Intelligent Channel Assignment for WI-FI System Based on Reinforcement Learning

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Abstract— This paper focuses on enhanced channel planning for WI-FI systems. Based on a real measurement of the frequency spectrum background, the quality of each channel has been classified. Machine learning algorithms are used to process these data and control the system. Reinforcement learning (a special example of machine learning) is used due to its complexity as a test-trial agents system. In the proposed system punishment and reward schema are utilized making it possible to change channels during the transmission and use the one with minimal interference. The promising increase of SINR up to 5% for outdoor scenarios and up to 30% for indoor scenarios should be applied to improve modulation schemas and increase data throughput.

1. INTRODUCTION

WI-FI has recently become a dominant wireless technology for local area networks (LAN) and personal area networks (PAN) worldwide. All modifications of IEEE 802.11 [1] became extremely popular over recent decades and WI-FI modules are now installed in various types of devices such as laptops, mobile phones, smart TVs, digital cameras etc. Even intelligent buildings need to be connected to the common, domestic, network devices such as laundry machines and fridges. The ISM frequency bands (2.4 GHz and 5 GHz) used for WI-FI systems are quite narrow resulting in a lack of the capacity for all the devices. Another issue which has to be solved is the demand for high transmission speed. To provide higher than 100 Mbit connectivity between the receiver and transmitter, new modulation schemes and connections between several consecutive channels (channel aggregation) have to be used. These solutions require high Signal-to-Noise-Ratio (SNR) and precise spectrum planning. Cognitive radio [2] ideas should solve the following frequency spectrum problems: low SNR, overfilled frequency spectrum and channel assignment. Cognitive radio is an intelligent autonomous system with the ability to change its parameters according to the environment (radiation power, modulation, and channel). In this paper we introduce intelligent channel allocation for a single-channel WI-FI system as well as an aggregated-channel WI-FI system (802.11n) [3]. Based on real measured data [4] from the spectrum survey, the entire WI-FI band is investigated in detail and channels are prioritized according to its occupancy. Each channel receives a score (the higher the score, the less suitable the channel) given by a weigh function from the reinforcement learning algorithms. Afterwards, this score is updated over time and the temporarily used channel should also decrease its score as a consequence of subsequent time steps. The learning is in continuous action.

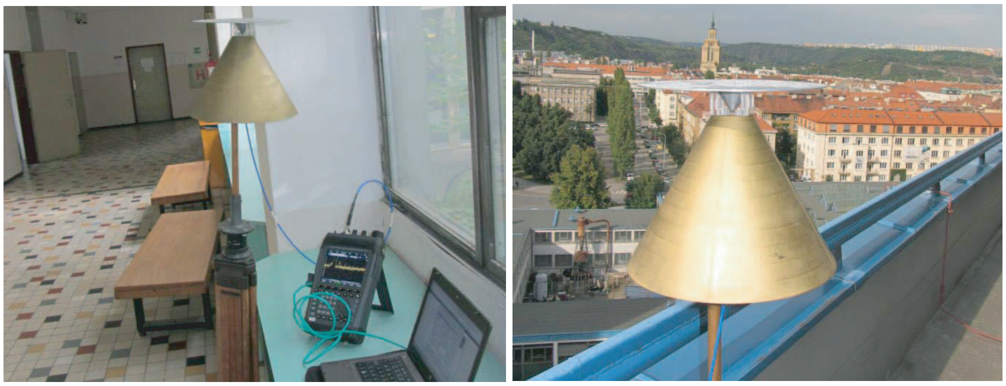
2. SCENARIO DESCRIPTION

The data in the simulation are based on a real measurement of spectrum background which is described in [2]. The data are collected by a fast and sensitive energy detector, an omni-directional antenna and post-processed in Matlab environment. Firstly, systematic errors are removed from the measured data via calibration. Secondly, we assume that the data (mdata) are structured as in (1):

$$m_{data} = m_{signal} + m_{noise}, \tag{1}$$

where m_{signal} stands for any signal at a particular frequency/frequency band. m_{noise} is an additive noise from the environment and the measurement system which is eliminated in calibration.

The measurements were performed in carefully chosen outdoor and indoor locations as depicted in Fig. 1. Indoor scenarios were measured in a university building to provide data from a heavily used wireless environment. The measurements ran during lectures and night hours to cover the difference in usage of the shared spectrum. The same parameters were chosen for outdoor measurements. For this paper we used data from the roof of the university building which covers a large geographical area occupied by numerous public and private wireless services.



(a) (b)

Figure 1: Measurement setup for indoor and outdoor locations.

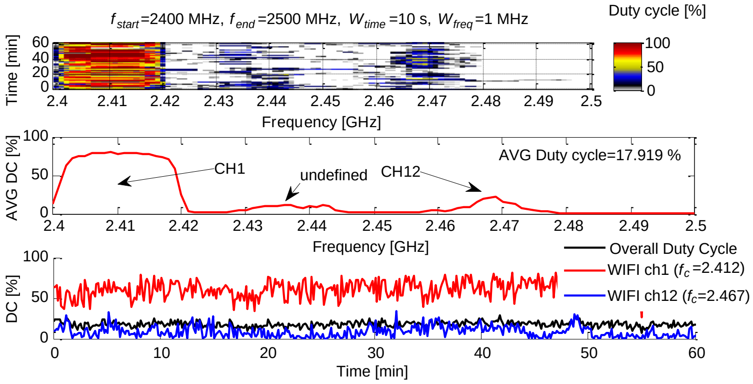


Figure 2: Occupation of the WI-FI band for an indoor scenario.

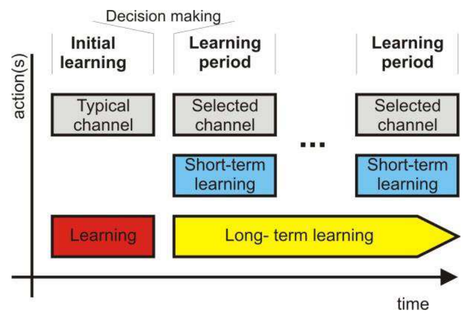


Figure 3: System description in time.

Energy detection for spectrum monitoring [3, 4] is sometimes called semi-blind because the decision threshold needs to be carefully estimated. For the measured data we chose a threshold level 12 dB over the baseline based on [5], where the calculation was made using the Q-function. Baseline was calculated as an absolute value of the measured data m_{data} and the calibration data m_{cal}. For the calibration we used the average value of 100 measured samples for each frequency point. This calibration reduced all noise created by the measurement system. All peaks detected over the threshold level (12 dB) were counted as "interference count" and they brought additional noise to the transmission.

The main indicator of spectrum utilization is not the level of the signal, but the *Duty Cycle* which is defined as the number of detected peaks over the threshold divided by the number of total frequency and time points in the measurement. These results for the WI-FI band are presented in Fig. 2.

The whole system works as depicted in Fig. 3. At the beginning of the communication, the connection starts normally. Clients are connected to a specific SSID (Service Set Identifier). During the communication, the initial learning is performed and the vector of suitable channels is picked up. We focused on the five best channels to have more choices. When several channels had the same score, the one with lowest number was chosen. Secondly, the wireless channel should be changed after the initial learning or kept the same if the currently used channel is listed in the five best channels. Otherwise, AP informs the clients about changing the transmission channel and the communication is transformed to a different channel.

3. SIMULATION RESULTS

The crucial parameter of the whole system is the machine learning [6] output — the vector of all channels with its scores. The scores are obtained from a reinforcement learning algorithm. That is a technique using an agent to learn from direct interaction with the environment to maximize its reward and perform a specific action [6]. Generally, the agent has no additional information and it needs to discover which available action yields the highest performance of the system. Reinforcement learning has 2 main features: test-and-trial and delay of reward. In our example, the reward gains the channel when there is interference on an investigated frequency point. The channel received punishment when the frequency point was used. The output of the algorithm is presented in Fig. 4.

Our reinforcement learning algorithm used the overlapping windows with window size (SW) set to 2. This value was set to increase the influence of consecutive interference for a particular channel (2). Each channel in our system had its own weight value (WR_{ch}). The state from the previous iteration ($W_{ch,t-1}$) is updated with a new reward/punishment (RP) score of a particular channel.

$$[WR_{ch} = W_{ch,t-1} + RP. \tag{2}$$

Our proposed system worked with restrictive punishment (3). Moreover, to disable the accumulating reward, due to several consecutive samples, we decided that RP needed to be zero or a positive number.

$$RP = \sum_{i=1}^{S_W} P_i + R_i = \sum_{i=1}^{S_W} \left(\sum_{y_i}^{n_i} 5^n - \sum_{z_i}^{m_i} 2^n \right) \quad \text{if} \quad P_i < R_i, \quad P_i + R_i = 0, \tag{3}$$

where SW is the number of samples in the window. R_i and P_i stand for total reward and punishment in the window. In each window, we were detecting n_i sub-windows containing interference where n is the number of consecutive samples with the same condition. When there is no interference detected we user m and m_i respectively instead of n.

Learning time needs to be discussed as well. We found the optimal learning time for initial learning to be two minutes. In the simulations, we compared initial learning with the results from all the measured dataset. By this calculation we are able to evaluate the accuracy of initial learning, see Fig. 5, where it is clearly proved that two minutes is the shortest initial learning time period.

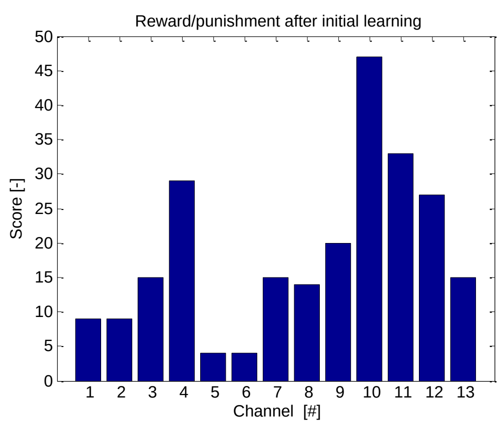


Figure 4: Scores from learning after 2 minutes.

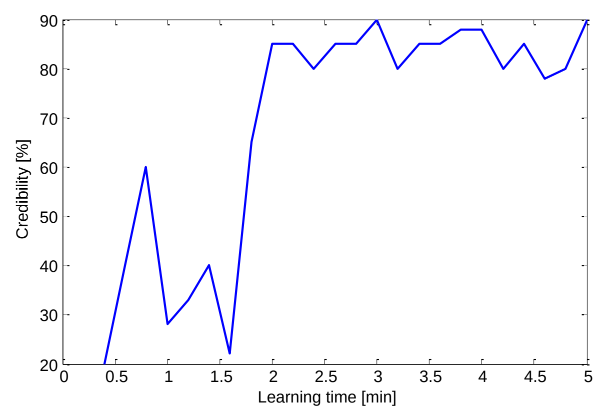


Figure 5: Credibility of the initial learning.

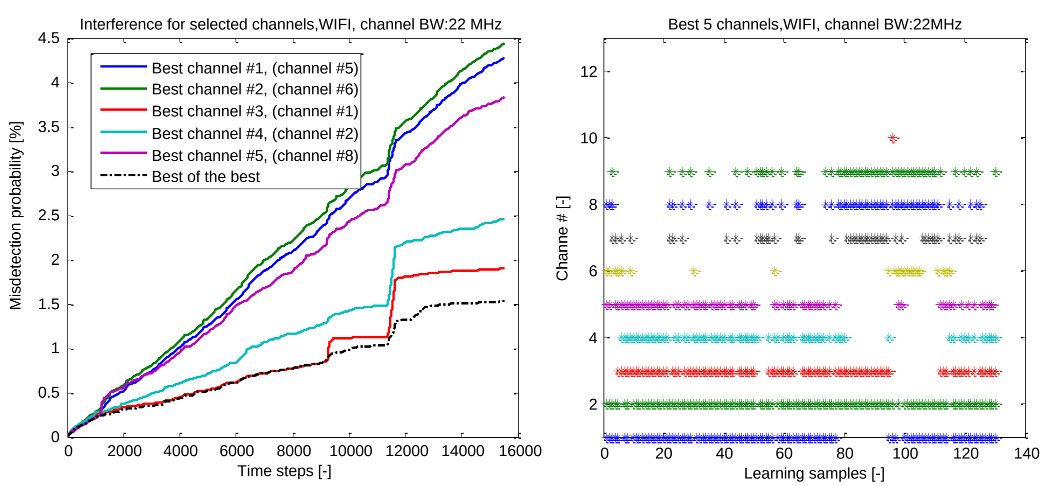


Figure 6: The best channel selection for outdoor heavily used system.

After initial learning we chose the best channel, then every 10 minutes (this time was chosen and verified with the same principle as the initial learning time) the scores were updated. Fig. 6 shows the misdetection probability, representing the total number of the interference count, which actually influences our system. This figure also presents the distribution of the five best channels in the system.

4. CONCLUSION

The preliminary results for channel selection for WI-FI were presented. We assume that modern WI-FI access points are continuously sensing the spectrum. These data are processed by a novel machine learning system and the vector of the available channels is created and updated over the whole transmission period. The presented system brings a significant improvement in WI-FI channel planning and interference noise of the chosen channel. Compared to traditional channel assignment, we improved the system by 2%–10% for outdoor systems and up to 30% for indoor systems. The improvement rate was calculated by counting the interference occurrences based on measured data.

ACKNOWLEDGMENT

This work was supported by the project CZ.1.07/2.3.00/30.0005 of Brno University of Technology.

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