EAI Endorsed Transactions
on Cognitive Communications

Research Article ICST.ORG

Hypernetworks based Radio Spectrum Profiling in Cognitive Radio Networks

Shah Nawaz Khan[1,*], Andreas Mitschele-Thiel[1]

[1]Integrated Communication Systems Group,
Technische Universität Ilmenau,
P.O. Box 100 565, Ilmenau 98693, Thüringen, Germany

Abstract

This paper presents a novel concept of active radio spectrum profiling for Cognitive Radio (CR) networks using evolutionary hypernetworks. Spectrum profiling enables cognitive radio nodes to abstract and predict usable spectrum opportunities in pre-defined Primary Users (PU) channels. The PU channels are actively monitored through spectrum sensing and the resulting binary time series are used for channel abstraction and prediction. An overlay spectrum sharing approach is assumed in this paper and the evolutionary hypernetworks are used for the realization of the radio spectrum profiling concept. The abstracted information not only facilitates the optimization of channel selection and mobility, but also improves the quality of service for the secondary user applications. This paper presents the main concepts, their application to CR ad hoc networks, and an analysis of its impact on the CR network performance.

Keywords: Channel prediction, Cognitive radio, Spectrum profiling

Received on 31 May 2014; accepted on 20 April 2015; published on 28 May 2015

doi:10.4108/cogcom.1.2.e5

1. Introduction

Radio spectrum is a very valuable but scarce resource, especially when considering the overall picture of the existing wireless communication systems. However, this resource has not been utilized in the most efficient way which has resulted in spectrum scarcity and under-utilization problems. The main cause for these problems is considered to be the fixed radio spectrum allocation strategies employed by the spectrum allocation authorities across the world. Realization of these problems have resulted in the formulation of opportunistic and dynamic spectrum access concepts which are generally discussed in conjunction with the Cognitive Radio (CR) networks. CR networks are assumed to be able to identify and utilize the spectrum opportunities provided by the existing wireless networks, the so called Primary User (PU) networks. In the existing literature, the spectrum sensing is considered to be the *Eyes and Ears* of a CR node through which it can facilitate the two most important tasks of identify spectrum opportunities and avoiding interference with the PUs. These tasks are generally considered to be interrelated as quick and accurate spectrum sensing can facilitate both function of a CR node. However, these two tasks have very different timing requirements which makes the use of spectrum sensing results impractical for both these tasks. Identifying spectrum holes requires the monitoring of the spectrum for a sufficiently longer period of time whereas interference avoidance with PUs should be instantaneous requiring immediate reaction to a sensing result. Spectrum sensing is also the enabler for the physical and link layer protocols which have stringent time constraints. In the traditional 802.11 family of protocols for example, the basic channel access tasks are in the scale of microseconds. If a similar functionality is assumed of CR MAC protocols, the spectrum sensing should be equally fast and accurate. We can summarize that for avoiding interference with PUs, the reliability and time-efficiency of spectrum sensing is very important. However, for identifying spectrum opportunities such primitive spectrum sensing results are not sufficient. There needs to be an abstraction process that can characterize spectrum holes from the primitive spectrum sensing results. Furthermore, the identified spectrum holes must be quantified to determine whether they can fulfill the SU applications' requirements. This serves as the basis for the proposed *Hypernetworks based Active Radio Spectrum Profiling* concept which aims to characterize the spectrum according to the application

*Corresponding author: shah-nawaz.khan@tu-ilmenau.de

requirements of the CR nodes. This concept is specially important for CR ad hoc networks which heavily rely on spectrum sensing and have no infrastructural support. The contributions of this paper in this outlined context can be summarized as follows:

- Introduction of a new *active radio spectrum profiling* concept for PU channels characterization,
- Application of *Evolutionary Hypernetworks* algorithm for the active radio spectrum profiling,
- Presentation of a new channel state prediction algorithm based on hypernetworks that can tolerate miss detection and false alarms of spectrum sensing algorithms and
- Analysis of CR ad hoc network performance with the new hypernetworks based active radio spectrum profiling concept.

The rest of the paper is organized as follows. Section 2 addresses the related work on spectrum characterization and channel prediction. An introduction to Hypernetworks is given in Section 3 before the details of the proposed evolutionary hypernetworks based spectrum profiling in Section 4. Simulation results are provided in Section 5 and the paper is concluded with a summary and future work in Section 6.

2. Related Work

To the best of our knowledge, the proposed hypernetworks based spectrum profiling concept is novel in the CR networks context. However, a number of research articles addressing channel prediction, channel recommendation and secondary access can be considered as related work since the hypernetworks based spectrum profiling aims to achieve similar objectives. Prediction techniques in CR networks have been applied for of PU activity and channel behavior prediction. The authors in [1] survey the main approaches applied in the literature for channel prediction in CR context. They overview the main approaches and classify them based on the prediction techniques used including Hidden Markov Models (HMM), Multilayer Perceptron Neural Networks, Bayesian Inference, Autoregressive Model, and Moving Average based prediction. As the results of channel prediction can be applied to the optimization of different CR functions, no comparative analysis of these techniques has been presented. The application of HMM to predict the basic state transitions involved in ON/OFF PU channel usage model can be found in many articles. The authors in [2] present a binary time series approach to spectrum prediction in CR networks. They apply HMM to predict the next state(s) of the channel based on the historic data. They essentially predict the next values of spectrum sensing and relate them to spectrum holes. The authors in [3] also apply HMM based prediction technique for multi-step-ahead prediction. They aim to avoid interference with PUs based on the results of the prediction. They measure the level of interference caused by CR network and propose to keep it to a predefined level. Similar technique is used by authors in [4] to evaluate the radio resource availability in 802.11 networks scenario and apply multi-step-ahead prediction derived through an auto-regression (AR) Model. They apply their technique to 802.11 network data traffic by measuring the radio resource availability through Network Allocation Vector (NAV). HMM based approach has also been used by authors in [5] to predict exponentially distributed PU activity over radio spectrum. For most of the HMM based approaches, the activities of the channel are modeled under Markovian assumptions. The authors in [6] however, present temporal spectrum sharing scheme based on PU activity prediction that considers bursty PU traffic whose characteristics are not captured effectively by Markovian process. They propose to adapt the SU transmission power levels that can be adapted to any source traffic model of PUs. The benefits of PU activity prediction have been shown to optimize different functions of a CR node specifically those related to the spectrum management and dynamic spectrum access. The authors in [7] show the application of fast discovery of spectrum opportunity in multichannel context to CR performance optimization. They propose an adaptive sensing period optimization algorithm together with an optimal channel-sequencing algorithm. This allows a CR node to find spectrum opportunities from a number of available channels efficiently without loosing significant spectrum opportunities provided by the considered radio spectrum. They also show that the channel discovery delay can be reduced to less than half a second with an optimized channel sensing and sequencing approach. The same prediction algorithm has been applied for proactive channel access in [8] in order to vacate a channel before the PU arrives. They essentially apply the results from [7] to a different optimization objective. The information about channels derived through spectrum sensing has also been considered for CR optimization outside the context of channel prediction. The authors in [9] present a channel recommendation framework in which distributed CR nodes complement each other's channel access by recommending a successfully used channel. They derive the inspiration from customer reviews system associated with major online retail systems. The same idea has been optimized in [10] where the authors formulate the problem as an average reward based Markov decision process. They compare the performance of a dynamic spectrum access system using the adaptive recommendation system with a static channel recommendation system and show a performance benefit of upto 15%.

The existing literature on channel characterization and prediction generally assumes the spectrum sensing to be 100 percent accurate. This assumption is made in order to have a realistic representation of PUs communication in a binary time series. However, it is well known that even the most sophisticated spectrum sensing algorithms are prone to miss-detections and false alarms. This renders the algorithms that predict next state(s) of binary time series prone to lower performance when considered in a realistic CR network scenario. Another assumption that is explicitly made or implied in literature is that zero bits in the binary time series represent spectrum holes for secondary access. Based on the discussion in Section 1, this assumption does not hold true in most realistic scenarios. If the spectrum sensing results are collected in the scale of microseconds, a single zero bit loses its significance for overall spectrum hole representation. However, the same bit will have a very high importance for the channel selection and interference prevention with PUs. The proposed active spectrum profiling concept does not rely on such assumptions and instead, applies an abstraction process that is mostly independent of the accuracy and time scale of spectrum sensing results.

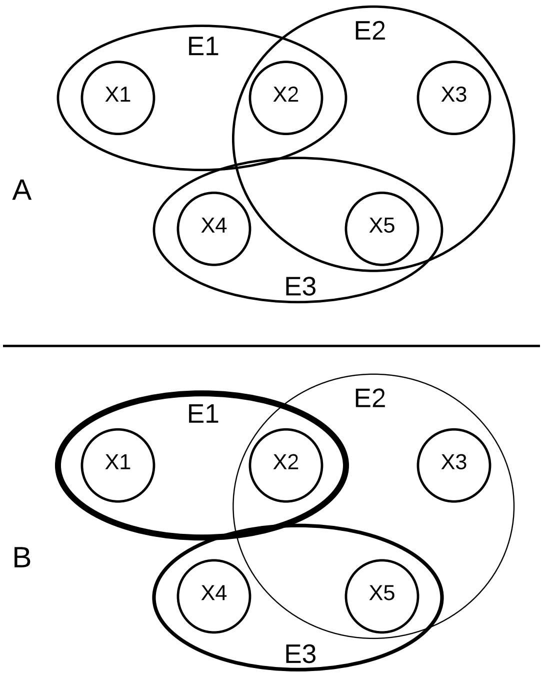

Figure 1. Hypergraph (A) and Hypernetwork (B) with five vertices and three edges

3. Hypernetworks

Hypernetworks is a relatively new research domain and a candidate architecture for cognitive learning and memory [11]. It is a graphical model that can abstract both low and high levels of interactions among elements of a dataset. Hypernetworks are an extension of the hypergraphs. A hypergraph is an undirected graph G, the edges of which can connect any number of non-null vertices. Formally, a hypergraph $G = \{X, E\}$, where $X = \{X_1, X_2, ...X_n\}$ is the set of elements of the dataset, $E = \{E_1, E_2, ...E_m\}$ is the set of edges and $E_i = \{x_{i_1}, x_{i_2}, ..., x_{i_k}\}$ represents the elements of the edge E_i. The edges E_i of a hypergraph are referred to as *Hyperedges*. Each hyperedge which is synonymous to a non-empty set, encapsulates some primitive relation in the dataset X. The number of elements k encapsulated in a hyperedge representing its cardinality, is referred to as a k-hyperedge. Figure 1-A shows an example hypergraph having five elements (X1-X5) and three hyperedges (E1-E3). In hypergraphs, each hyperedge encapsulate an association in the primitive dataset and is unique.

Hypernetworks are a generalization of the hypergraphs in which we assign a particular weight to the hyperedges. Graphically, this weight is represented by the width of the hyperedges in the hypernetworks. The more stronger a relation is in the dataset, the larger the width of the hyperedge. Formally, a hypernetwork is a triple $H = (X, E, W)$ where X represent the set of vertices or elements of the data set, E represents the set of hyperedges, and W represents the set of weights associated with each hyperedge showing its strength in the dataset. The cardinality (number of enclosed elements) of a hyperedge is referred to as the order of that hyperedge. Figure 1-B shows a hypernetwork that is synonymous to the hypergraph in figure 1-A. The elements of a hyperedge are generally ordered. A hypernetwork can also be represented through a corresponding incidence matrix. The incidence matrix corresponding to the hypernetwork in Figure 1-B is given below.

$$\begin{array}{c} \\ E1 \\ E2 \\ E3 \end{array} \begin{array}{c} \begin{array}{cccccc} w & X1 & X2 & X3 & X4 & X5 \end{array} \\ \begin{pmatrix} 10 & 1 & 1 & & & \\ 2 & & 1 & 1 & & 1 \\ 5 & & & & 1 & 1 \end{pmatrix} \end{array}$$

The first column w in the incidence matrix represents the associated weight of the hyperedges in a hypernetwork. This weight can be in any appropriate form of a numerical representation. The exact value of the weight assigned to a particular hyperedge is determined by the weight function used in the hypernetwork development and learning process. In general, the weight of a hyperedge is increased proportional to the order of the hyperedge. Hyperedges with a smaller order tend to have a higher weight as they represent information that is very general/redundant in the actual dataset.

An important aspect of the hypernetworks is their complexity which can increase very rapidly depending upon the base of the dataset elements and the minimum and maximum order of the hyperedges. From a given dataset $D = \{x^{(n)}\}_{n=1}^{N}$ of N example patterns, the hypernetwork represents the probability of generating the dataset D as:

$$P(D|W) = \prod_{n=1}^{N} P(x^{(n)}|W) \tag{1}$$

The W term in Equation 1 represents both the weight of the hyperedge and its structure. With a mixed order of the hyperedges, both low and high level features of the dataset can be encapsulated into the memory of the hypernetwork. The varying order of the hyperedges allows hypernetworks to keep a large number of random memory fragments $x_{i_1}^{(n)} x_{i_2}^{(n)} ... x_{i_k}^{(n)}$ to estimate the probability of any particular fragment. The probability of an individual fragment or pattern can be given as [11]:

$$P(x^{(n)}|W) = \frac{1}{Z(W)} \exp\left[\sum_{k=1}^{K} \frac{1}{C(k)} \times \sum_{i_1, i_2, ... i_k} w_{i_1, i_2, ... i_k}^{(k)} x_{i_1}^{(n)} x_{i_2}^{(n)} ... x_{i_k}^{(n)}\right] \tag{2}$$

where $Z(W)$ is a normalizing term and $C(k)$ is the number of possible hyperedges of order k. The number of possible patterns or fragments grows exponentially and therefore an evolutionary approach of selection, replacement, and reinforcement towards finding an appropriate ensemble of hyperedges can be applied to collect information of complex datasets. Readers are encouraged to follow [11] for a deeper understanding of the hypernetworks based memory and cognition concept. Related work on hypernetworks have demonstrated their ability to predict future states from previous observations as well as its ability to mimic artificial intelligence [12–14]. Hypernetworks have also been compared to other approaches of learning and prediction and the results have shown the hypernetworks to be comparable in overall achievable results [15].

4. Hypernetworks based Spectrum Profiling

We coin the term *Radio Spectrum Profiling* as the process of abstracting usable channel information from primitive spectrum sensing that is performed by all the CR nodes in a network. This abstracted information is then used to optimize the performance of the CR nodes in terms of their channel access and handovers. Moreover, the spectrum profiling enables the CR network to develop a distributed network support architecture in which all the nodes maintain information about their local radio environment and can share it with other peers [16]. Hypernetworks are well suited to the realization of the radio spectrum profiling concept introduced in this paper for the CR networks. We apply the hypernetworks based algorithm for the abstraction and prediction of spectrum holes from primitive spectrum sensing data which are given in the form of binary time series. Hypernetworks can achieve these objectives by keeping many fragments of the PU channel activity patterns in the hyperedges of different order which is determined based on the requirements of secondary user applications. Each hyperedge encapsulates a pattern of interest in the dataset for a specific secondary user application requirements. For example a hyperedge H_1 can encapsulate the pattern of interest for an application App_1. The encapsulated pattern consists of two parts i.e. the input part and the predicted output part. The total elements of the hyperedge $H_1 = input + output$. Encapsulating the inputs and outputs within the same hyperedge makes the prediction straightforward once the input pattern is matched. Over the course of the hypernetwork learning and evolution, the hyperedges are either reinforced or discarded based on their relevance in the original dataset. The underlying assumption for all prediction based CR research is that the events observed through spectrum sensing are repeated probabilistically and therefore intelligent decisions can be made based on their prediction. This assumption holds true for most of the activities of PUs operating in different frequency bands. However, these patterns have different time-scales over which they occur which can be captured by a varying order of the hyperedges. In general, the higher the correlation between training and testing dataset, the better the performance of the prediction algorithms in terms of accuracy. We shall now explain the main steps of the hypernetworks based spectrum profiling concept.

4.1. Hypernetwork Initialization

We apply the hypernetworks based learning approach to spectrum sensing results that can be collected over time by each CR node in the network. For simplicity, we shall explain the hypernetworks based spectrum profiling for a single CR node. The hypernetwork initialization/creation process is depicted in Fig. 2. The primitive input to the hypernetworks based spectrum profiling is the output of the spectrum sensing module in a CR node. We assume that all CR nodes are capable of detecting the PU activity with sufficient accuracy and timing constraints. From the basic binary time series of the spectrum sensing data, with an acceptable level of miss-detection and false-alarm errors, the hypernetwork first abstracts the patterns of interest for the SU applications. A pattern in essence is a variable sequence of bits (2 or more) in the provided

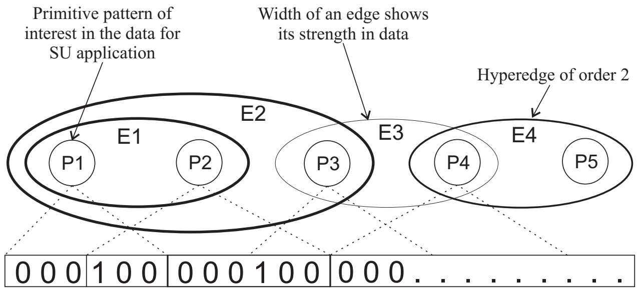

Figure 2. Hypernetwork with 4 hyperedges and 5 patterns

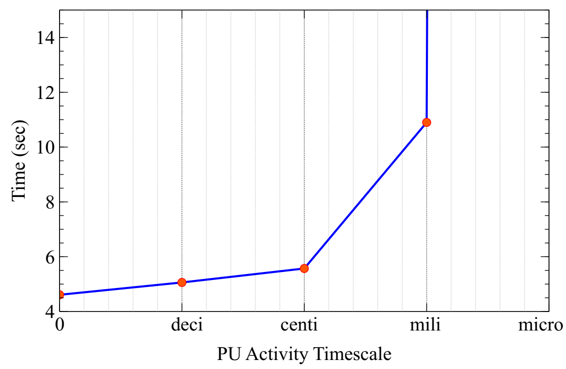

Figure 3. Throughput achieved over 2 GSM channels with varying time-scales of PU activity

binary time-series data. These patterns are selected based on the minimum requirements of the secondary user applications. The requirements of applications are diverse and can be represented in many forms such as in terms of reliability, throughput, security and etc. In this paper, these requirements are represented by the amount of channel access time the SU applications need to send their data over an opportunistically accessed PU channel. This approach is valid as many application require different throughput from the channel to function properly e.g. an email application and a high definition video stream have throughput requirements that are poles apart. This implies that the extracted patterns from the dataset represent variable lengths of spectrum holes and PU transmissions. Therefore, in our CR context, the patterns are essentially variable-length sequences of zeros implying the durations of no PU channel activity and ones implying busy channel states. The use of the variable length patterns enables the hypernetworks to be able to abstract and predict different durations of the PU activities on a channel.

The fundamental reason for deriving the patterns from the binary time series is to ensure that the hypernetworks are trained on the datasets that are usable for opportunistic spectrum access. Assuming that miss-detections and false-alarms are not sequentially redundant, each pattern can neglect some incorrect bits in the overall pattern by replacement. In Fig. 2 for example, pattern P1 can ignore the existence of the bit '1' in the sequence and treat the whole pattern as a sequence of zeros. Ignoring the existence of such sparse *erroneous bits* has to be based on a clear understanding of how the PU activity is represented in the binary time series. If the spectrum sensing is assumed to be fast enough to detect the smallest levels of PU channels access, then it is easier to differentiate such erroneous bits from the real PU activity patterns in the dataset. Another reason to ignore the significance of the individual bits in the binary time series is that these bits are not the actual representation of the spectrum holes on a PU channel. In order to avoid all possible interference instances with the PU network, the spectrum sensing has to work on a very minute time-scale in order to detect the smallest levels of the PU channel access. With such a reduced time-scale of the spectrum sensing, the usefulness of detected idle instances of the PU channel also reduces. This aspect is highlighted in Fig. 3 which shows the time required to opportunistically transmit 1MB of data over two GSM channels having fixed PU duty cycles of 70 and 40 percent respectively. The x-axis shows the same duty cycle mapped on to different time scales. When the PUs are off (point 0 on x-axis), the time required to transmit the 1MB data is approximately 4.6 seconds, an indication of the maximum throughput achievable on a 200Khz GSM channel in the simulated network. When the PUs are active and operate at varying time-scales, the time required to send the same data increases considerably, an indication of reduced throughput. When the PU provides spectrum access opportunity in the order of a few milliseconds, the time required to send the data increases to infinity which is an indication of zero throughput as no secondary user connection can be established in such a short channel idle phase. From this result it is clear that a spectrum opportunity provided in the scale of microseconds is not suitable for any secondary application. Although the result from figure 3 it is a self-evident observation for such durations of spectrum holes, it signifies that the channel differentiation and prediction should not be based directly on the spectrum sensing results and justifies the utilization of the proposed patterns which aim to abstract application-specific spectrum opportunities from these sensing results.

An opposite argument to this proposal could be that the spectrum sensing duration can be increased to a point at which the binary time series becomes representative of the spectrum opportunities but this creates two problems. Firstly, the time scale at which the physical and link layer protocols operate (micro-seconds in existing networks) requires the spectrum sensing to be equally fast. Otherwise, the CR nodes cannot avoid interference with the PU networks. Secondly, the decision of accessing a spectrum hole must be taken at the very beginning of that opportunity and not after a long observation. In PU channels with heavy traffic, the spectrum opportunities for the CR nodes may require very quick access and mobility in order to avoid interference. The transformation of the binary time series into a sequence of patterns for the hypernetworks avoids both these problems without compromising on the interference constraints. The creation of the patterns also serve to smooth out the effects of miss-detection and false alarms which may be caused by the deficiencies of the spectrum sensing mechanism itself or because of the temporal variations of the RF spectrum. Another benefit of the extraction of the patterns from the binary time series is the reduction of the complexity of the hypernetworks. As stated before, the complexity of the hypernetworks can grow exponentially and working on a reduced set of patterns keeps this complexity under manageable bounds. This in theory, should also reduce the hardware and energy requirements as well. Furthermore, as different applications require different channel access guarantees, the patterns derived from the binary time series can be a representation of these requirements and can classify the PU channels based on these requirements.

The binary time series is transformed into a sequence of application-specific patterns which serve as the basic input to the hypernetworks. From this sequence of patterns, the hypernetwork randomly creates hyperedges of the specified order. The hypernetwork in Fig. 2 for example, has four hyperedges formed from five basic patterns. The total number of possible hyperedges in a hypernetwork depends upon the specified minimum and maximum order of the hyperedges and and this number grows exponentially. The maximum number of possible hyperedges are therefore equal to $\sum_{O=min}^{max}(Tp)^O$ where T_p represents the total number of the primitive patterns abstracted from the dataset and O represents the order of hyperedge. The patterns encapsulated inside a hyperedge are ordered based on their abstraction from the spectrum sensing data. In other words, each hyperedge encapsulates a sequence of observations on a predefined channel. The hyperedge creation process is undertaken using random sampling of the pattern sequences. The parameters that control the complexity of the hypernetworks are the min and max order of the hyperedges. If $min = max$ then a fix order hypernetwork is created where each hyperedge encapsulates the same number of sequential patterns. If $min \neq max$ then a mixed order hypernetwork is created where small order hyperedges encapsulate small memory fragments and higher order hyperedges encapsulate larger, more specific channel activity information. The initial weight of a hyperedge is set to the same value i.e. 1, unless otherwise specified at the time of initialization. Explicit initial weights can be assigned to certain types of hyperedges in order to emphasize the importance of that particular relationship in the dataset. For example, a hyperedge encapsulating the patterns associated with PU connection and transmission phases can be assigned a higher weight in the hypernetwork. The process of the creation of a hypernetwork from a series of abstracted patterns is given in the pseudo-code in Algorithm 1.

From the given pattern series D, generate a hypernetwork H with vertices, edges and weights V, E, W using specified order $K_{min} - K_{max}$, and the number of hyperedges I per history window h;

```
H = (V, E, W) = null;
Initialize N as sizeOf(D);
Initialize I as the sampling rate;
for i = 0; i < N; i++ do
    /* select the history window from the dataset */
    h ← D[i...sizeOf(h)];
    /* select the last element as current tag */
    tag = lastElement(h);
    for (j = 1; j<I; j++) do
        E' ← null;
        /* Select an order for E' based on the
        selected distribution */ ;
        O = distribute(K_min...K_max);
        for k = 0; k<O; k++ do
            v' ← h[random(1, sizeof(h − 1))];
            E' ← E' ⋃ v';
        end
        /* sort the elements in order */
        E' ← sort(E');
        /* Assign the tag */
        E' ← E' ⋃ tag;
        /* Assign the initial weight to the newly
        created hyperedge */
        W ← W';
        /* Update the E and W sets with new
        information */
        E ← E ⋃ E';
        W ← W ⋃ W' ;
    end
end
H ← {V, E, W};
```

Algorithm 1: Hypernetwork creation process

4.2. Hypernetworks Learning Process

The hypernetwork learning is an iterative process through which it evolves and assigns different weights to the abstracted hyperedges. This process implies that the assigned weights are a representation of the relative frequency of the patterns in the dataset. The number of iterations is also a parameter of the learning algorithm and can be set at the beginning of the learning process. In the classical hypernetworks, the set of randomly sampled hyperedges remain alive throughout the lifetime of the learning process. An evolutionary approach is more suited to more complex hypernetworks where the addition of new hyperedges as well as the removal of the weak/old hyperedges is allowed. In our approach, on every iteration j, a new hyperedge E' of order $k \in \{min, max\}$ is created from the patterns in the dataset. Since the new hyperedge is created from the same patterns pool, the encapsulated elements can be matched to the previously sampled hyperedges. The weight of the matched hyperedge w_E is updated by a reward function for the next iteration $j+1$:

$$w_E^{j+1} = w_E^j + \delta(E, E^{'}) \tag{3}$$

where δ is a reward function. We utilize the same approach for the reward function as is used in [15] which bases the reward on the order of a hyperedge. The reward function bases its weight adjustment on the last element of the hyperedge which we refer to as the *tag* t_E of a hyperedge. The tag of the hyperedge is important as it is used for the prediction of the channel patterns when given an input from the spectrum sensing module. We consider the last pattern of the hyperedge as the tag of the hyperedge but in principle, the tag can be a combination of more that a single pattern. If E matches E' along with their respective tags, the reward is equal to the order of E which is added to the previous weight of the hyperedge. If the tags do not match, a penalty is imposed instead which is equal to the negative of the order of E. Formally,

$$\delta(E, E') = \begin{cases} k, & \forall_i \in [1, k'], \exists_j \in [1, k] : e_i^{'} = e_j \wedge t_E = t_E^{'} \\ -k, & \forall_i \in [1, k'], \exists_j \in [1, k] : e_i^{'} = e_j \wedge t_E \neq t_E^{'} \\ 0, & otherwise \end{cases} \tag{4}$$

where E is a k order hyperedge with tag t_E, and E' is the new hyperedge with tag t'_E. In the classical hypernetworks which do not utilize the evolutionary functions of replacement and weakening of the hyperedges, the number of randomly sampled hyperedges is usually kept very high in order to cover most of the search space from the dataset. The initial abstraction of binary time series into patterns of interest allows to keep this complexity under bounds. Furthermore, we employ the Data-driven Evolutionary Training approach [15] to optimize the learning process. When a newly generated hyperedge from the pattern pool is not matched with any of the existing sampled hyperedges, one of the smallest weight hyperedge is replaced with the newly created hyperedge from the dataset. This allows for a continuous exploration of search space while keeping the hypernetwork information relevant to desired objectives. If the newly added information is relevant, its weight will increase in future iterations otherwise it will be discarded through the evolutionary process. To summarize, hyperedges encapsulate different levels of secondary channel access opportunities through different ordered hyperedges. During the evolutionary learning process, the relevant information in the hyperedges is reinforced that can serve to characterize channels and optimize CR node spectrum management functions.

4.3. Hypernetworks based Prediction

Once the hypernetwork is trained over the patterns pool, the desired information is reflected in the developed structure of the hypernetwork and the forecasting process is very straightforward. The most frequent patterns in the dataset are reflected in the weights of their respective hyperedges. The patterns that are least frequent in the dataset have very weak hyperedges i.e. with a small weight. The structure of the hypernetwork also represents the different parameters set for the initialization and training i.e. $min - max$ order of the hyperedges, evolution and iterations. When a new pattern extracted from spectrum sensing data is given as input to the trained hypernetwork it is first matched to the candidate hyperedges.

During the CR node operation, it actively monitors the current state of a channel and classifies it into the predefined patterns. These patterns are given as real-time input to the trained hypernetwork. The input pattern is always a subset of the patterns encapsulated inside the hyperedges of the hypernetwork. The hypernetwork structure can forecast the probability of next pattern in the dataset based on the strength of the matched hyperedge. For example, the real-time patterns may match five hyperedges in the hypernetwork. If there is a different tag associated with these matched hyperedges, the weights of these matched hyperedges is considered for the final prediction. The correct prediction of a future pattern is of higher significance to a CR application than the prediction of spectrum sensing results considered in many related literature. If the tag of the hyperedge is a representation of the absence of PU for a specific time frame, the channel access can be initialized by a CR transmitter. The drawback of the current hypernetwork structure however, is that it can only abstract one channel at a time, unless multiple channels are sensed simultaneously and their state represented with a single bit. This may be possible through a wide-band spectrum

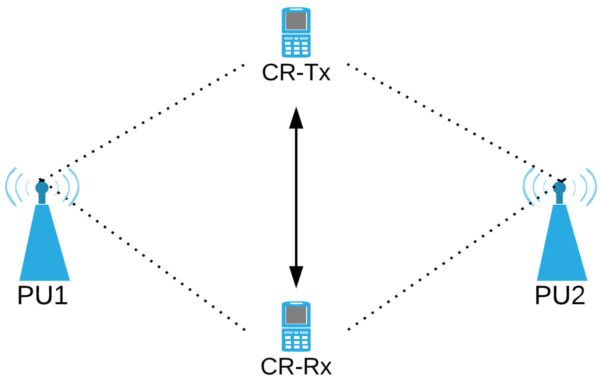

Figure 4. Simulated network scenario

sensor which can classify the channels' states from a single sensing iteration.

5. Simulation Analysis

In order to analyze the effectiveness of the hypernetworks based spectrum profiling in a CR networks, we carried out system level simulations using crSimulator platform [17]. This platform provides an detailed architecture of the CR nodes as well as PU nodes with adaptable activity patterns and duty cycles. As the CR ad hoc networks have to rely on spectrum sensing more than infrastructure-based networks, we simulated ad hoc connections under the influence of different primary users. Since a multi-hop CR ad hoc network can be considered as an extension of many single-hop links, we analyze the effect of the hypernetwork based spectrum profiling on a single multi-channel CR link. The evaluated network scenario is presented in Fig. 4 where two CR nodes attempt to use two PU channels (GSM specification) opportunistically. It should be noted however, that the selection of the GSM channels specification for the evaluation over any other spectrum band is of little significance for the proposed spectrum profiling. The important aspect is the representation of accurate channel state based on the PU activity profiles and the existence of secondary access opportunities. Representation of realistic PU activity profiles is an active area of research in itself as it is very difficult to have a generalized model for different locations and spectrum bands. From the numerous spectrum measurement campaigns, it has been observed that the PU activity can scale from completely free channels such as in the TV broadcast bands in remote locations, to 100% utilization of the spectrum such as in UMTS downlink or WiFi bands depending upon time and location [18]. In literature, two extremes can be found for the PU activity modeling which are using a fixed pattern with predefined duty cycles and a fully stochastic behavior with different random distributions. The actual PU activity distribution in any particular location can be assumed to lie somewhere in the middle of these two extremes. In order to evaluate the performance of the hypernetworks based spectrum profiling, we employ the binary (ON/OFF) model for PU activity with time varying duty-cycles (30 to 70%) during the course of simulation time [19].

Table 1. Hypernetwork parameter settings

Parameter	Value
Order min	3
Order max	6
Patterns max	3
Reward function	δ
PU Activity	Variable Duty Cycle (30-75%)
Dataset size	100

Table 2. Successful forecasts

Setup	Avg Order	Success Rate
EHN(3,6)δ	4.4	74%
EHN(3,5)δ	4	71%
EHN(3,4)δ	3.4	71%
EHN(3,3)δ	3	68%

5.1. Successful forecasts

Table 1 shows the settings used for the formation and the training of the hypernetworks. The spectrum sensing results are abstracted into three distinct patterns based on the requirements of two different secondary user applications. The first two patterns abstract two distinct spectrum access opportunities in time-domain while the third pattern represents a busy channel state. With these three basic patterns, any binary time series data of spectrum sensing can be abstracted and fed into a hypernetwork structure representing different sequences of channel busy and idle states. This process essentially transforms the binary data into time series of the three primitive patterns. The association among these patterns is learned by the hypernetwork through the iterative evolution process described in the previous section. Table 2 gives the results of the forecasting process. The notation $EHN(3,6)\delta$ denotes an evolutionary hypernetwork with $min - max$ order of 3-6 of the hyperedges and a reward function of δ. The success rates shown for the different order hypernetworks are for the test cases where similarity between training patterns and and the test patterns was upto 60% only. If certain patterns of activity on PU channels repeat to a higher degree, the success rates of hypernetworks

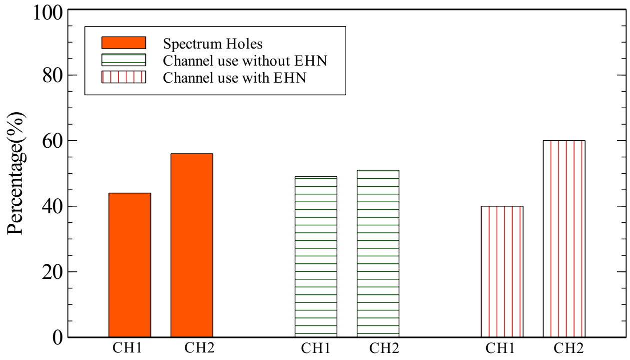

Figure 5. Percentage of spectrum opportunities on two PU channels and their opportunistic usage

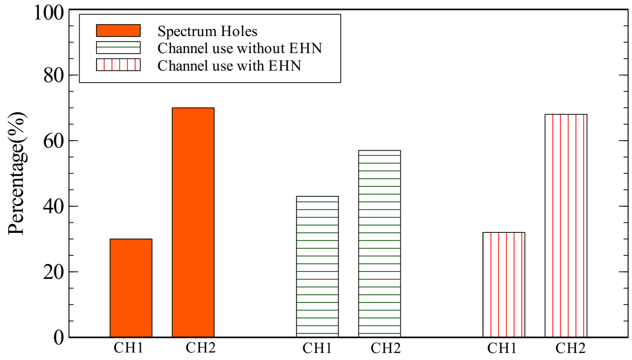

Figure 6. Secondary channel access with clear differentiation between channels

also increase proportionally. The success rates achieved through hypernetworks based channel state forecasting are significant and can potentially be optimized further by using more sophisticated approaches to the hypernetwork training and evolution process.

5.2. Channels characterization

The hypernetworks based spectrum profiling can characterize the available channels based on the application requirements. To test this, a time variant duty cycle between 60 to 70% was applied to the network scenario of Fig. 4 where each PU (PU1, PU2 in Fig. 4) followed its independent time-scale of transmission. In such a scenario, without spectrum profiling, the CR nodes will attempt to access both PU channels with equal probability and random access. With hypernetworks based spectrum profiling however, the CR nodes check for the probability of the next pattern in the channel and try to access that channel which has a predicted pattern of interest in the forecast. This effect is shown in Fig. 5 which shows the distribution of spectrum opportunities during the simulation on both PU channels and their utilization by CR nodes. The hypernetworks based profiling enables CR nodes to access the suitable channel (CH2) more frequently. This result shows that CR network performance can be optimized by differentiating among channels that generally look to provide similar spectrum access opportunities. The performance benefit increase even more when there is a clear difference between the channels as shown in Fig. 6. This performance improvement can also be seen in the number of channel handovers performed by CR network during the simulation and the achieved throughput as shown in Fig. 7. For the analysis of the impact on handovers, we assumed that the channel switching does not incur considerable time overhead. In real scenarios however,

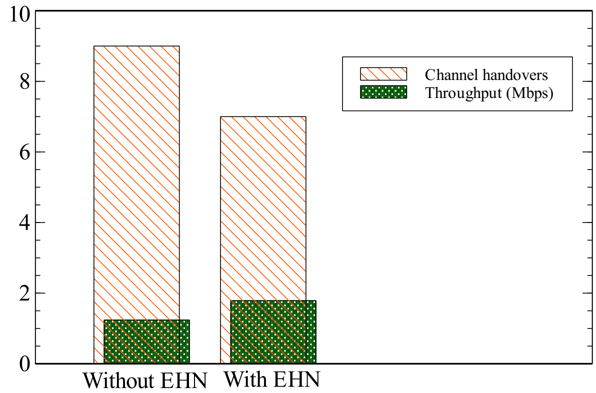

Figure 7. Achieved throughput and performed handovers

performing spectrum handovers will require some pre-agreement, about back-up channels through control message exchange, or through certain policies which may incur considerable time costs. Figure 8 shows the impact of the CR transmission on the PU transmission in terms of packet collisions per MB of data transmitted over the CR link. In our simulated network, a packet collision occurs whenever the CR nodes transmit a data packet simultaneously to the simulated PU nodes. This may happen when the PU nodes start transmission while the CR nodes were utilizing a spectrum hole on the licensed channel. It should be pointed out here, that the probability of creating zero interference with the PU nodes may be impossible for the CR network which utilizes the spectrum holes in an overlay manner. No matter how fast is the spectrum sensing of the CR nodes, it cannot guarantee that the PUs will not be switching to transmit state during the accessing of the spectrum holes. For the analysis of the impact of the spectrum profiling on the interference with PU nodes, we compared the hypernetworks based profiling with the channel recommendation scheme presented in [10] and a random channel access scheme.

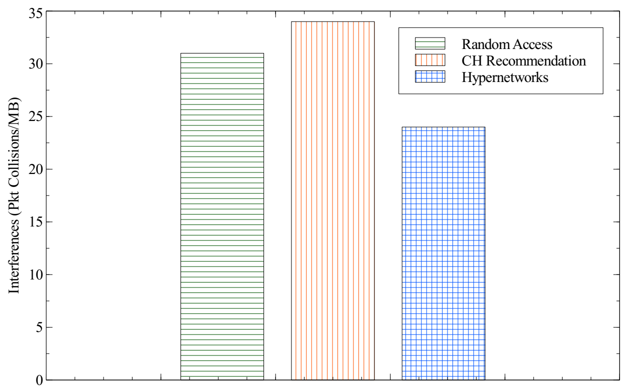

Figure 8. Collision instances with PU transmission

In the channel recommendation scheme, the CR nodes prioritizes the channel for access that was successfully used for the previous transmission. The random access scheme utilizes a uniform random distribution for the selection of the PU channel. In all three approaches, a reactive spectrum mobility approach was used for vacating a channel in response to the PU appearance. As can be seen in figure 8, the hypernetworks based spectrum profiling reduces the number of collision instances considerably when compared to the other two approaches. We acknowledge that the representation of the impact on the interference levels through packet collisions is not very representative and should be shown through SNR values. This shortcoming however does not invalidate the result shown in figure 8 as we expect a similar level of improvement when simulated on a signal level simulator.

6. Conclusion and Future Work

In this paper we presented a novel radio spectrum profiling framework that is based on the evolutionary hypernetworks. The hypernetworks can effectively capture and abstract the patterns of interest from the primitive spectrum sensing data and enable the characterization of the the available PU channels based on secondary users' application requirements which are represented through different ordered hyperedges. It was shown that spectrum holes can be identified from primitive binary time series of spectrum sensing results and utilized for differentiating among the available channels for spectrum management. In contrast to other channel prediction techniques e.g. those based on Hidden Markov Models, the hypernetworks do not require the spectrum sensing data to be 100 percent accurate and can reliably forecast the future channel states. Hypernetworks are suited to identifying spectrum opportunities for different types of applications. The implicit data smoothing through formation of patterns in the primitive sensing data also serves to mitigate the effect of minor channel fluctuations in RF environment. Currently, a hypernetwork learns from a single dataset which implies that only one channel/band can be abstracted and multiple instances are required for multiple channels. A future extension this proposal could be to analyze a cross-channel pattern creation process for a single hypernetwork especially for adjacent frequency channels. This paper provided the analysis of hypernetworks for a single link CR network where the environment was similar for both the transmitter and the receiver nodes. However, in a distributed ad hoc network, disagreements about channel states among network peers will happen because one node may be affected by PU more than the other. This problem can be addressed through a consensus approach and is the subject of further investigations in future.

Acknowledgement. This work is being carried out within the scope of the International Graduate School on Mobile Communications (Mobicom) at Ilmenau University of Technology, supported by the German Research Foundation (GRK1487) and the Carl Zeiss Foundation, Germany.The authors would like to further acknowledge Dr. Elena Bautu at Ovidius University, Constanta Romania, for her guidance, help and support.

References

[1] X. Xing, T. Jing, W. Cheng, Y. Huo, and X. Cheng, "Spectrum prediction in cognitive radio networks," *Wireless Communications, IEEE*, vol. 20, no. 2, pp. 90–96, 2013.

[2] S. Yarkan and H. Arslan, "Binary time series approach to spectrum prediction for cognitive radio," in *Vehicular Technology Conference, IEEE 66th*, 2007, pp. 1563–1567.

[3] R. Min, D. Qu, Y. Cao, and G. Zhong, "Interference avoidance based on multi-step-ahead prediction for cognitive radio," in *Communication Systems, 11th IEEE Singapore International Conference on*, 2008, pp. 227–231.

[4] S. Kaneko, S. Nomoto, T. Ueda, S. Nomura, and K. Takeuchi, "Predicting radio resource availability in cognitive radio - an experimental examination," in *Cognitive Radio Oriented Wireless Networks and Communications, 3rd International Conference on*, 2008, pp. 1–6.

[5] C.-H. Liu, W. Gabran, and D. Cabric, "Prediction of exponentially distributed primary user traffic for dynamic spectrum access," in *Global Communications Conference (GLOBECOM), IEEE*, 2012, pp. 1441–1446.

[6] K. W. Sung, S.-L. Kim, and J. Zander, "Temporal spectrum sharing based on primary user activity prediction," *Wireless Communications, IEEE Transactions on*, vol. 9, no. 12, pp. 3848–3855, 2010.

[7] H. Kim and K. Shin, "Efficient discovery of spectrum opportunities with mac-layer sensing in cognitive radio networks," *Mobile Computing, IEEE Transactions on*, vol. 7, no. 5, pp. 533–545, 2008.

[8] L. Yang, L. Cao, and H. Zheng, "Proactive channel access in dynamic spectrum networks," *Physical Communication*, vol. 1, no. 2, pp. 103 – 111, 2008.

[9] X. Chen, J. Huang, and H. Li, "Adaptive channel recommendation for dynamic spectrum access," in *IEEE Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN)*, May 2011.

[10] H. Li, "Customer reviews in spectrum: Recommendation system in cognitive radio networks," in *New Frontiers in Dynamic Spectrum*, *IEEE Symposium on*, april 2010, pp. 1–9.

[11] B.-T. Zhang, "Hypernetworks: A molecular evolutionary architecture for cognitive learning and memory," *Computational Intelligence Magazine, IEEE*, vol. 3, no. 3, pp. 49–63, 2008.

[12] J.-K. Kim and B.-T. Zhang, "Evolving hypernetworks for pattern classification," in *Evolutionary Computation, IEEE Congress on*, 2007, pp. 1856–1862.

[13] H.-W. Kim, B.-H. Kim, and B.-T. Zhang, "Evolutionary hypernetworks for learning to generate music from examples," in *Fuzzy Systems, IEEE International Conference on*, 2009, pp. 47–52.

[14] S. Kim, S.-J. Kim, and B.-T. Zhang, "Evolving hypernetwork classifiers for microrna expression profile analysis," in *Evolutionary Computation, IEEE Congress on*, 2007, pp. 313–319.

[15] E. Bautu, S. Kim, A. Bautu, H. Luchian, and B.-T. Zhang, "Evolving hypernetwork models of binary time series for forecasting price movements on stock markets," in *Evolutionary Computation, IEEE Congress on*, 2009, pp. 166–173.

[16] S. N. Khan, M. A. Kalil, and A. Mitschele-Thiel, "Distributed resource map: A database-driven network support architecture for cognitive radio ad hoc networks," in *Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), 4th International Congress on*, 2012, pp. 188–194.

[17] S. Khan, M. A. Kalil, and A. Mitschele-Thiel, "crsimulator: A discrete simulation model for cognitive radio ad hoc networks in omnet++," in *Wireless and Mobile Networking Conference (WMNC), 6th Joint IFIP*, 2013, pp. 1–7.

[18] L. Stabellini, "Quantifying and modeling spectrum opportunities in a real wireless environment," in *Wireless Communications and Networking Conference (WCNC), IEEE*, 2010, pp. 1–6.

[19] M. Lopez-Benitez and F. Casadevall, "Empirical time-dimension model of spectrum use based on a discrete-time markov chain with deterministic and stochastic duty cycle models," *Vehicular Technology, IEEE Transactions on*, vol. 60, no. 6, pp. 2519–2533, 2011.