The training data was separated into batch sizes of 5000 and the learning parameter was degraded by 0.6 per batch (value determined using exhaustive search). The bias term at the output layer was also optimized in order to increase the F_2 score. We also display the effect of changing the SNR threshold of the training data while keeping the threshold for the test data at τ_{te} = 10dB in Fig. 3.



(a) Accuracy vs τ_{tr}



(b) Accuracy vs τ_{tr}

Fig. 3 : Effect of threshold (τ_{tr}) on the performance

3 Conclusions and Future Directions

The best results were achieved when we obtain the model with the same testing and training thresholds (τ_{tr}= τ_{te}= 10 dB), with a 0.6 degradation in learning parameter over batches and with a bias in the final layers set to 0.75. Comparing our initial results to the state of the art is difficult due to the nature of the data collected since the overall occupancy rate of our recorded data is very small compared to the assumptions made about simulated data sets [6], [7]. In [8], the authors vary the occupancy rate, and with the resolution and cross-referencing their plots, we estimate their accuracy as close to 0.97-0.98 for similar occupancy rates to ours. This implies [8] outperforms our scheme; however, a genetic learning algorithm was utilized in [8] to optimize the parameters. Without this modification their recorded accuracy is closer to the 0.93-0.95 that our base model was able to surpass. As part of future research, we will improve performance of our CNN-based algorithm by optimizing the initial learning parameter, batch size, and possibly using alternatives to gradient-descent algorithm. Utilizing genetic algorithms for optimizing initial parameters is another possible future direction.

4 References

[1] http://www.ettus.com/product

[2] Federal Communications Commission, ``Spectrum Policy Task Force", Rep. ET Docket no. 02-135, Nov. 2002.

[3] J. Mitola, ``Cognitive radio: An integrated agent architecture for software defined radio", Doctor of Technology, Royal Inst. Technol. (KTH), Stockholm, Sweden, 2000.

[4] S. Haykin, ``Cognitive Radio: Brain-Empowered Wireless Communications", IEEE Journal on Selected Area in Communications, vol. 23, no. 2, February 2005.

[5] Y. Lecun, L. Bottou, Y. Bengio and P. Haffner, ``Gradient-based learning applied to document recognition," in Proceedings of the IEEE, vol. 86, no. 11, Nov 1998.

[6] V. K. Tumuluru, P. Wang and D. Niyato, ``A Neural Network Based Spectrum Prediction Scheme for Cognitive Radio", ICC 2010 , Cape Town, 2010, pp. 1-5.

[7] Z. Zhang, K. Zhang, F. Gao and S. Zhang, ``Spectrum prediction and channel selection for sensing-based spectrum sharing scheme using online learning techniques," PIMRC 2015, Hong Kong, 2015, pp. 355-359.

[8] S. Bai, X. Zhou and F. Xu, ``Spectrum prediction based on improved-back-propagation neural networks", ICNC 2015, Zhangjiajie, 2015, pp. 1006-1011.