Automatic Modulation Classification for Adaptive Power Control in Cognitive Satellite Communications

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Abstract*—Spectrum Sensing (SS) and Power Control (PC) have been two important concepts of Cognitive Radio (CR). In this paper, a mechanism combining these two topics 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 suggested SS technique considers Higher Order Statistical (HOS) features of the signal and an efficient Machine Learning (ML) detector, the Support Vector Machine (SVM), in order to constantly monitor the modulation scheme of the PU. Once the Automatic Modulation Classification (AMC) is ensured, 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 modulation scheme due to interference. When the SU detects the change of the PU's modulation scheme, then it reduces its transmitting power to a lower level so as to regulate the induced interference. This Adaptive Power Control (APC) algorithm converges to the aforementioned interference limit and guarantees preservation of the PU link QoS.

Keywords*—*Cognitive Radio, Spectrum Sensing, Automatic Modulation Classification, Higher Order Statistics, Support Vector Machine, Adaptive Power Control, Adaptive Coding and Modulation

I. INTRODUCTION

Over the past years, wireless communications have faced a steadily growing demand of services. Given also the policy of assigned bands, a saturation of the available spectrum has been reached. A solution to this problem is the Dynamic Spectrum Access (DSA) concept, which suggests that some services may coexist in specific frequency bands [1]. DSA can be achieved with the development of Cognitive Radios (CR) which sense, understand, adapt and interact with their surroundings based on the user's demands and the environment's limitations [2].

The main enabler of the CRs is the sensing part. SS has thus become an important aspect of this idea in order to give "eyes" and "ears" to the "body" of this intelligent radio. One way of making the CR aware of its environment 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 schemes. This SS technique concerning the modulation detection is termed Automatic Modulation Classification (AMC) and has been realized by extracting features of the signal and classifying it based on them.

The simplest and most common feature is the energy of the signal. A lot of research in signal classification has been performed depending only on the energy, but it is not considered a distinctive characteristic for low SNR environments [3–6]. Its most successful application [5] has accomplished error free detection at $SNR = -10dB$ but in the expense of complexity of the classifying method. Moreover, it was merely able to discriminate the noise only case and the noisy BPSK signal case. Other features exploited in AMC are the cumulants of 2nd, 3rd, 4th, 6th and 8th order [7–11], which have distinctive theoretical values among different modulation schemes and even though they demand a great amount of samples, they are easy to calculate. Using more sophisticated techniques, like the FFT algorithm, we can obtain the maximum value of the spectral power density of the normalized instantaneous amplitude, the standard deviation of the absolute value of the normalized centered instantaneous amplitude or even statistical metrics of the normalized Power Spectrum Density (PSD) of the received signal [8], [10], [12], [13].

Finally, the hardest to extract characteristics are the cyclostationary (CS), coherent and time-frequency ones. These are derived respectively from spectral correlation or coherence functions, coherent processing and Time-Frequency (TF) distributions (short time Fourier transform, Wigner-Ville distribution etc.) [10–12], [14–21]. As far as these characteristics are concerned, the FFT algorithm is again the main tool for estimating them. One of these very interesting features is the α-domain profile which is derived from the CS processing of the signal and was first established by Gardner [22]. The use of cyclic spectral analysis has been very efficient in signal classification, especially when combined with robust detection tools. In [19], the set of BPSK, QPSK, FSK, MSK and AM signals was categorized with probability of detection $P_{DE} = 100\%$ at $SNR = -7dB$.

As far as the classification methods used in the literature are concerned, there has been significant progress using ML to identify correctly the type of the signal. So, the function of these learning machines is to collect some of the aforementioned features, process them and classify a group of samples as noise or any other kind of signal. One very plain structure to achieve this is the polynomial classifier [23]. A very easy to implement learning machine, with simple calculations, but without strong mathematical foundation. Another very popular option has been the Neural Networks (NNs) [6], [10], [11], [13], [18], [19], [24]. The kinds of NNs used are feedforward networks with multiple layers and back propagation networks with multiple layers. A powerful classification tool that previous researchers used are the SVMs [3–5], [8], [9], [12], [15], [16]. They have been helpful in many categorization problems and they are the most frequent tool of previous work in this field achieving $P_{DE} = 100\%$ at $SNR = -12dB$ [15]. Other techniques are the Self-Organizing Map (SOM) [5] and the Chinese Restaurant Process clustering [14], [20], [21] which have been proven efficient in grouping data. In the end, for determining patterns there are classifiers based on Hidden Markov Models (HMMs) [11], [17] or k-Nearest Neighbor algorithm (k-NN) [3], [9].

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. Previous work in this field has considered a great variety of assumptions and protocols. There has been extensive research work which is usually assuming though the knowledge of the PU's channel or the interference channel, the exact SIR of the PU or other SU's, the SIR thresholds of all the users or the existence of a control channel between the PU and the SU or among the SU's. That knowledge has helped the research community form and solve different kinds of PC problems, but in reality most of the times this information must be estimated.

An interesting approach in this topic, suitable for a network of CRs without any collaboration, is the distributed and non-cooperative one. In this case, no information is exchanged among any SU and there is no common strategy. Most studies in this field have employed iterative methods such as pricing models, Iterative Water-filling or one bit control channel and usually they provide a game theoretic framework to prove their convergence to an equilibrium [25–28].

In this paper, an integrated application is demonstrated which concerns an SU and focuses on both AMC and PC. The examined scenario considers a terrestrial microwave link changing its modulation scheme based on an ACM protocol and operating in its assigned band together with a satellite link entering this band [29–32]. In this work, it is proposed the cognitive satellite 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 modulation scheme of the PU, which changes dynamically itself based on the ACM protocol. The transmitting power is adapted whenever it degrades the modulation scheme of the PU.

The chosen SS technique extracts HOS cumulants of the signal and classifies them with a reliable and sophisticated ML detector, the SVM. Although a plethora of features exists, only HOS cumulants can be used to discriminate the PSK and QAM modulation schemes of an ACM protocol and are easily computed. 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. So the system model is distributed and non cooperative and the used 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 HOS features exploited and presents the SVM, as well as its configuration. 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

The cognitive scenario examined in this paper consists of a terrestrial microwave PU link and a satellite SU link as shown in Fig. 1. Furthermore, the propagation of the signal from the PU link is received by the cognitive user using a secondary omnidirectional antenna only for sensing and assuming an AWGN channel. As far as the interference to the PU link is concerned, this is caused by the terrestrial part of the satellite SU link to the receiver of the microwave PU link. Considering a LOS interference link, this may have a severe effect on the modulation scheme chosen by the PU link. In this scenario, the interference is analyzed and it contributes to the formulation of the APC problem.

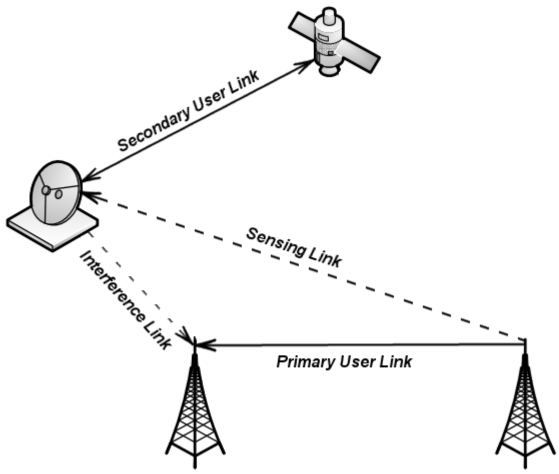

Fig. 1. Cognitive Satellite Link and Terrestrial Microwave Link

In addition, assuming that the CR achieves symbol synchronization in sensing the PU signal, the received symbol samples can be written 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). According to the ACM protocol of most commercial microwave link products, the transmitted symbol $s[i]$ can be of QPSK, 8PSK, 16QAM, 32QAM, 64QAM or 128QAM modulation scheme. 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 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:

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

III. Automatic Modulation Classification

Communication signals contain many statistical characteristics that give us information about 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 $C_{2,0}^r$, $C_{2,1}^r$, $C_{4,0}^r$, $C_{4,1}^r$, $C_{4,2}^r$, $C_{6,0}^r$, $C_{6,1}^r$, $C_{6,2}^r$, $C_{6,3}^r$, $C_{8,0}^r$, $C_{8,1}^r$, $C_{8,2}^r$, $C_{8,3}^r$, $C_{8,4}^r$.

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. For example,

$$\begin{aligned} C_{X_1,X_2,X_3} =& E\{X_1X_2X_3\} - E\{X_1X_2\}E\{X_3\} \\ &- E\{X_1X_3\}E\{X_2\} - E\{X_2X_3\}E\{X_1\} \\ &+ 2E\{X_1\}E\{X_2\}E\{X_3\}. \end{aligned} \tag{7}$$

Consequently, the pth-order mixed cumulant $C_{p,q}^r$ of the complex received signal can de derived from the joint cumulant formula in (6) as:

$$C_{p,q}^r = C_{\underbrace{r, ..., r}_{\text{(p-q) times}}, \underbrace{r^*, ..., r^*}_{\text{(q) times}}} \tag{8}$$

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 $C_{p,q}^r = C_{p,p-q}^r$.

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 [33]. A major drawback of the SVMs is that initially they require a lot of computations to train themselves offline but they can become very accurate. At this point, it must be noted that in the AMC literature the SMO algorithm and the Online Bayes Point Machines have not been examined in order to reduce this computational complexity and to investigate the efficiency and the adaptivity of the online training of the SVM respectively.

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 as shown in Fig. 2. This is called the maximum-margin hyperplane. But the most interesting contribution of the SVMs is in the non-linear separation of data. This machinery with some small adaptations and using the so-called kernel trick can be used to map indirectly input feature vectors into a high dimensional space in which they become linearly separable. The impressive part of this high dimensional approach is that it happens without any extra computational effort.

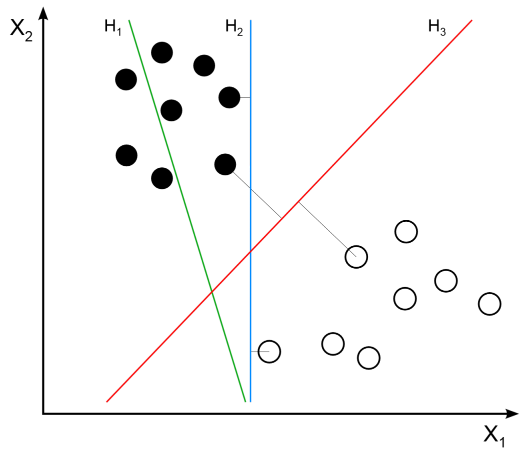

Fig. 2. Maximum-margin separating hyperplane

The reason this non-linear mapping Θ does not add any extra computational burden lies on the way the SVM operates. For a simple linear separation in the initial feature space, the SVM training has to solve a Quadratic Programming (QP) problem which considers only the dot products of the training feature vectors. Extending this idea to a high dimensional space, the SVM again needs only to know the dot products of the dimensional expansions of the training feature vectors. This enables us to surpass the obstacle of knowing this non-linear mapping Θ and just calculate the dot products of the training feature vector mappings.

This is the point where the kernel trick is used. Given two vectors from the training feature space $\boldsymbol{x}$ and $\boldsymbol{y}$, the dot product of their mappings in some high dimensional feature space is:

$$K(\boldsymbol{x},\boldsymbol{y}) = \Theta(\boldsymbol{x})\cdot\Theta(\boldsymbol{y}) \tag{9}$$

where $K(\boldsymbol{x},\boldsymbol{y})$ denotes the kernel function. In most classification applications, the polynomial function (10) and the Gaussian radial basis function (GRBF) (11) are used as kernels.

$$K(\boldsymbol{x},\boldsymbol{y}) = (1+\boldsymbol{x}\cdot\boldsymbol{y})^d \tag{10}$$

$$K(\boldsymbol{x},\boldsymbol{y}) = \exp(-\frac{\|\boldsymbol{x}-\boldsymbol{y}\|^2}{2\sigma^2}) \tag{11}$$

In previous work, the most commonly used kernel is the GRBF which is actually a polynomial kernel of infinite degree.

Because of its already tested practical use and accuracy, in this paper the GRBF is used as well. As far as σ in (11) is concerned, it is a free operational parameter whose value affects the SVM's performance and can only be found by trial and error. Also, the multi-class classification of a test signal into one of the 6 available modulation schemes of the ACM, the classes, is implemented by combining $\frac{4 \cdot 3}{2}$ 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 labelling 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.

IV. Adaptive Power Control

The purpose of the AMC technique is to act as a feedback to a closed-loop PC algorithm, which will guide 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 communicate with the PU and obtain any direct knowledge of the induced interference. The simplest blind method for achieving the interference cancellation is the SU to adapt its power with adjustable steps and monitor the reaction of the PU. Similar PC schemes exist in literature [26] with proven convergence to the optimum solution. In this paper, a comparable algorithm is proposed considering an AWGN interference channel.

In the considered scenario, the SU transmitting power P_{SU} must converge to an unknown threshold P_{max} over which it causes the PU to change its modulation scheme. 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. $Mod(n)$ is the sensed modulation 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 permissible number of the P_{max} violations, $\Delta(n)$ 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}.

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 purpose of the algorithm is the more P_{max} violations happen the more reluctant 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.

Algorithm 1 Adaptive Power Control algorithm

```
Sense Mod(0)
Transmit P_SU = P_min
Sense Mod(1)
if Mod(1) ≠ Mod(0) then
  Do not transmit at all
else
  Increase P_SU by step Δ(1)
end if
repeat
  Sense Mod(n)
  if Mod(n) ≠ Mod(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
```

V. Results

In this section, the performance of the AMC method and the progress of the P_{SU} and throughputs vs time are presented. First, it must be mentioned that the received PU signal through the sensing link, as shown in Fig. 1, can be of 6 types, QPSK, 8PSK, 16QAM, 32QAM, 64QAM and 128QAM, and of lower SNR level than the one in the receiver of the PU link. Also, 2 numbers of symbol samples are tested in the simulations, $Ns_1 = 2048$ and $Ns_2 = 65536$ and the performance of the SVM binary classifier network is examined in the SNR ranges of $[-5, 10]$ and $[-11, 5]$ respectively. Moreover, for each case of Ns and SNR, 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 AMC method for a class j is the probability of correct classification (P_{cc}), which is defined as:

$$P_{cc} = \frac{N_{cc}}{N_{test}} \tag{12}$$

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

In Fig. 2 and 4, 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, for a specific SNR the P_{cc} is higher, if the number of symbol samples is increased. Additionally, one can notice that the lower the order of the constellation to be classified, the easier it is for the SVM to recognize it. Another interesting result derived from Fig. 2 and 4, is that the P_{cc} vs SNR curves form 3 groups. This indicates that some classes have similar P_{cc} behaviour, because some modulation schemes have the same constellation pattern. The 3 groups formed are the QPSK-8PSK, the 16QAM-64QAM and the 32QAM-128QAM. Apparently, the SVM classifier has similar performance for modulation schemes of almost identical pattern, such as the rectangular one for the 16QAM-64QAM pair and the cross-like one for the 32QAM-128QAM pair. One more conclusion which has to be noted is that for $P_{cc} = 1$ in all classes, the minimum required SNR for $Ns_1 = 2048$ and $Ns_2 = 65536$ is $10dB$ and $4dB$ respectively.

Following, the progress of the P_{SU} and throughputs vs time are presented based on the APC algorithm described in the

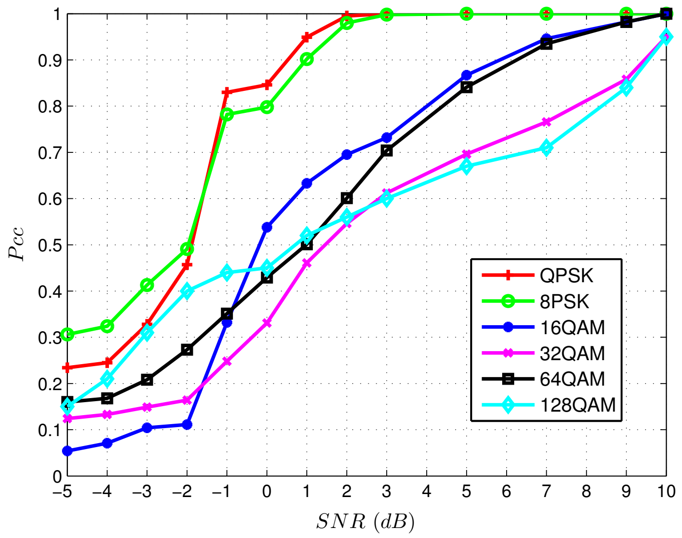

Fig. 3. P_{cc} vs SNR for $Ns_1 = 2048$

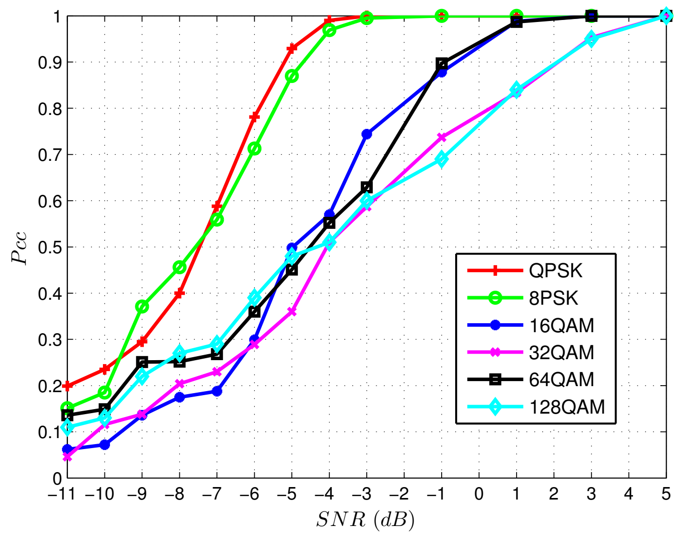

Fig. 4. P_{cc} vs SNR for $Ns_2 = 65536$

previous section. The examined scenario considers a DVB-RCS SU, that recognizes perfectly the modulation scheme of an ACM microwave PU link. The sensing of the PU signal is implemented with an omnidirectional secondary antenna of low gain. In Fig. 5, the P_{SU} vs time diagram can be seen, where the initial P_{SU} and the unknown threshold P_{max} are considered to be $0dW$ and $10dBW$ respectively and the transmitting power update happens every 100ms.

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}

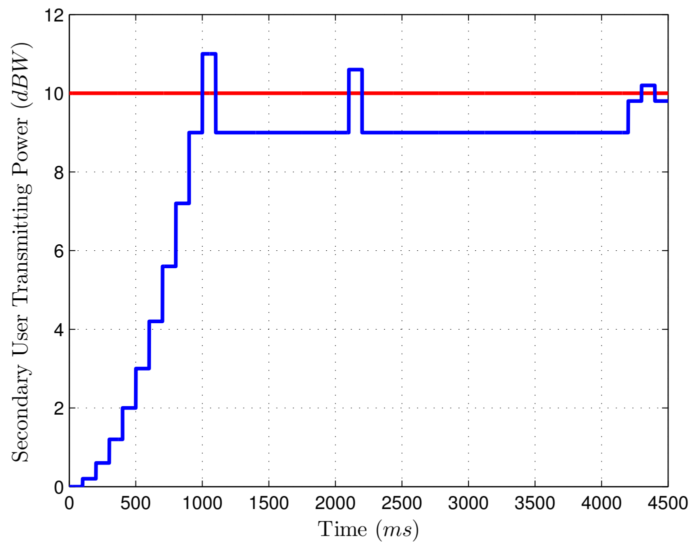

Fig. 5. P_{SU} vs time

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 $P_{max} = 10dBW$. 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. 6 and 7. 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.

VI. Conclusions

In this paper, an integrated solution for interference management in a CR context is proposed using a powerful AMC technique as feedback for a closed-loop PC algorithm. The AMC technique exploits HOS features of the PU signal and a robust classifier, the SVM, in order to detect even in low SNR level when the PU modulation 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.

Future work will attempt to alleviate a number of ideal assumptions of the described system model. Encountering them, can lead this work to a more complete form in the future. The first assumption is the synchronized received symbol samples. In reality, a sampling rate without any synchronization and other important parts of telecommunications system, such as

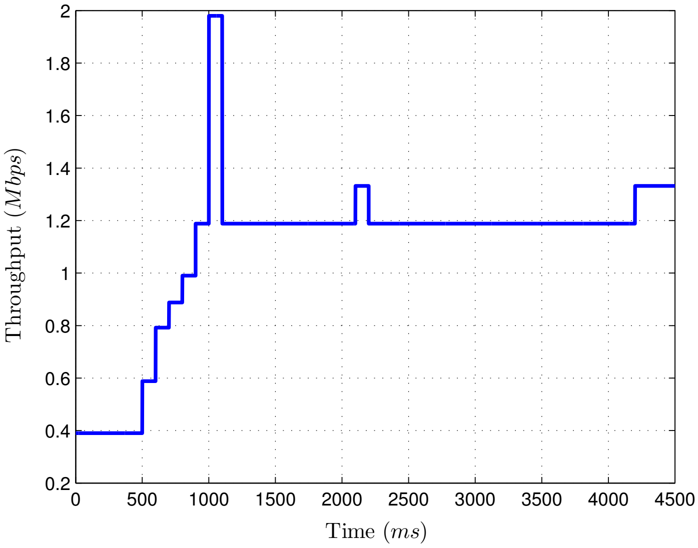

Fig. 6. The SU Throughput

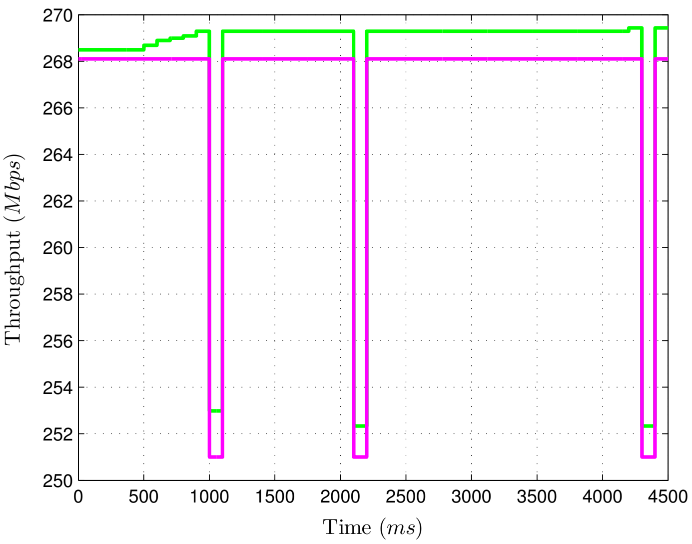

Fig. 7. The PU and total Throughput

pulse-shaping and filtering in the sides of the transmitter and the receiver, have to be considered. 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 and the European Commission (EC) under the CoRaSat project (FP7 ICT STREP Grant Agreement n. 316779).

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