Modulation and Coding Classification for Adaptive Power Control in 5G Cognitive Communications

Anestis Tsakmalis, Symeon Chatzinotas and Björn Ottersten
SnT - securityandtrust.lu, University of Luxembourg
Email:{anestis.tsakmalis, symeon.chatzinotas, bjorn.ottersten}@uni.lu

(Invited Paper)

***Abstract*—A key concept suggested for 5G networks is spectrum sharing within the context of Cognitive Communications (CC). This efficient spectrum usage has been explored intensively the last years. In this paper, a mechanism is proposed to allow a cognitive user, also called Secondary User (SU), to access the frequency band of a Primary User (PU) operating based on an Adaptive Coding and Modulation (ACM) protocol. The Spectrum Sensing (SS) technique used considers Higher Order Statistical (HOS) features of the signal and log-likelihood ratios (LLRs) of the code syndromes in order to constantly monitor the modulation and coding scheme (MODCOD) of the PU respectively. Once the Modulation and Coding Classification (MCC) is completed, a Power Control (PC) scheme is enabled. The SU can attempt to access the frequency band of the PU and increase its transmitting power until it causes a change of the PU's transmission scheme due to interference. When the SU detects the change of the PU's MODCOD, then it reduces its transmitting power to a lower level so as to regulate the induced interference. The proposed blind Adaptive Power Control (APC) algorithm converges without any interference channel information to the aforementioned interference limit and guarantees the preservation of the PU link throughput.**

Keywords*—Cognitive Communications, Spectrum Sensing, Modulation and Coding Classification, Higher Order Statistics, Log-Likelihood Ratios, Code Syndromes, Adaptive Power Control, Adaptive Coding and Modulation

I. INTRODUCTION

Dynamic Spectrum Access (DSA) is a key technique to achieve the coexistence of some services in specific frequency bands [1]. Towards that direction, the development of CC has enabled many aspects of DSA [2]. The realization of the CC begins with the sensing part. One way of enhancing CC with environment awareness is signal detection. This new radio must be able to identify all kinds of signals and a simple approach can be the recognition of their modulation and coding schemes. This SS mechanism concerning the modulation and coding detection is termed Modulation and Coding Classification (MCC) and has been realized by extracting features of the signal and classifying it based on them.

As far as modulation classification is concerned, the features exploited in this paper are the signal cumulants of 2nd, 3rd, 4th, 6th and 8th order [3–6], which have distinctive theoretical values among different modulation schemes and even though they demand a great amount of samples, they are easy to calculate. These statistical characteristics are fed into a powerful classification tool, the SVM, which has been frequently used in the literature [4], [5], [7–11]. For the coding identification part, the most common statistical features in previous work are the LLRs of the received symbol samples [12], [13]. The detection technique in this case involves the comparison of the average LLRs of the error syndromes derived from the parity-check relations of each code.

Another aspect of the DSA concept that has to be examined is the PC strategy under which the SU is accessing the frequency band of the PU. An interesting approach in this topic, suitable for a CC network is the distributed one. In this case, we focus on a 2×2 cognitive channel, consisting of a PU link and a SU link and without any control channel between them. Most studies in this field have employed iterative methods such as pricing models or one bit control channel and usually they provide a game theoretic framework to prove their convergence to an equilibrium [14–16].

In this paper, an integrated application is demonstrated which concerns an SU and focuses on both MCC and PC. The examined scenario considers a PU link changing its modulation and coding scheme based on an ACM protocol and operating in its assigned band together with an SU link entering this band. In this work, it is proposed the cognitive user to apply SS techniques in order to control its interference to the PU. The interference control is achieved by having the coexisting cognitive SU constantly sensing the transmission scheme of the PU, which changes dynamically based on the ACM protocol. The transmitting power is adapted whenever it degrades the modulation or coding scheme of the PU. The proposed DSA application concerns only the SU's side without adding any complexity in the infrastructure or a control channel between the two links in order to exchange information about the channel or the induced interference and the APC mechanism is a simple power scaling with a variable step.

The remainder of this paper is structured as follows: Section II provides the system and signal model. Section III introduces the MCC implementation. Section IV analyzes the APC technique. Section V shows the results obtained by the combination of the above. Finally, Section VI gives the concluding remarks and future work in this topic.

II. SYSTEM AND SIGNAL MODEL

In this paper, the 2×2 cognitive system consists of a PU link and a SU link in the same frequency band as shown in Fig. 1. Furthermore, the signal from the PU link transmitter is received by the cognitive user using a secondary omnidirectional antenna only for sensing and assuming propagation in an AWGN channel. As far as the interference to the PU link is concerned, this is caused by the transmitter part of the SU link to the receiver of the PU link. Considering a LOS interference link, this may have a severe effect on the modulation and coding scheme chosen by the PU link. Moreover, the interference from the PU link to the receiver of the SU link is regarded to be negligible. In this scenario, the former interference is analyzed and it contributes to the formulation of the APC problem.

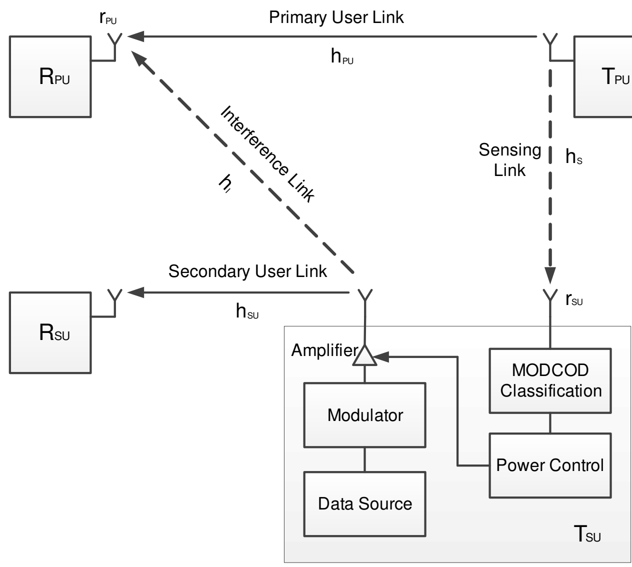

Fig. 1. The 2×2 cognitive system

In addition, the received symbol samples can be written[1] as:

$$r_{SU}[i] = h_S * s_{PU}[i] + n_{SU}[i] \tag{1}$$

where h_S is the sensing channel gain, $s_{PU}[i]$ is the transmitted symbol from the PU and $n_{SU} \sim \mathcal{N}(0, N_{SU})$ is the Additive White Gaussian Noise (AWGN). On the PU side, the received symbol samples can be written as:

$$r_{PU}[i] = h_{PU} * s_{PU}[i] + h_I * s_{SU}[i] + n_{PU}[i] \tag{2}$$

where h_{PU} is the PU channel gain, h_I is the interference channel gain, $s_{SU}[i]$ is the transmitted symbol from the SU and $n_{PU} \sim \mathcal{N}(0, N_{PU})$ is the AWGN. It also has to be remarked that the channels used in this paper are flat and their gains are not varying. Additionally, the transmitting powers of the PU and the SU are expressed as:

$$P_{PU} = E\{s_{PU} s_{PU}^*\} \tag{3}$$

$$P_{SU} = E\{s_{SU} s_{SU}^*\} \tag{4}$$

and the $SINR$ of the PU is defined as:

[1]The SU achieves symbol synchronization in sensing the PU signal.

$$SINR_{PU} = 10 \log \left(\frac{|h_{PU}|^2 * P_{PU}}{|h_I|^2 * P_{SU} + N_{PU}} \right). \tag{5}$$

From a system perspective, an arbitrary ACM scheme is adopted close to the technical specifications of the 802.11 protocol set. According to that, the PU cannot vary its transmitting power P_{PU}, its transmitted symbol $s[i]$ can be of QPSK, 16QAM or 64QAM modulation scheme and the coding used in bit level is based on a binary low-density parity-check (LDPC) code of rates 1/2, 2/3, 3/4 or 5/6. Their combinations provide us with the available MODCOD set: QPSK 1/2, QPSK 3/4, 16QAM 1/2, 16QAM 3/4, 64QAM 2/3, 64QAM 3/4 and 64QAM 5/6. In order to increase the efficiency of the MCC, these blind identification techniques can operate given a predefined candidate set of modulation schemes and code rates. This means that if the cognitive user intends to access the frequency band of the PU link, it needs to have knowledge of the aforementioned MODCOD set and also of the error correcting code the PU uses.

III. Modulation and Coding Classification

Statistical processing of communication signals can provide us with critical features indicating their nature. Assuming the signal model described in (1), we can obtain the 2nd, 4th, 6th and 8th order mixed cumulants of the r_{PU} complex received signal $C^r_{2,0}$, $C^r_{2,1}$, $C^r_{4,0}$, $C^r_{4,1}$, $C^r_{4,2}$, $C^r_{6,0}$, $C^r_{6,1}$, $C^r_{6,2}$, $C^r_{6,3}$, $C^r_{8,0}$, $C^r_{8,1}$, $C^r_{8,2}$, $C^r_{8,3}$, $C^r_{8,4}$.

Cumulants are best expressed in terms of raw moments. A generic formula for the joint cumulants of several random variables $X_1, ..., X_n$ is

$$C_{X_1,...,X_n} = \sum_{\pi} (|\pi| - 1)!(-1)^{|\pi|-1} \prod_{B \in \pi} E\left\{\prod_{i \in \pi} X_i\right\} \tag{6}$$

where π runs through the list of all partitions of $1, ..., n$, B runs through the list of all blocks of the partition π and $|\pi|$ is the number of parts in the partition. Consequently, the pth-order mixed cumulant $C^r_{p,q}$ of the complex received signal can de derived from the joint cumulant formula in (6) as:

$$C^r_{p,q} = C_{\underbrace{r, ..., r}_{\text{(p-q) times}}, \underbrace{r^*, ..., r^*}_{\text{(q) times}}} \tag{7}$$

where r^* is the the complex conjugate signal. Because of the symmetry of the considered signal constellations pth-order mixed cumulant for p odd are equal to zero and also it can be easily proven that for p even $C^r_{p,q} = C^r_{p,p-q}$.

The estimates of the previous statistical characteristics are going to be the features fed into a pattern recognition structure which will decide the modulation scheme the signal belongs to. A powerful and new classification tool that previous researchers used is the SVM. Its mathematical foundation is statistical learning theory and it has been developed by Vapnik [17].

The SVMs operate by finding a hyperplane in a high dimensional space which divides the training samples in two classes. This hyperplane is chosen so that the distance from it to the nearest data points on each side is maximized. Non-linear separation of data is also possible with some small adaptations and using the kernel trick. An indirect mapping of input feature vectors into a higher dimensional space can be achieved in which they become linearly separable.

The multi-class classification of a test signal into one of the 3 available modulation schemes of the ACM, the classes, is implemented by combining $\frac{3\cdot 2}{2}$ binary classifiers to find to which class it most likely belongs compared to every other one. Following this one-against-one approach, the most usual strategy for labeling a test signal is to cast a vote to the resulting class of each binary classifier. After repeating the process for every pair of classes, the test signal is assigned to the class with the maximum number of votes.

As far as the LDPC code rate classification is concerned, previous work [12], [13] has been based on the unique parity-check matrix that each code rate has. A candidate LDPC encoder θ' has an exclusive parity-check matrix $\mathbf{H}_{\theta'} \in \mathbb{Z}_2^{N_{\theta'} \times N_c}$, where $N_{\theta'}$ is the number of parity check relations of the candidate encoder and N_c is the length of the produced by the encoder θ' codeword, which for the examined LDPC code rates is always equal to 64800. Given a codeword $\mathbf{c}_\theta \in \mathbb{Z}_2^{N_c \times 1}$ from encoder θ, in a noiseless environment the following

$$\mathbf{H}_{\theta'}\mathbf{c}_\theta = \mathbf{0} \tag{8}$$

holds over the Galois field $\mathbb{GF}(2)$ if and only if $\theta' = \theta$. Due to noise in the codeword though, some errors occur in (8) even when choosing the correct encoder θ. These errors are called code syndromes e^k and for a candidate encoder θ' in vector form they are defined as

$$\mathbf{e}_{\theta'} = \mathbf{H}_{\theta'}\mathbf{c}_\theta \tag{9}$$

where $\mathbf{e}_{\theta'} \in \mathbb{Z}_2^{N_{\theta'} \times 1}$ and every line represents a parity-check relation. In order to use the code syndromes $\mathbf{e}_{\theta'}$ in code rate identification, a soft decision metric was introduced in [18] and exploited by later researchers. This feature is the average LLR of the code syndromes and it is considered as a reliability estimate of the syndromes. To compute this, one needs to calculate the LLR of each bit of the codeword $\mathbf{c}_\theta$, which after some processes in the log-likelihood domain is obtained as

$$LLR(c[m]|r_{SU}[n]) = LLR(r_{SU}[n]|c[m]) \tag{10}$$

where $c[m]$ is the considered bit and $r_{SU}[n]$ is the corresponding received symbol sample. This is the result of the log-likelihood soft decision demodulation. Subsequently, if $e^k_{\theta'}$ is the syndrome derived from the k^{th} parity check relation of the candidate encoder θ'

$$e^k_{\theta'} = c[k_1] \oplus c[k_2] \oplus ... \oplus c[k_{N_k}] \tag{11}$$

where N_k is the number of codeword bits taking part in the XOR operations of the parity check relation, then the LLR of $e^k_{\theta'}$ is given by

$$LLR(e^k_{\theta'}) = 2tanh^{-1}\left(\prod_{q=1}^{N_k} tanh\left(LLR(c[k_q])/2\right)\right). \tag{12}$$

Finally, the average syndrome LLR is calculated as

$$\varGamma_{\theta'} = \frac{\sum_{k=1}^{N_{\theta'}} LLR(e^k_{\theta'})}{N_{\theta'}}. \tag{13}$$

Once, the average syndrome LLRs of all the candidate encoders are calculated, the estimated encoder can be identified as

$$\hat{\theta} = \arg\max_{\theta' \in \Theta} \varGamma_{\theta'} \tag{14}$$

where Θ is the set of the LDPC encoder candidates.

IV. Adaptive Power Control

The purpose of the MCC procedure is to act as a feedback to a closed-loop PC algorithm, which will instruct the SU how to regulate its transmitting power and thus the induced interference to the PU. Based on this PC scheme, the cognitive user does not need to exchange information with the PU and obtain any direct knowledge of the induced interference. A blind method for mitigating the interference is the SU to adapt its power with adjustable steps and monitor the reaction of the PU. Similar PC schemes exist in literature [14] with proven convergence to the optimum solution. In this paper, a comparable algorithm is proposed considering an AWGN interference channel.

In this cognitive scenario, the SU transmitting power P_{SU} must converge to an unidentified threshold P_{max} over which it causes the PU to lower its MODCOD. The suggested iterative APC algorithm, presented in Algo. 1, is a heuristic method for solving this PC problem with a minimal number of P_{max} violations. Initially, a description of its parameters must be given. $MODCOD(n)$ is the sensed transmission scheme of the time instant n, P_{min} is the minimum power the SU can transmit, N_{PLV} is the number of P_{max} violations from the beginning of time, N_{max} is the maximum acceptable number of the P_{max} violations, $\varDelta(n)$ is the adjustable transmitting power step and T_p is the period after a P_{max} violation during which the P_{SU} is set to a power level below P_{max}.

Algorithm 1 Adaptive Power Control algorithm

```
Sense MODCOD(0)
Transmit P_SU = P_min
Sense MODCOD(1)
if MODCOD(1) ≠ MODCOD(0) then
    Do not transmit at all
else
    Increase P_SU by step Δ(1)
end if
repeat
    Sense MODCOD(n)
    if MODCOD(n) ≠ MODCOD(n − 1) then
        Set P_SU to previous level and repose for time T_p
    else
        Increase P_SU by step Δ(n)
    end if
until N_PLV ≥ N_max or P_SU converges
```

According to this APC method, the SU starts transmitting the minimum P_{SU} and then gradually boosts it until a P_{max} violation occurs with increasing step $\Delta(n)$, which depends on its previous value $\Delta(n-1)$. After every P_{max} violation, the SU sets P_{SU} to the precedent level not altering the modulation scheme of the PU, reposes for a period of time T_p and after that starts increasing it again. The target of the algorithm is the more P_{max} violations happen the more cautious the SU should become to increase P_{SU}. This is achieved by determining T_p as an ascending function of N_{PLV} and $\Delta(n)$ as a descending function of N_{PLV}. Eventually, P_{SU} converges to a value below P_{max} without breaching this power limit many times.

V. RESULTS

In this section, the performance of the MCC method and the progress of the P_{SU} and throughputs vs time are presented. Initially, it must be noted that the received PU signal through the sensing link is of lower SNR level than the one in the receiver of the PU link. Additionally, the performance of the MCC method is tested in the SNR range of $[-11, 14]$. Also, the number of symbol samples considered to be sensed in the simulations is $Ns = 64800$ which for QPSK, 16QAM and 64QAM constellation schemes corresponds to 2, 4 and 6 64800-bit frames respectively. Moreover, the training and testing procedures were performed using number of the signals $N_{train} = 10000$ and $N_{test} = 1000$ from each modulation scheme. The metric used to measure the detection performance of the MCC method for a class j is the probability of correct classification (P_{cc}), which is defined as:

$$P_{cc} = \frac{N_{cc}}{N_{test}} \tag{15}$$

where N_{cc} is the number of correctly classified signals of class j.

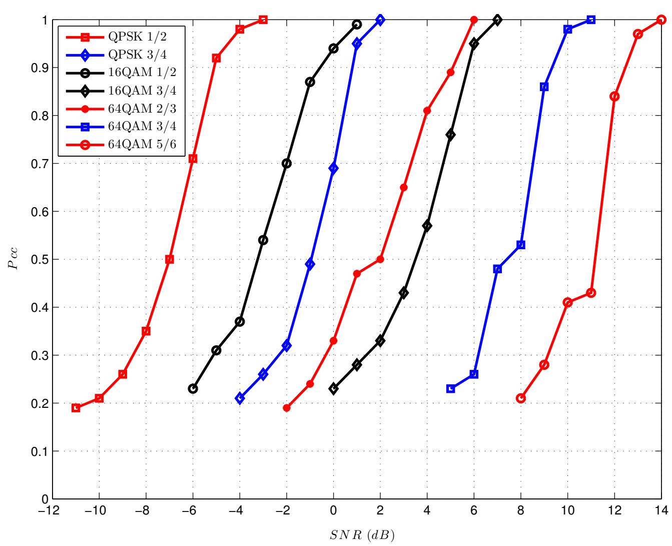

Fig. 2. P_{cc} vs SNR for $Ns = 64800$ symbol samples

In Fig. 2, the P_{cc} of the simulations is shown. Initially, an obvious remark is that the higher the SNR of the test signal, the higher the P_{cc}. Furthermore, one can notice that the lower the order of the constellation or the code rate to be classified, the easier it is to recognize it. Also, the P_{cc} curves are very steep, mostly due to the performance of the code rate classifier. One more conclusion which has to be noted is that for $P_{cc} = 1$ in all classes, the minimum required SNR is $14dB$.

Following, the progress of the P_{SU} and throughputs vs time are presented based on the APC algorithm described in the previous section. The examined scenario considers a cognitive SU, that recognizes perfectly the transmission scheme of an ACM PU link. The sensing of the PU signal is implemented with an omnidirectional secondary antenna of low gain. In Fig. 3, the P_{SU} vs time diagram can be seen, where the initial P_{SU} and the unknown threshold P_{max} are considered to be $15dBm$ and $25dBm$ respectively and the transmitting power update happens every 100ms.

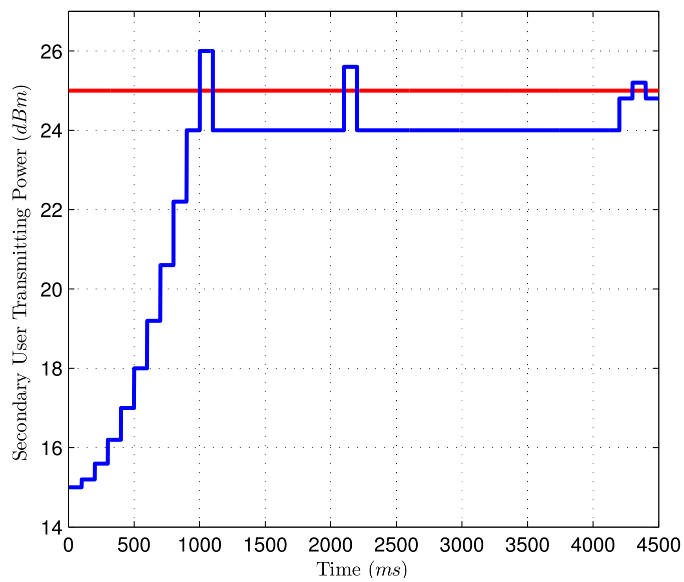

Fig. 3. P_{SU} vs time

The main principles of the APC algorithm can be observed in the P_{SU} diagram. At the beginning, P_{SU} increases aggressively, until a P_{max} violation occurs. After each violation, it can be seen that the SU rests to a non violating value of P_{SU} for a period proportional to the total number of violations. Also, the more violations the SU performs, the more reluctant it becomes to increase its power and finally it converges to the acceptable $P_{max} = 25dBm$. Using a particular set of parameters, only 3 times the SU exceeds the unknown power limit and it requires 45 power adjustments to achieve that.

Another aspect of the APC algorithm is presented in Fig. 4. Here, the throughput of the SU, the PU and the total one can be viewed in time. They are depending on the instant value of P_{SU} and what has to be marked is the distinct throughput drops of the PU and in total whenever a P_{max} violation occurs and the convergence of the last one to a maximum value. This proves that a considerable total throughput gain is achieved using Algo. 1 while preserving the PU throughput level.

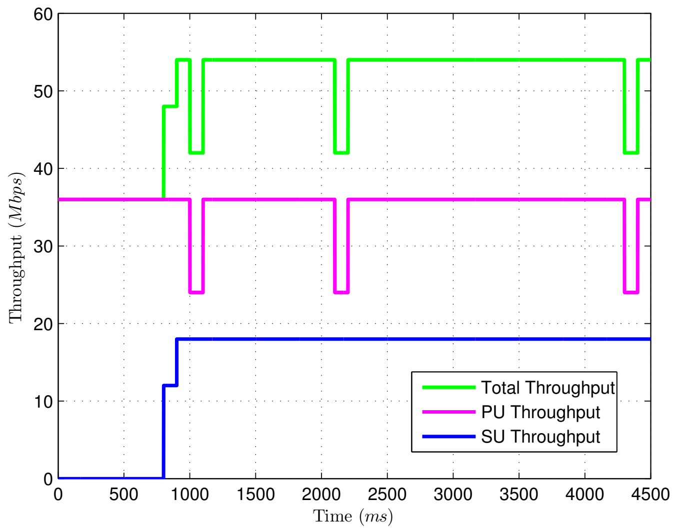

Fig. 4. The SU, PU and Total Throughputs

VI. Conclusions

In this paper, an integrated solution for interference management in a CC context is proposed using a powerful MCC technique as feedback for a closed-loop PC algorithm. The MCC technique exploits HOS features and average code syndrome LLRs of the PU signal in order to detect even in low SNR level when the PU transmission scheme changes and thus adjust P_{SU} to innocuous values. The proposed APC method performs a power scaling with flexible steps, so that the induced to the PU interference is mitigated. Through simulations, it is shown that the performance of the suggested system is excellent with controllable characteristics which affect convergence speed and number of P_{max} violations.

Tackling a number of ideal assumptions of the described system model can guide our future work. The first assumption, concerning the code rate recognition stage, is that the cognitive receiver is able to identify the beginning of a PU frame. Solutions on frame synchronization exist in the literature and they can be used to complete this work. Furthermore, realistic channel modelling can be taken into account, like fading. Another practical concept which can lead to future work is the introduction of channel prediction in order to use it in a PC algorithm. Also, further studies can focus on the behaviour of the PC scheme, like its convergence considering a large number of SUs or $P_{cc} < 1$. Finally, other PC algorithms can be examined which are based on pricing and tested using a variety of utility and price functions.

VII. Acknowledgement

This work was supported by the National Research Fund, Luxembourg under the CORE project ”SeMIGod: SpEctrum Management and Interference mitiGation in cOgnitive raDio satellite networks”.

References

[1] Q. Zhao and B. Sadler, “A Survey of Dynamic Spectrum Access,” *IEEE Signal Processing Magazine*, pp. 79–89, 2007.

[2] J. Mitola, “Cognitive radio an integrated agent architecture for software defined radio,” Ph.D. dissertation, KTH Royal Institute of Technology Stockholm, Stockholm, Sweden, 2000.

[3] O. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, “Cyclostationarity-based modulation classification of linear digital modulations in flat fading channels,” *Wireless Personal Communications*, pp. 699–717, 2010.

[4] M. Petrova, P. Mahonen, and A. Osuna, “Multi-class classification of analog and digital signals in cognitive radios using Support Vector Machines,” *7th International Symposium on Wireless Communication Systems (ISWCS)*, pp. 986–990, 2010.

[5] R. Kannan and S. Ravi, “Second-order Statistical Approach for Digital Modulation Scheme Classification in Cognitive Radio using Support Vector Machine and K-Nearest Neighbour Classifier,” *Journal of Computer Science*, pp. 235–243, 2013.

[6] B. Ramkumar, “Automatic Modulation Classification for Cognitive Radios Using Cyclic Feature Detection,” *IEEE Circuits and Systems Magazine*, pp. 27–45, 2009.

[7] D. Liu and J. Liu, “A Novel Signal Recognition Algorithm Based on SVM in Cognitive Networks,” *12th IEEE International Conference on Communication Technology (ICCT)*, pp. 1264–1267, 2010.

[8] K. M. Thilina, K. W. Choi, N. Saquib, and E. Hossain, “Pattern classification techniques for cooperative spectrum sensing in cognitive radio networks: SVM and W-KNN approaches,” *IEEE Global Communications Conference (GLOBECOM)*, pp. 1260–1265, 2012.

[9] Z. Dandan and Z. Xuping, “SVM-Based Spectrum Sensing in Cognitive Radio,” *7th International Conference on Wireless Communications, Networking and Mobile Computing (WiCOM)*, 2011.

[10] H. Yang, X. Xie, and R. Wang, “SOM-GA-SVM Detection Based Spectrum Sensing in Cognitive Radio,” *8th International Conference on Wireless Communications, Networking and Mobile Computing (WiCOM)*, 2012.

[11] H. Liu, D. Yu, and X. Kong, “A New Approach to Improve Signal Classification in Low SNR Environment in Spectrum Sensing,” *3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, 2008.

[12] T. Xia and H. Wu, “Novel Blind Identification of LDPC Codes Using Average LLR of Syndrome a Posteriori Probability,” *IEEE Transactions on Signal Processing*, pp. 632–640, 2014.

[13] R. Moosavi and E. Larsson, “A Fast Scheme for Blind Identification of Channel Codes,” *IEEE Global Telecommunications Conference (GLOBECOM)*, pp. 1–5, 2011.

[14] J. D. Herdtner and E. K. P. Chong, “Analysis of a Class of Distributed Asynchronous Power Control Algorithms for Cellular Wireless Systems,” *IEEE Journal on Selected Areas on Communications*, pp. 436–446, 2000.

[15] C. U. Saraydar, N. B. Mandayam, and D. J. Goodman, “Efficient Power Control via Pricing in Wireless Data Networks,” *IEEE Transactions on Communications*, pp. 291–303, 2002.

[16] T. Alpcan, T. Basar, R. Srikant, and E. Altman, “CDMA Uplink Power Control as a Noncooperative Game,” *Proceedings of the 40th IEEE Conference on Decision and Control, 2001*, pp. 197–202, 2001.

[17] V. N. Vapnik, *The Nature of Statistical Learning Theory*. Springer, 1999.

[18] J. Hagenauer, E. Offer, and L. Papke, “Iterative decoding of binary block and convolutional codes,” *IEEE Transactions on Information Theory*, pp. 429–445, 1996.