

# Standard Recognising Self Organizing Map based Cognitive Radio Transceiver

M.I.Taj<sup>1,2</sup>, M.Akil<sup>2</sup> and O.Hammami<sup>1</sup>

<sup>1</sup>LEI /ENSTA-ParisTech 32 Bvd. Victor 75015 Paris France  
{taj,hammami}@ensta.fr

<sup>2</sup>Université Paris-Est, Laboratoire d'Informatique Gaspard-Monge, Equipe A3SI  
ESIEE Paris Cité Descartes, BP 99, 93162 Noisy Le Grand Cedex, France  
{tajm,akilm}@esiee.fr

**Abstract**— Cognitive Radio (CR) Systems have transceivers with the ability to adjust their operating parameters after observing the results in order to decide to operate in a specific radio configuration, expecting to move the radio towards some optimized operational state. Framed within this statement, this paper introduces and evaluates the use of Self-Organizing Maps (SOM) and Linear Vector Quantization (LVQ), which are both Unsupervised Neural Network (NN) Schemes as an effective technique for reconfiguring transceivers after recognizing the specific standard based on input parameters extracted from the signal. We exploit the inherent property of SOM, tonotopy, to recognize the standard in our proposed multi-standard cognitive transceiver. We target at cognition incorporation in our Software Defined Radio (SDR) waveform, designed [1,2] on a Network-on-chip (NoC) based multi-core, single chip Xilinx Virtex-4 FPGA.

## I. INTRODUCTION

Multimode reconfigurable devices adapt their behaviour to the changes in environment. As an example, second and third generation cellular radio access technologies and 802 wireless standards can be quoted. In this respect, future CR devices, candidates for 4G radio interface networks, will have the capability to optimize their state thereby adjusting their operating parameters accordingly, after sensing the environment variables. This is explained in cognition cycle[4]. One such example of moving the radio in an optimized state after sensing the parameters is that of an universal transceiver that is capable of operating in many transmission systems and that can be made to operate in a desired standard, by intelligence incorporation. In this paper, we deal with such intelligence incorporation techniques in the transceiver. We address the problem of intelligent detection of a wireless standard among a predefined list of standards to address the challenge of multimode reconfigurable devices. We target at the identification of characteristics of a signal, pertaining to different layers of a communication system, thus cross-optimizing cognitive transceiver. We propose to identify the parameters specific to a particular standard using Unsupervised Neural Networks (NN) called Self-Organizing Maps (SOM) and Linear vector Quantization (LVQ)[5]. The difference between Supervised and Unsupervised NNs is the existence or non-existence of desired output during learning. Multi-Layer Feed Forward NN (MFNN) and Multi-Layer Perceptron (MLP) are the most common examples of Supervised NN. We opt for unsupervised learning NN as they are more suitable in building CRs that require minimal pre-configuration. The motivation to use SOM and LVQ for our standard recognition problem comes from their inherent property of tonotopy, explained in our problem context in Section 3. The experimental results discussed in Section 4 demonstrate SOM and LVQ as potential solution to the standard recognition problem.

The rest of the paper is organized as follows: In section 2, we review the other candidate solutions to the CR design problem. Section 3 describes and explains our proposed approach. Section 4 presents and explains our experimental

results. We conclude in Section 5.

## II. RELATED WORK

Since Lackey [6] described the idea of a reconfigurable receiver, SPEAKeasy, there have been some proposals describing cognition incorporation within a radio. Traditional CR proposals rely on a priori characterization of the radio states, which are often derived from analytical models. These analytical models are not always very practical due to the limitation of modelling assumptions and non-ideal behaviour in real life scenarios. In order to overcome this limitation, there are more pragmatic approaches, that talk of Genetic Algorithms[7,8] and Fuzzy Logic[9]. However, the common drawback of both the approaches is that they do not provide any means of learning from past experiences, thus failing to exhibit one of the key properties of CR. Also the convergence in Multi-Objective Genetic Algorithms is slower and that makes this solution less viable in real time scenario of CR parameter detection[10]. In [11] Markov-based channel prediction algorithm (MCPA) is presented for dynamic spectrum allocation in cognitive radio networks. However Hidden Markov Models, in general, can not be considered for performance modelling in CRs, primarily due to the difficulty of representing the type of input/output relationship needed for orientation, as explained in cognition cycle. All these CR proposals have a common drawback, i.e. if any new parameter has to be added in the system input, these models have to be re-designed from scratch.

The motivation towards neural network based solutions to the standard recognition problem in CR scenario comes from all these observations. Cognitive Radio can effectively learn as we train the neural network characterizing system performance with data obtained from observations performed by the CR itself. There has been some work based on intelligence incorporation using neural networks in CR. Tsagkaris [12] uses a set of 3000 training data input values to predict the anticipated capabilities taking into account recent information sensed. However, his work is oriented towards data rate prediction only, rather than standard identification. Baldo [14,15] presents MFNN to predict the throughput performance of an infrastructured 802.11 cell, leading to dynamic channel selection. Ustundab[16,17] uses MATLAB to simulate MLP neural network based decoding receiver, which uses frequency and amplitude to distinguish between signal patterns leading to an efficient communication bandwidth. MLP and MFNN are supervised learning schemes that make them less pragmatic for our application as we want to recognize the transmission system in use without any prior knowledge about the signal at the receiver, i.e. desired outputs do not exist during learning procedure. Bixio [18] distinguishes between two transmission standards based on their extracted features using Simplified Fuzzy ARTMAP (SFAM) neural network ensembles. In a similar effort to ours, Hachemani [19] proposes the idea of a standard recognizing sensor, although his proposal is limited to physical layer

features pertaining to a standard. The implementation details of such a sensor are not addressed. For each standard to be recognized the features to be tested are different, thus leading to some a priori knowledge regarding the standard to be recognized.

This overview shows that there has not been any effort in considering the parameters pertaining to different layers to recognize a standard. We consider application layer parameters such as localization and positioning characteristics as well, a part from physical layer and transport layer features of a signal that makes our work unique. Our work is also different from all these proposed approaches as it uses an adaptable solution that exploits two unsupervised NNs to recognize different standards, thereby allowing CR to switch in the specific standard mode, optimizing the radio configuration to give the best Quality of Service (QoS) and self management capability. Our solution is adaptive as it switches to appropriate neural network either SOM or LVQ based on the features of input signal sensed. We can also add further more parameters from different layers to increase the performance of our CR.

### III. OUR PROPOSED APPROACH

Section A presents a brief overview of our implementation of SOM and LVQ NNs in our problem context and section B explains their detailed exploitation for our problem.

#### A. SOM and LVQ Implementation

SOM has properties of vector quantization that makes it suitable for easy LVQ adaptation with minor modifications. If prototype vectors are positioned on a regular grid in an ordered fashion, three execution phases are to be considered. The first phase consists of computing the distances  $d_j(j=1,2,..k)$  between the input vectors and weights of various neurons using Minkowski distance function ( $L_2$  norm) shown in equation 1.

$$d_j = \sqrt[p]{\sum_{i=1}^n (X_i - W_{ij})^p} \quad (1)$$

$X \in R^n$  where  $n$  is the number of network's input features and  $W \in R^{nk}$ , where  $k$  is the number of neurons. For  $p=2$ , it represents Euclidean distance function which is referred to as  $L_2$  norm and gives better precision than  $L_1$  norm (Manhattan distance function). During the second phase, the winning neuron called Best Matching Unit (BMU) is determined by comparing these distances. In the third phase, the weight of BMU,  $W_c$  is updated using Subtractive method of weight updates, using equation 2.

$$W_j(t+1) = W_j(t) + h_{ci}(t)[X_i(t) - W_j(t)] \quad (2)$$

If LVQ is used, then only winning neuron's weight is updated, which means that there does not exist any neighborhood function. However, in the case of SOM, weights of neighboring neurons are updated as well. The neighborhood function around the BMU is Gaussian and is defined by  $h_{ci}(t)$  which is a non-increasing function around the BMU and is given by equation 3, where  $r_c$  and  $r_i$  are the distances of winning neuron and neighboring candidate neuron respectively,  $\sigma(t)$  is the neighborhood radius at time  $t$  and  $\alpha(t) \in [0,1]$  is the leaning rate for each epoch and is a decreasing function of time. The neighborhood radius used is  $\sigma(t)=2$ .

$$h_{ci}(t) = \alpha(t) \exp \left[ -\frac{\|r_c - r_i\|^2}{2\sigma^2(t)} \right] \quad (3)$$

This whole procedure is depicted in Figure 1.

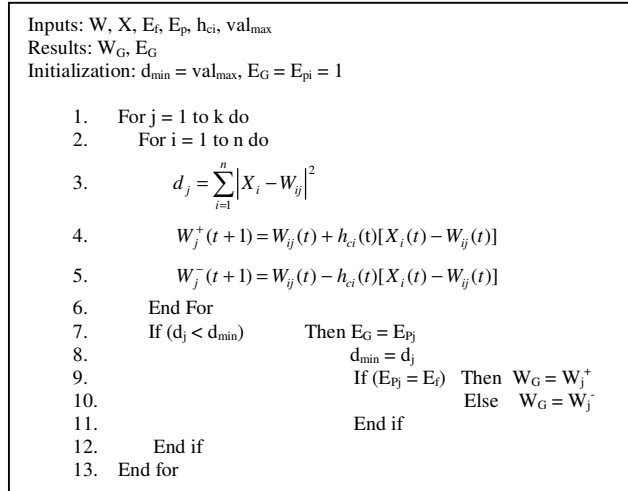


Figure 1: SOM Algorithm for BMU (Standard) determination and weight update.

The inputs to algorithm are:

- W (a matrix with  $n \times k$  elements).
- X (an input vector with  $n$  elements).
- E<sub>r</sub> (reference label).
- E<sub>p</sub> (k expert's label).
- h<sub>ci</sub> (neighborhood function) for SOM, or  $\alpha$  (learning parameter) for LVQ, depending on extracted features of signal.

The algorithm gives the following results:

- W<sub>G</sub> (weight of the winning neuron).
- E<sub>G</sub> (label of the winning neuron).

The following two principles are followed while calculating new weight vectors:

1. **Competitive Learning:** The proto-type vector most similar to a data vector is modified so that it is even more similar to it, called positive weight calculation. This way map learns the position of the data cloud.
2. **Co-operative Learning:** Not only the most similar prototype vector, but also its neighbors on the map are moved towards the data vector. This way the map self-organizes.

Also, the negative weights are calculated to increase the distance between input vector and weight, in case of least similar vectors. In the case of LVQ,  $h_{ci}$  is replaced with  $\alpha$ . In Figure 1, after initialization, the algorithm calculates in two overlapping loops (loop 1, line 1– 13 and loop 2, line 2 – 6) the distances, the positive and negative weights, weight update of winning neuron and its label assignment.

We have chosen SOM and LVQ as they inherently suit our problem, because of their property of tonotopy. This property states, in our problem context, that the spatial location of a specific standard corresponds to a particular feature of input patterns, so that all the signals from a particular standard are plotted at the same place at the output grid, thus forming a cluster. Mathematically, let  $P(a,b,c,d)$  be the four distinguishing parameters, namely channel bandwidth, frequency band, range and data rate considered for a signal. We quantize this set of four parameters using a 2-D map,  $M$ , organized in a hexagonal grid, so the mapping  $K$  is defined as,

$$K: P \rightarrow M, p = (a,b,c,d) \in P \rightarrow K(p) \quad (4)$$

These parameters are extracted after analysing the received signal which may be the result of the summation of many standards, each standard itself the summation of several

modulated carriers. The choice between SOM and LVQ is decided upon by extracted features. Then, the features identified are fed as input to trained NN, resulting in the identification of standard because of their spatial location at output grid and the property of tonotopy.

After recognizing the standard, the receiver switches to that specific standard mode to detect the right demodulation software or download the software in a self organized manner. Figure 2 illustrates our approach showing the architecture of our unsupervised NNs, SOM and LVQ which includes:

1. The *input layer* representing the space of inputs  $X$  of dimension  $n$ .
2. The *hidden layer* models the competition space of inputs.
3. The *linear layer* of decisions.

We explain in detail about the selection between SOM and LVQ and their suitability for different set of standards in our proposed solution, in the following sub-section.

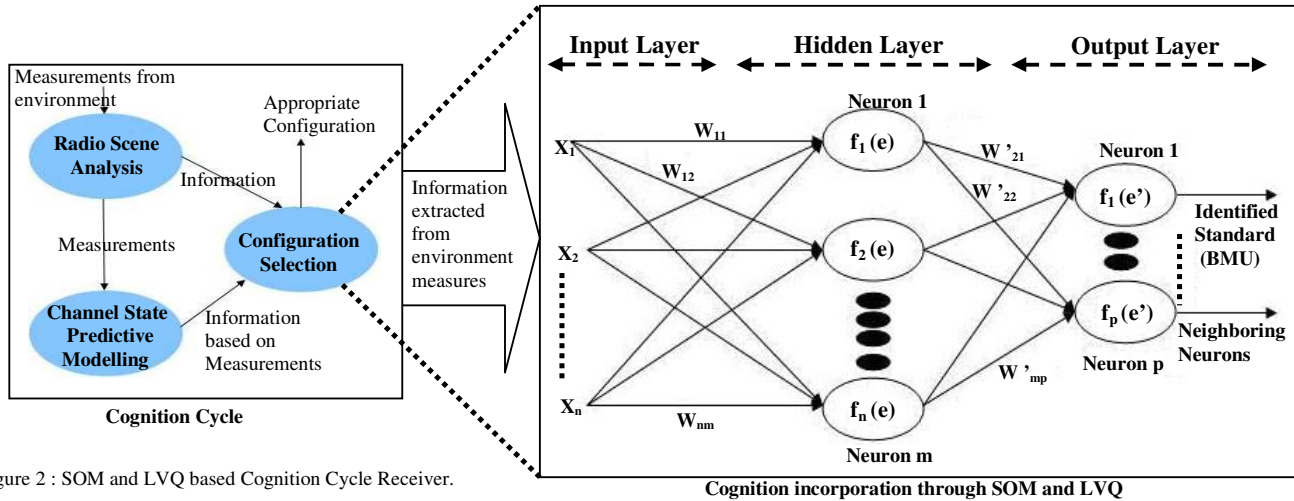


Figure 2 : SOM and LVQ based Cognition Cycle Receiver.

**B. SOM, LVQ for Cognitive Radio Standard Identification**

The predefined list of Standards are shown in Tables 1 and 2. The corresponding parameters that we propose to identify a specific Standard (four in the case of Table 1 and one in the case of table 2) are shown against each standard. We have used the MATLAB SOM toolbox[20] to implement the SOM and LVQ explained in Section 3-A. The standards to be recognized are divided in two categories. The first category comprises of ten standards shown in Table 1. These standards are identified by the help of four parameters: channel bandwidth, frequency band, data range and data rate. Every standard needs a neighborhood function, as it is probable that the next signal may be of another closely related standard making SOM a natural choice in this case. The second category of fifteen standards is shown in Table 2. Each standard in Table 2 is recognized on the basis of one single parameter, channel bandwidth. As LVQ follows ‘winner takes all’ strategy, it is the natural solution for standard recognition

for Table 2 standards. An earlier effort to recognize these 15 standards attempted the use of supervised Radial Basis Function Neural Networks [21]. We suggest LVQ because of their unsupervised learning character, apart from their adaptability to SOM to recognise a number of more standards by just removing neighborhood function. As shown in Figure 2, these distinguishing parameters for each standard are the inputs to the first state of cognition cycle. We construct the data by taking samples of each standard. Each standard corresponds to 50 signals. Each row in the MATLAB ‘struct’ represents specific standard and each column represents a specific parameter of all signals of all standards. We have named the ‘struct’ as *Standard*. The labels field represent the specific standard that is formed by the combination of all four variables. Then we normalize this data so that the data range of each parameter is given equal importance, e.g. if the channel bandwidth is 20 MHz and data range is 2 Mbps, then without normalization, the channel bandwidth will almost

completely dominate the output grid, which is not desirable. We avoid this by normalizing the variance of all the parameters to unity and its mean to zero, thus giving all parameters equal weight in Euclidean distance calculation, using equation 1. Then we first choose the output grid size, based on our data, followed by initializing the map using linear initialization and finally we use batch algorithm to train the map. The batch training algorithm uses all the standard samples to present it to the map before any adjustments are made. Once all samples are presented to SOM our proposed iterative structure of the algorithm starts calculating the BMU, using the algorithm shown in Figure 1, to determine the Final Tonotopy Error.

Each unit map has two sets of co-ordinates, the prototype vectors in the input space and position on the map in the output space. The training is done in two phases: first with large neighborhood radius, and then fine tune with small

Standards	Channel Bandwidth	Frequency Band	Range	Data Rate
IEEE 802.11g	20 MHz	2.4 GHz	140m	54Mbps
IEEE 802.15.4	2 MHz	915 MHz	75m	40 kbps or 250 kbps
IEEE 802.11b	1 or 25 MHz	2.4 GHz	100m	11 Mbps
IEEE 802.15.1	1 MHz	2.4 GHz	10 m	3Mbps
IEEE 802.11 a	20 MHz	5.4 GHz	120m	54Mbps
IEEE 802.11n	20 MHz	2.4/5GHz	250m	248Mbps
IEEE 802.11h	20 MHz	5 GHz	100m	-
IEEE 802.11j	20 MHz	2.4 GHz	120m	54Mbps
IEEE 802.16d	20 MHz	2 to 11 GHz	7 km	75 Mbps
IEEE 802.16e	20 MHz	2 to 6 GHz	3.5 km	30 Mbps

Table 1: Standards recognised using SOM

Standards	Channel Bandwidth
PDC	25 kHz
ADC (D-AMPS)	30 kHz
CT2	100 kHz
GSM	200 kHz
PHS	300 kHz
Bluetooth	1 MHz
IS95, Global Star	1.25 MHz
DAB	1.712 MHz
DECT	1.728 MHz
UMTS (FDD)	5 MHz
DVB-T, LMDS	7-8 MHz
Hiperlan 1	20 MHz
DVB-S	32-36 MHz
LMDS	32-36 MHz
Hiperlan 2	50 MHz

Table 2: Standards recognized using LVQ

radius. By using a larger neighborhood radius, the property of tonotopy, explained in equation 4, is exploited. Then finally we visualize the map using the Unified distance matrix (U-matrix) that shows distances between the neighboring units and thus visualizes the cluster structure of the map.

**IV. EXPERIMENTAL RESULTS**

This section analyses the experimental results. The training data to act as input to our NNs is based on Exponential Moving Average Algorithm, used in several modern wireless applications [12]. We have chosen hexagonal lattice of the SOM grid, *Standard*, with a size of 11 x 6, which is shown in Figure 3 for standards mentioned in Table 1. We can see in Figure 3 that clusters are formed which comprise of different standards, e.g. the first two rows form a cluster of all the signals that correspond to 802.11.g standard. This means that each time a signal is encountered that translates to 802.11.g standard, it will always be ported to this formed cluster. Each standard’s cluster formation depends on the parameter values of a specific signal shown in Tables 1 and 2. The clusters are formed due to the weight vector densities across the lattice. The weight vectors having similar densities tend to occupy neighboring positions, forming a specific standard’s cluster. Each cluster is identified as a distinguishing standard, with the only exception of IEEE 802.15.1 and IEEE 802.11.b, which appear to be slightly mixed up. This can be explained because of the superimposition of the two standards at the same bandwidth of 2.4 GHz. The Final Tonotopy Error for mapping at 11 x 6 grid is 0.0133, which is an excellent result. However, by solving this particular problem with respect to these two standards, we can further reduce this error value. This can be done by the addition of more parameters in Table 1, e.g. the use of Wigner-Ville Transform as suggested in [22] can further discriminate in the two standards. The fact that each input signal to our proposed SOM will map at a specific location of the output grid verifies our approach of standard recognition using the property of tonotopy. Each location forming a cluster represents a standard and thus the cognitive radio can identify the standard based on its position at output grid. Then it can switch its operating parameters respectively to move its state to an optimized form. The visualization of the SOM standards Lattice with respect to distance between input vector and weight vector is shown in Figure 4. This U-matrix shows the distance “between” map-units as well, apart from distance “at” the map-units. As an example, the initial rows of U-matrix form a cluster that corresponds to all the signals with distances between and at map units from 802.11.g. High values on the U-matrix mean large distance between neighboring map-units and thus indicate cluster borders, that

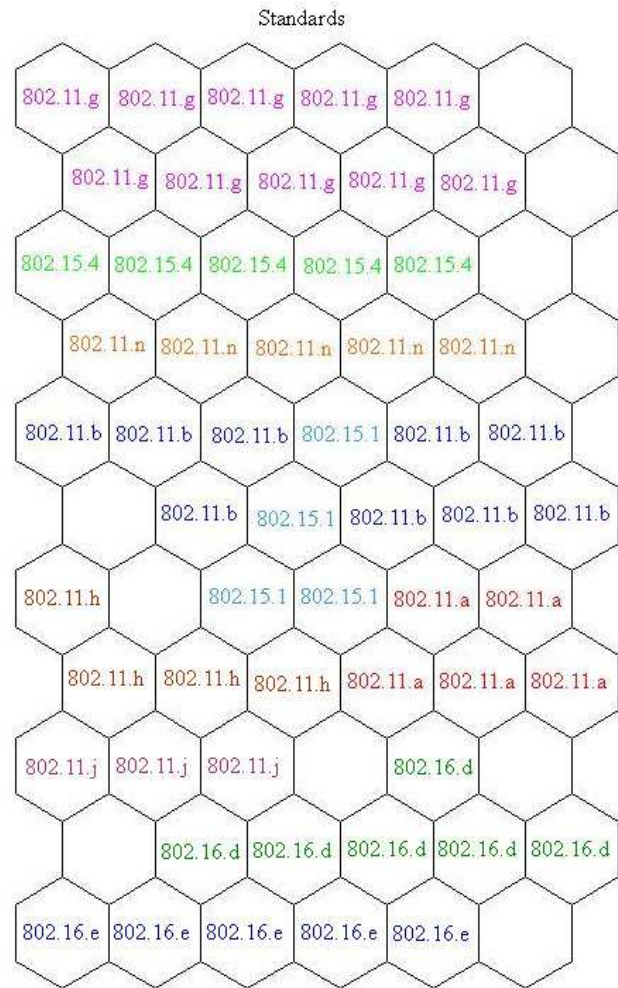


Figure 3: Output grid showing different standards forming a cluster

are shown as uniform areas of low values. The colour bar at the right shows which colour means high values. Figure 5 shows a magnified view of map units in U-matrix. The three map units are IEEE 802.11.g and the same colour between the map units depicts that the distance between all three map units is constant. This constant distance between any two map-units of same standard leads to cluster formation of a particular standard.

The same cluster formation is observed for the standards mentioned in Table 2. We chose to have the same dimensions of output grid (11 x 6) and so each Standard is recognized with the help of its location at the output grid. The only difference is the absence of the neighborhood function, as we have used LVQ and not SOM. Thus, for each new signal received, the map can be used to classify it. The Final Tonotopy Error is 0.0133 which outperforms the counterpart neural network techniques [12,13,16,17,21] used for cognition incorporation in radios. A comparison is done in Table 3 that shows the error values for best cases by using different neural network techniques. Table 3 clearly shows that SOM and LVQ give much better results than other NN techniques proposed for cognition incorporation in SDRs.

**V. CONCLUSIONS AND FUTURE WORK**

The future of wireless communications will be characterized by highly varying environments with multiple diverse features. In such an unfamiliar scenario, CRs need some efficient



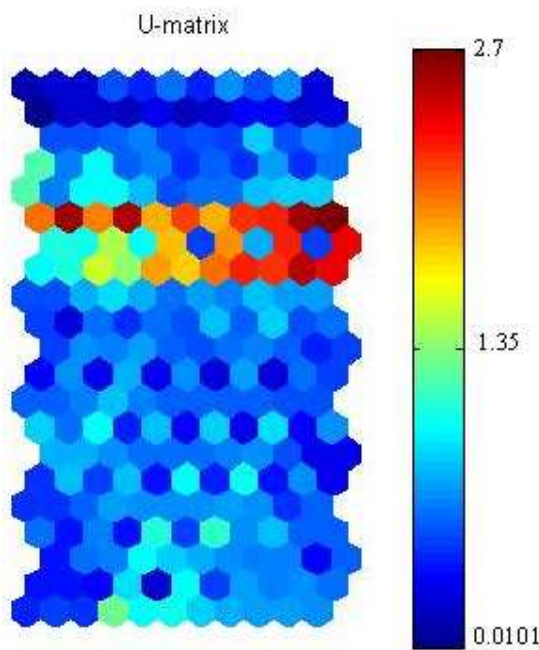


Figure 4: U-matrix for normalized parameters for all Standards.



Figure 5: U-matrix row showing equal distance between three map units of a cluster comprising of 802.11.g Standard.

Researcher	Neural Network Technique	Error Value
Tsagkaris[12]	Custom	0.0637
Tsagkaris[13]	Focused Time Delay	0.0518
Orcay[16,17]	Multi Layer Perceptron	0.0625
Roland[21]	Radial Basis Function	0.021
<b>Our approach</b>	<b>SOM and LVQ</b>	<b>0.0133</b>

Table 3 : comparison with other neural network techniques

information processing algorithm. Self Organizing Maps are widely different from conventional information processing as they have the ability to self organize from given examples thus being able to perform in cognitive tasks. In this respect, we carried out the feasibility study of standard recognition using SOM and LVQ in a Cognitive Radio context using the MATLAB SOM tool box. The preliminary results we obtain are very promising and clearly show that SOM and LVQ outperform other solutions, as shown in Table 3 and thus are an efficient solution to cognition incorporation in the radio. Using SOM and LVQ, our proposed CR model recognized the standard based on parameters received as input to the neural network, moving the radio in the recognized standard mode to make adequate decisions. This leads to optimize radio resource use (spectrum, battery, carrier frequency). Our future work includes the development of parallelization techniques for SOM and LVQ to exploit multi-processor architecture. We target at mapping our algorithm on a multi-core single chip platform that is developed on a Xilinx FPGA Virtex-4 FX based chip [1,2]. The motivation for mapping CR

based algorithms on our NoC based MPSoC comes from the fact that Multi-cores are emerging as solutions for high performance requiring agile frequency CR devices. Since mode switching from one standard to another is a real time constraint, these MPSoC devices can be an efficient answer to CR algorithms embedded implementation, thus leading to cognition incorporation in our designed SDR waveform.

REFERENCES

- [1] M.I. Taj, O.Hammami and K. Huggins“Performance Evaluation of SDR on embedded platform: The case of OSSIE” The 2nd IEEE Conference on Computer, Communications and Control, 2009. **Best Paper Award**
- [2] M.I. Taj, K. Huggins and O.Hammami “OSSIE Signal Processing Functions Performance Enhancements through Parallelization in an embedded multiprocessor architecture” 2009 Software Defined Radio Technical Conference and Product Exposition, Madrid, Spain, April,2009
- [3] [www.wirelessinnovation.org](http://www.wirelessinnovation.org)
- [4] S.Haykin, “Cognitive Radio:Brain Empowered Wireless Communication”, IEEE JSAC, 23(5), pp.201-220, Feb. 2005.
- [5] T.Kohonen,“The Self-Organizing Map”, Proceedings of the IEEE, Vol.78 No.9, September 1990.
- [6] R.J. Lackey and D.W.Upmal,“SPEAKEasy, the Military Software,” IEEE Communication Magazine, 1995
- [7] T. W. Rondeau et al., “Cognitive radio formulation and implementation,” in Proc. of CROWNCOM, June 2006
- [8] T.R. *et al.*, “Cognitive engine implementation for wireless multicarrier transceivers,” Wiley Wireless Communications and Mobile Computing, Sept. 2006
- [9] N. Baldo and M. Zorzi, “Fuzzy Logic for Cross-layer Optimization in Cognitive Radio Networks,” IEEE Communications Magazine, vol. 46 T.W.
- [10] F.Ge, Q.Chen, Y.Wang and C.W.Bostain, “Cognitive Radio: From Spectrum Sharing to Adaptive Learning and Reconfiguration,”IEEE Aerospace Conference, 2008.
- [11] I.A.Akbar, W.H.Tranter, “Dynamic Spectrum Allocation in Cognitive Radio using Hidden Markov Models: Poisson Distribution Case”, IEEE 1-4244-1029-0/07 2007
- [12] K.Tsagkaris, A.Katidiotis and P.Demestichas”Neural Network based learning schemes for cognitive radio systems” Computer Communications Journal Vol.31, issue 14, September, 2008. Pages 3394-3404
- [13] K.Tsagkaris, A.Katidiotis, P.Demestichas “Enhancing Learning in Cognitive Radio Systems by means of Artificial Neural Networks”, ICT-Mobile Summit 2009 Conference Proceedigns Paul Cunningham and Miriam Cunningham (Eds) IIMC International Information Management Corporation, 2009 ISBN: 978-1-905824-12-0
- [14] N.Baldo and M.Zorzi,“Learning and Adaptation in Cognitive Radios using Neural Networks”, IEEE Consumer Communications and Networking Conference 2008,Las Vegas, USA.
- [15] N.Baldo,B.R.Tamma, B.S.Manoj,”R.Rao and M.Zorzi,”A Neural Network based Cognitive Controller for Dynamic Channel Selection”, IEEE, ICC-2009 Proceedings.
- [16] B.Ustundab and O. Orcay, “Pattern Based Encoding for Cognitive Communication”, IEEE CROWNCOM 2008, Singapore
- [17] O.Orcay and B.Ustundag,“Pattern Recognition in Cognitive Communication”, 23<sup>rd</sup> International Symposium on Computer and Information Sciences 2008.Turkey.
- [18] L.Bixio, M.Ottonello, H.Sallam, M.Raffetto and C.Regazzoni, “Signal Classification based on Spectral Redundancy and Neural Network Ensembles”, IEEE CROWNCOM 2009.
- [19] R.Hachemani,J.Palicot and C.Moy”A New Standard Recognition Sensor for Cognitive Radio terminals”, 15<sup>th</sup> European Signal Processing Conference (EUSIPCO 2007), Poland, September, 3-7, 2007
- [20] <http://www.cis.hut.fi/projects/somtoolbox/>
- [21] C.Roland and J.Paligor,“A New Concept for Wireless Reconfigurable Receiver”, IEEE Com Mag,July, 2003.
- [22] M.Gandztto,A.F.Cattoni,M.Musso and C.S.Regazzoni,“Distributed Cooperative Mode Identification For Cognitive Radio Mode Applications” XXVIIIth General Assembly of International URSI October, 23-29, 2005, New-Delhi, India.