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EXPERIMENTAL STUDY OF THE SPECTRUM SENSOR ARCHITECTURE BASED ON DISCRETE WAVELET TRANSFORM AND FEED-FORWARD NEURAL NETWORK

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Abstract. In this paper, we present an experimental study of a new spectrum sensor architecture based on application of discrete wavelet transform for preprocessing and feed forward neural network for classification. For the experimental study, we select three different wavelets: Haar, Daubechies and Symlet. The discrete wavelet transform is applied to radio signal spectral components. The output of wavelet transform we use as an input to the feed-forward neural network (FFNN). The hypothesis on the presence of the primary user signal is made by FFNN with binary output activation function. The proposed spectrum sensor is implemented in FPGA based system and tested on a real environment measures. The spectrum sensing results compared with spectrum sensor based on cyclostationary features. The results of the experimental study shows the ability to use effectively the Haar wavelet in conjunction with FFNN while the amount of not detected primary user emissions remains less than 1.6%. The signal processing is performed in real-time and ads only 52 ns delay.

Key words: spectrum sensing, discrete wavelet transform, neural network, cyclostationary, FPGA.

1. INTRODUCTION

The increasing number of communication devices, which requires high data rates, makes current static frequency allocation schemes ineffective. The use of cognitive radio increase the effectiveness of the use of various frequency bands not occupied by licensed users. The most challenging task for establishing the cognitive radio is the determination of the frequency bands not occupied by primary user. A number of spectrum sensing methods are proposed to detect the absence of primary users in analyzed. The most known spectrum sensing algorithms are based on: energy detector, signal waveform analysis, detection of cyclostationarity features, transmission technology detection.

In this paper, we present the application of the wavelet transform in conjunction with Feed-Forward neural network (FFNN) for detection of primary user signal in the Cognitive Radio systems. An experimental study is performed on a proposed in this paper spectrum sensor, implemented in FPGA. The performance of the spectrum sensor is compared to primary user detection results with alternative spectrum sensor, based on the cyclostationary signal features estimation. The application of cyclostationary features for spectrum sensing requires computationally intensive operations. The idea, presented it this paper, is to use a Haar wavelet for the real-time preprocessing of the signal spectrum components in the selected band. Additionally two alternative (Daubechies and Symlet) wavelet transforms were experimentally tested in order to compare the simple Haar wavelet transform to the alternative ones.

The decision about the presence of the primary user signal usually is made by the threshold function. However, the manual tuning of the threshold value is not acceptable for the spectrum sensors, in order to use them on different signal transmission systems. Therefore, we propose a FFNN network instead of the threshold function with the ability to train FFNN for different wireless transmission systems.

Previous study of energy detectors combined with neural network for primary user signal detection has shown the ability to replace the semiautomatic threshold function [1, 2, 3]. However the energy detector based spectrum sensing have limitations in low signal-to-noise ratio environments. Therefore the cyclostationary feature detectors which has the ability to separate the interested signal from noise or interference, are preferable [4, 5, 6].

The computational complexity of cyclostationary feature based detectors adds limitations for application of these algorithms in low power real-time systems [7]. The use of wavelet transform in recent spectrum sensors has shown the abilities to replace the cyclostationary feature detector with a new, wavelet transform based, solution [8, 9, 10, 11]. Xiaomin Liu *et al.* proposed a spectrum sensor based on compressed sensing to solve the wideband high sampling problem and apply the two-dimensional wavelet transform to the two-dimensional signal matrix in order to reduce the influence of noise to the detector [11]. Adoum, B. A. *et al.* uses the wavelet transform to reduce the noise influence to the second stage of signal analysis based on the cyclostationary features estimated during multiresolution spectrum sensing [12].

The novelty of solution presented in this paper lays in the computationally non-intensive algorithm with FPGA implementation for real-time sensing of the radio spectrum. Proposed spectrum sensor use the output of the wavelet transform as a feature vector for FFNN, which makes the final decision. The proposed solution is experimentally tested in real environment with unpredictable behavior of the signals laying in the 25 MHz band.

2. METHODS

Three different wavelets are implemented for the experimental study: Haar, Daubechies and Symlet. The differences between these wavelets (from the FPGA implementation viewpoint) lays in complexity of implementation and energy consumption.

The implementation of Haar wavelet in the FPGA system is the most efficient (from the energy consumption viewpoint) comparing to alternative wavelets [12, 13]. For the implementation only the addition (or subtraction) and binary shifting is required:

$$\psi_{\mathrm{L}}^{\mathrm{Haar}}(n) = \frac{H(n) + H(n-1)}{2}; \tag{1}$$

$$\psi_{\mathrm{H}}^{\mathrm{Haar}}(n) = \frac{H(n) - H(n-1)}{2}. \tag{2}$$

Here $\psi_{\mathrm{L}}^{\mathrm{Haar}}(n)$ is the low frequency signal, received after Haar transform; $\psi_{\mathrm{H}}^{\mathrm{Haar}}(n)$ is the high frequency signal, received after Haar transform; $H(n)$ is the system input signal and n is the signal sample number. The Daubechies wavelet has more complex implementation, because the multiplications are needed:

$$\psi_{\mathrm{L}}^{\mathrm{D}}(n) = \sum_{k=1}^{N} H(k) h_{\mathrm{L}}(n-k); \tag{3}$$

$$\psi_{\mathrm{H}}^{\mathrm{D}}(n) = \sum_{k=1}^{N} H(k) h_{\mathrm{H}}(n-k). \tag{4}$$

Here $\psi_{\mathrm{L}}^{\mathrm{D}}(n)$ is the low frequency signal, received after Daubechies transform; $\psi_{\mathrm{H}}^{\mathrm{D}}(n)$ is the high frequency signal, received after Daubechies transform; h_{L} is the impulse response of the low-pass filter; h_{H} is the impulse response of the high-pass filter; N is the filter order. The implementation of the Symlet wavelet is the same as Daubechies wavelet implementation, given in Eq. (3) and Eq. (4). The difference lays in the filter coefficients h_{L} and h_{H} used during wavelet application.

2.1. Application of the discrete wavelet transform for spectrum sensing

The wavelet transform is applied for radio signal frequency components $H(n)$ in discrete time domain. The illustration of the spectrogram is given in Fig. 1. The purpose of analyzed spectrum sensor is to detect the primary user signal in the selected frequency band. The analysis of the frequency band is performed continuously.

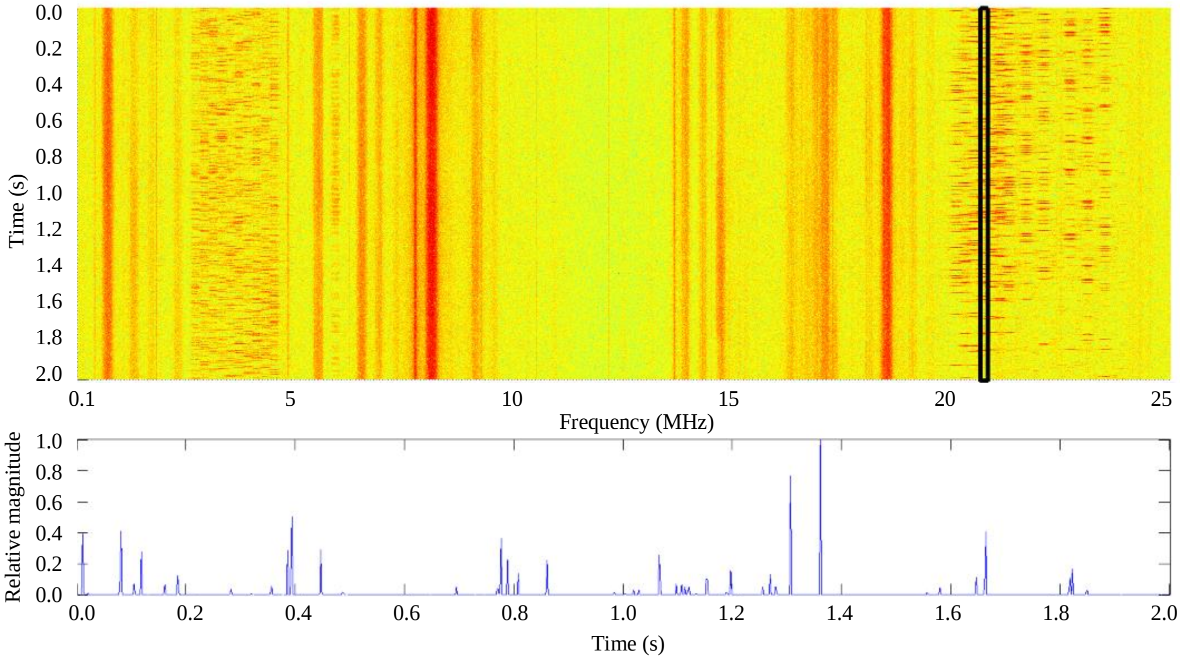

Fig. 1 – An illustration of the spectral component magnitude changes in time.

Figure 2 illustrates the structure of the platform used in this experimental study. I/Q stream is acquired using ETTUS Research B200 Software Defined Radio unit [14]. The resulting data stream is analyzed using FPGA or computer-based system. At the first stage, the FFT is estimated and the wavelet transform is applied to the selected frequency coefficient changes in time. If the resolution of the FFT is higher for selected frequency band (several spectrum coefficients lay in the selected band), the average value of the magnitude is estimated. The experimental study was performed using 1 kHz resolution of the signal spectrum for the 25 MHz analyzed radio band.

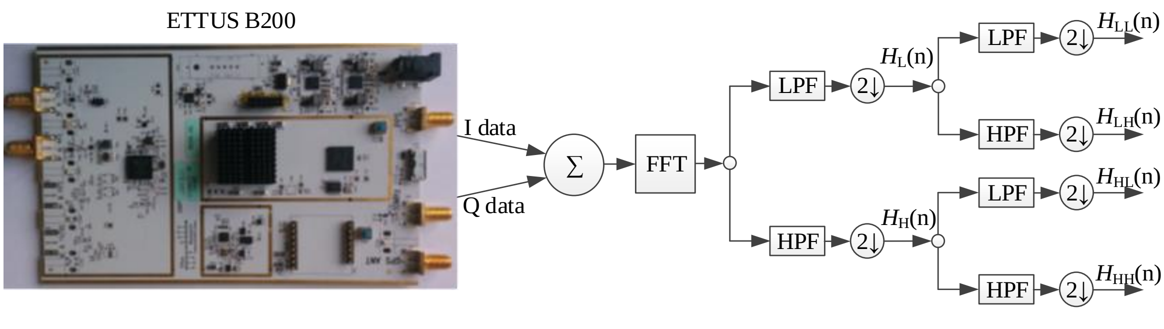

Fig. 2 – Structure diagram of the platform sued for experimental study.

The discrete wavelet transform is performed in two steps. The first step consists of low-pass and high-pass filtering, performed in parallel. This gives $H_{\mathrm{L}}(n)$ and $H_{\mathrm{H}}(n)$ signals (Fig. 2), which additionally are filtered using low-pass and high-pass filters in the second step. As a result, the four signals are received in the output of the system (Fig. 2):

- $H_{\mathrm{LL}}(n)$ is received after double low-pass filtering and gives the envelope of the spectral component changes in time;
- $H_{\mathrm{HH}}(n)$ is received after double high-pass filtering and is useful to detect when the primary user signal transmission begins and when it ends;

- $H_{LH}(n)$ is received after low-pass filtering followed by high-pass filtering;
- $H_{HL}(n)$ is received after high-pass filtering followed by low-pass filtering.

The importance in practical application of $H_{LH}(n)$ and $H_{HL}(n)$ signals is not clear so they are used as an input for the FFNN in order to automatically estimate their influence to the spectrum sensor output. $H_{LL}(n)$ and $H_{HH}(n)$ also are used as FFNN inputs and the weight of each signal to the final decision (do the primary user signal is present) is estimated during the training of FFNN.

2.2. Structure of the Feed-Forward Neural Network

The main purpose of the FFNN, used in the spectrum sensor is to make a decision, do the primary user signal is present in analyzed spectrogram band or not. Therefore, the output layer of the network consists of single neuron, having binary step activation function.

The decision block, based on artificial neural network is selected because of possibility to apply automatic training to neural network in order to estimate parameters of the system (decision block). A simplest structure of the binary classifier is a Single-Layer Perceptron. However, there might be additional nonlinearities in the relations between signals, received of the wavelet transform. So the two-layer perceptron network structure is proposed for the current application.

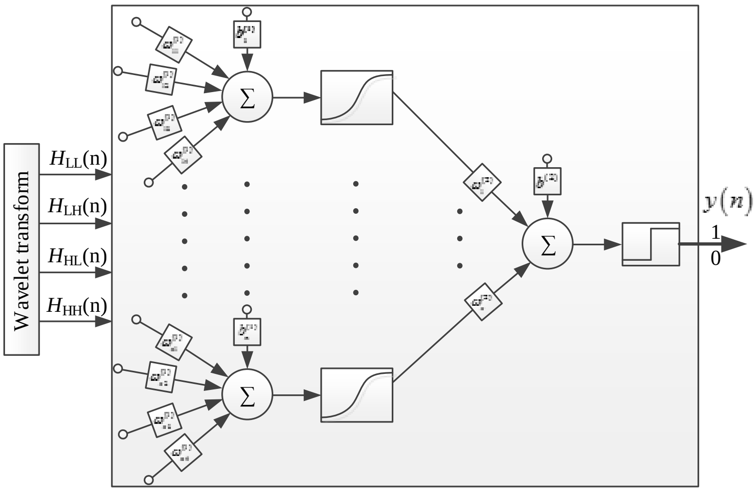

Fig. 3 – Structure diagram of the FFNN.

The training of the multilayer neural network with binary step activation function is a challenging task [15]. However there are logistic sigmoidal activation functions in the hidden layer which are differentiable and gives possibility to apply the Levenberg Marquardt backpropagation training algorithm for the feed-forward neural network with the linear output neuron activation function. The binary step is implemented as the additional function, applied to the network output with fixed threshold at zero. The structure diagram of the FFNN is given in Fig. 3.

The number of neurons in the hidden layer is to be estimated during experimental study and comparing the performance and primary user signal detection capabilities of the spectrum sensor. The experimental investigation results, received by selecting different number of hidden neurons are given in Section 3.

2.3. Spectrum Sensor Implementation in FPGA

Two main blocks of the spectrum sensor are implemented in FPGA. The first block calculates the wavelet transform and the second block calculates the output of the FFNN [16, 17]. Two separate versions of the first block are implemented: version with Haar wavelet transform and version with Daubechies wavelet transform. The Symlet wavelet transform is performed using Daubechies wavelet transform with different filter coefficients.

The Spartan-6 FPGA based system was selected for the experimental study. The implementation of the Haar wavelet transform requires 291 Slice Registers (from 54 576 available in the chip) and 554 Slice Luts (from 27 288 available on the chip). The total delay for Haar wavelet transform is only 4 clock periods. With the 2 ns period of single clock, the total delay is 8 ns.

The Daubechies and Symlet wavelet transforms requires a filter bank to be implemented [12, 18]. For both types of wavelet transform, the same size of the filter bank is used (only the coefficients are different). The filter band requires 1417 Slice Registers and 871 Slice Luts reserved on the chip. Because of the additional Multiply–accumulate (MAC) operations that are needed for the application of the filter bank to the input signals, additionally 18 DSP48A1s elements (from 58 available on the chip) are needed. The total delay, estimated for Daubechies and Symlet wavelet transforms is 40 clock periods (80 ns).

The number of hardware elements needed for FFNN implementation varies depending on the selected network structure [19]. The FFNN with two neurons in the hidden layer requires 569 Slice registers, 781 Slice Luts, 13 DSP48A1s elements and two block RAM elements (from 116 available on the platform). The delay of the FFNN is 44 ns (implementation requires 22 clock periods).

The architecture of the FPGA chip give us possibility to implement several parallel calculation processes. Therefore, number of hidden neurons can be increased keeping the same 44 ns delay in the second block of the spectrum sensor. The limitation in implementation lays in the number of Slice Regiters, Slice Luts, block RAM and especially in the number of DSP48A1s elements, available on the chip. The FFNN with six hidden neurons requires 1073 Slice Registers, 1305 Slice Luts, 37 DSP48A1s elements and 6 block RAM elements. These hardware resources should be shared between two spectrum sensor blocks unless two separate FPGA chips are used for implementation of the ach spectrum sensor block.

3. MATERIALS AND METHODS

An experimental investigation is performed in two stages. At the first stage, the manually set threshold is used for primary user signal detection using one of the wavelet transform block outputs. At the second stage, the FFNN is used for decision making accordingly to all four received output signals.

3.1. Spectrum Sensor Sensitivity Analysis using One Wavelet Transform Output Signal

The illustration of the four output signals, received after Haar wavelet transform is given in Fig. 4. The red line indicates the output of the threshold function, used for making a decision. The threshold is selected manually and is not changed during experimental study. The "1" at the function output indicates the presence of the primary user in the analyzed frequency band. Each output signal is analyzed individually at this stage of experimental study. It is seen in Fig. 4, that individual analysis of each signal gives good sensing results, but some (such as $H_{\mathrm{LH}}(n)$ or $H_{\mathrm{HH}}(n)$) output signals are more suitable for sensing than the rest.

The comparison of the received spectrum sensing results is made using alternative spectrum sensing technique, based on the cyclostationary signal features. The results are shown in Fig. 4. Three types of mismatches are observed:

- Market with line situations, when the primary user signal is disappeared (accordingly to cyclostationary features based approach), but the first wavelet transform iteration still shows the presence of the primary user;
- Market with ellipsis situations, when the wavelet transform based spectrum sensors finds some attributes of the primary user signal but the cyclostationary features based spectrum sensor did not find any transmitted signal;
- Market with square situations, when the primary user signal is present accordingly to cyclostationary features based spectrum sensor, but the wavelet transform based spectrum sensor did not find any primary user attributes.

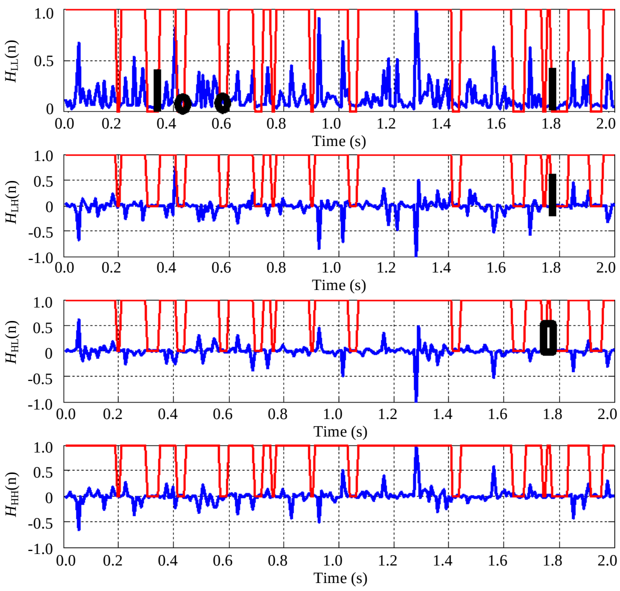

Fig. 4 – Spectrum sensing results using Haar wavelet transform.

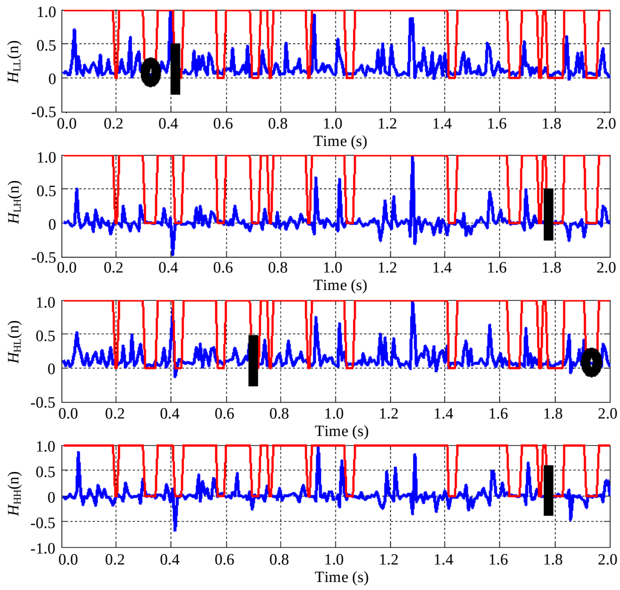

Fig. 5 – Spectrum sensing results using Daubechies wavelet transform.

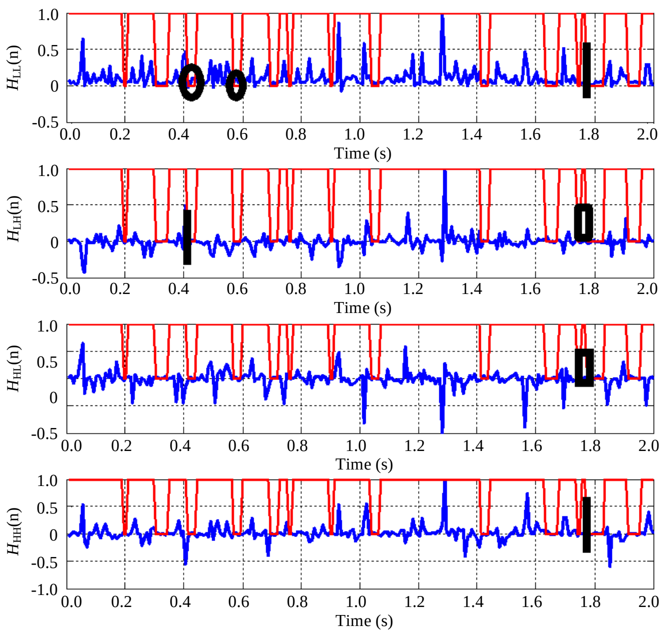

Fig. 6 – Spectrum sensing results using Symlet wavelet transform.

There are three situations market with line for the Haar wavelet transform, two market with ellipsis and one with the square. Looking at the received results it seems that only the $H_{HH}(n)$ signal can be used for spectrum sensing applications without the need of calculation the rest three signals.

Analyzing the results of the same type experimental investigation using Daubechies wavelet transform (Fig. 5) and Symlet wavelet transform (Fig. 6), the number of situations market by line increases to 4 for Daubechies wavelet, remains the same for Symlet wavelet. The difference in primary user signal detection is comparatively not very high. Therefore, the application of simple Haar wavelet transform is preferred because of the high computational efficiency and low delay (8 ns). The results received during the experimental study shows that the decisions of the spectrum sensor, made accordingly to only one output signal are not stable and frequently differs. *E.g.* signal with Daubechies wavelet transform applied shows line market failure of spectrums sensor, which was not able to detect the end of active primary user transmission in $H_{HH}(n)$ but efficiently worked for $H_{LL}(n)$ and $H_{HL}(n)$ signals. In this situation, an additional spectrum sensor block, making decisions accordingly several simultaneous signals should be used to take the final decision. Such decision block, based on the FFNN, is proposed in this paper.

3.2. Spectrum Sensor Sensitivity Analysis using Feed-Forward Neural Network

The structure of the FFNN could make an influence to the network capabilities to work as a classifier. The experimental study is performed by selecting different number of FFNN hidden neurons and by using different input signals, received after performing: Haar, Daubechies or Symlet wavelet transform. The training data consists of signal spectrum measurement results and cyclostationary features based spectrum sensor output, which gives target values for the network. During the training procedure the data values from the training set are taken in random order, leaving 15% of measurements for validation and additional 15% of data for testing. The structure of the FFNN is changed by adding two additional neurons in the hidden layer. The spectrum sensing results for the spectrum sensor with Haar wavelet transform and FFNN are given in Table 1.

Table 1

Spectrum sensing results using Haar wavelet

Number of neurons in the hidden layer	Emissions not detected	False alarm ratio
2	1.530%	0.358%
4	1.529%	0.356%
6	1.525%	0.359%
8	1.539%	0.358%
10	1.528%	0.358%

Table 2

Spectrum sensing results using Daubechies wavelet

Number of neurons in the hidden layer	Emissions not detected	False alarm ratio
2	1.989%	0.173%
4	1.469%	0.369%
6	1.157%	0.438%
8	1.961%	0.278%
10	1.534%	0.504%

As it is seen form the results of experimental investigation, the increase of the number of neurons does not reduce the amount of not detected emissions by the proposed spectrum sensor. It is worth to mention that the amount of not detected emissions and the ratio of false alarm does not changes much when the Haar wavelet transform is applied. Therefore, the structure of the FFNN with two neurons in the hidden layer could be selected as an optimal one.

The application of Daubechies wavelet transform gives more varying results (Table 3) and makes it possible to reduce the amount of not detected emissions from 1.525% (Haar wavelet case) to 1.157% with the increase of false alarm ratio from 0.359% to 0.438%. The higher false alarm ratio reduces the efficiency of the spectrum utilization; however, the amount of not detected emissions may lead to the interference with primary user signal, which should be avoided.

Table 3

Spectrum sensing results using Symlet wavelet

Number of neurons in the hidden layer	Emissions not detected	False alarm ratio
2	1.989%	0.173%
4	1.469%	0.369%
6	1.157%	0.438%
8	1.961%	0.278%
10	1.534%	0.504%

The spectrum sensing results for the Symlet wavelet and FFNN based spectrum sensor are given in Table 3. The amount of not detected emissions for this spectrum sensor increases twice comparing to the previous two. The false alarm ratio is much lower for all analyzed structures. However, it is more important to reduce the amount of not detected emissions. Therefore, the Symlet wavelet should not be used as an alternative to Haar or Daubechies wavelets.

4. CONCLUSIONS

An experimental study, presented in this paper shows the ability to apply the discrete wavelet transform based signal analysis techniques together with FFNN in spectrum sensing for cognitive radio applications.

The computational complexity of cyclostationary feature based spectrum sensing methods could be replaced with wavelet transform based signal analysis in time domain with additional FFNN attached for the decision about the presence of the primary user in the analyzed spectrum band.

The performance of the spectrum sensor depends on the discrete wavelet transform type, selected for the sensor. The application of Daubechies wavelet leaves less amount of not detected primary user emissions (1.157% using FFNN with six neurons in the hidden layer). However, the most energy efficient spectrum sensor based on Haar wavelet with two neurons in the hidden layer of FFNN leaves 1.53% emissions not detected and it is only 0.37% difference comparing to the best result, received using Daubechies wavelet.

The FPGA implementation of the spectrum sensor, based on the Haar wavelet and FFNN requires 860 Slice registers (569 for $\psi_{\mathrm{L}}^{\mathrm{Haar}}(n)$ and 291 for FFNN), 1335 Slice Luts (781 for $\psi_{\mathrm{L}}^{\mathrm{Haar}}(n)$ and 554 for FFNN), 13 hardware DSP blocks and 2 Block RAM elements. It gives in total 52 ns delay (8 ns for $\psi_{\mathrm{L}}^{\mathrm{Haar}}(n)$ and 44 ns delay for the FFNN, implemented in FPGA).

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