Role of neighbour discovery in distributed learning and knowledge sharing algorithms for cognitive wireless networks

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***Abstract*—This work investigates the impact of neighbour discovery on distributed learning schemes applied on optimal network selection based on the acquisition by the selecting device of context information on the capabilities and status of surrounding networks. The work introduces the problem of neighbour discovery in multiple channel and cognitive networks, and identifies the trade-offs between neighbour discovery performance and overall network performance. Next, an optimal network selection algorithm based on distributed learning is introduced, and key parameters and components relevant to its operation are presented, focusing in particular on the common control channel required to exchange the context information. Finally, the paper discusses the relation between neighbour discovery and the distributed learning process at the basis of the context information acquisition; a model for mapping the learning process on a neighbour discovery problem is proposed, and the potential impact of neighbour discovery failures on the performance of the optimal network selection scheme is discussed.**

I. Introduction

Neighbour discovery can be defined as the process of acquiring information about the local environment, aiming at determining the presence of other devices, the capabilities of such devices, and the information available at them. Neighbour discovery is instrumental in the setup and operation of a wireless network since it forms the basis of key functions like network association, network organization (e.g. clustering) and support for both local (e.g. Medium Access Control) and end-to-end algorithms and protocols (e.g. routing in multi-hop networks).

In the general case of networks where multiple channels are available, neighbour discovery can be defined as a two steps process:

1) Allow devices to converge on the same channel;
2) Exchange the information required to achieve discovery before one of the devices moves to a different channel.

The problem of neighbour discovery is particularly challenging in the case of cognitive wireless networks, as the set of channels may differ among devices due to different decisions on the presence of other systems on some of the potentially available channels. For this reason, neighbour discovery in the context of cognitive radio networks has been investigated by several groups of researchers, see for example [1], [2], [3], [4].

Algorithms that rely on an accurate and fast neighbour discovery include in particular distributed learning and knowledge sharing.

This work will focus in particular on distributed learning mechanisms applied to the problem of optimal selection by a device in a set of candidate networks/configurations, in terms of the QoS levels that can be achieved. In particular, for the implementation of the learning mechanism, concepts from Bayesian statistics will be considered to build knowledge on the context of the device [5], [6], leading to the estimation (based on the collection of measurements) of the conditional probabilities for a certain network to achieve a certain QoS level for a particular application. In this context, it is essential to complement learning mechanisms with a reliable solution for the exchange and distribution of information.

To this respect, Cognitive Control Channels (CCC) have been identified as a key feature required for Cognitive Radio Systems (CRS). In general, a CCC can be defined as a channel for transmitting elements of information necessary to manage and realize various operations within a CRS. An open issue is however how to converge to a cognitive pilot channel shared between the cognitive devices. In [7], for example, the setup of a Local Cognitive Pilot Channel (LCPC) is proposed, but the underlying difficulties of setting up the LCPC when no predefined frequencies are reserved to this aim are not discussed. In general, the set-up of a common channel will foresee a neighbour discovery phase. An accurate performance evaluation of distributed learning algorithms requires thus to take into account the efficiency in the establishment of a common communication channel, and thus of the underlying neighbour discovery scheme, in order to determine the impact of missed neighbour detections and the corresponding incomplete local information.

In this framework, the goal of this work is to analyze the impact of neighbour discovery, and in particular of discovery failures, on algorithms for distributed learning, focusing on the issue of reduced efficiency in setting up a common communication channel.

The paper is organized as follows. Section II introduces the solutions for distributed learning considered in this work, and discusses the need for a common communications channel. Section III presents key issues related to neighbour discovery and reviews potential solutions proposed in the literature. Section IV discusses the impact of the efficiency degree of neighbour discovery in setting up a common communications channel on the performance of the considered distributed learning solution. Finally, Section V draws conclusions.

II. Distributed learning for optimal network selection

Considering an arbitrary user that carries a terminal and has a subscription with a Network Operator (NO), distributed learning mechanisms can provide the status of a device and of its environment; this includes for example the available networks belonging to or collaborating with the NO, their Quality of Service (QoS) capabilities. Focusing on the QoS level capabilities that can be obtained, and assuming the application of Bayesian statistics concepts, the learning mechanism collects measurements and updates the conditional probabilities that a certain network can achieve a certain QoS level for a particular application. The user can use a certain set of applications, based on his/her subscription. The corresponding context information for this user includes:

- A set of candidate networks. The set of candidate networks is a subset of the available networks. It comprises networks that are compliant also with the policies of the Network Operator, i.e. the selection of these networks for the particular user and terminal is allowed.
- The set of QoS levels, for each network and application, at which an application can be offered by a certain network. This set of QoS levels comprises those that are achievable in the particular context of operation (e.g., radio channel conditions) and compliant with the policies of the operator for each application. A QoS level corresponds to a set of QoS parameters, such as bit rate, delay, jitter, etc. It should be noted that the scheme presented here is generic with respect to selected QoS parameters. Each parameter can be associated with a set of reference values for a specific network. For example, for the bit rate parameter a set of reference values could include the values 6, 12, 24, 36, 48, 54 Mbps. A QoS parameter can take a value among this set of reference values when a particular network is considered. In this respect, the set of QoS levels that can be achieved in a particular context can derive as the Cartesian product of the various reference value sets for the QoS parameters.
- The conditional probabilities, which provide an estimation of how probable it is that a specific QoS parameter, will reach a certain value, for an application, given a certain configuration.
- A probability density function value, which quantifies the knowledge regarding context. The probability density function offers a more aggregate estimation regarding the probability to achieve a certain combination of QoS parameters, which corresponds to a QoS level, for an application, given a certain network. This expresses the probability that a certain network will support a specific application and QoS level combination. In other words, the values of the density function express the knowledge on how probable a particular network-application-QoS level triplet is, compared to all other possible triplets.

The update of the conditional probabilities and probability density function values constitutes the learning process. The update of these relies on approaches suggested in [8], [9], [10], [11]. It should be noted that the update of context information and knowledge is continuous, while the device is on the move. As a device moves there is usually some degree of overlap between its previous context and its current context. Thus, when the device moves into a new area, the context learning process does not have to start from the beginning. Previously obtained applicable information and knowledge, in the form of conditional probabilities and the probability density function, may still be exploited.

A. *Cognitive Control Channels*

As already noted, solutions for distributed learning rely on the capability of exchanging information on a Cognitive Control Channel, where information may be conveyed from network infrastructure elements to user equipment. Furthermore, the CCC may be exploited for the exchange of information between terminals, so as to increase the accuracy of obtained knowledge on the context of the environment.

The role of such a CCC, known as Cognitive Pilot Channel (CPC) has been studied for the specific context of heterogeneous CRS [12]. The CPC is defined as a channel (logical or physical) which conveys the elements of necessary information facilitating the operations of Cognitive Radio Systems and can be seen as an enabler for providing information from the network to the terminals, e.g., frequency bands, available RATs, and spectrum information and spectrum usage policies. These results have been provided as inputs to the International Telecommunication Union, Radio communication Sector (ITU-R) within the matter of addressing regulatory measures to enable the introduction of software-defined radio (SDR) and CRS. The concept of the CPC has then been further extended to also include the concept of exchange of cognitive data among user devices. These studies were exploited as inputs to standardization: the IEEE Dynamic Spectrum Access Networks (DYSPAN) Standards Committee (formerly IEEE Standards Coordinating Committee 41 (SCC41)) published the IEEE 1900.4 standard [13], [14] in 2009 related to the efficient operation of heterogeneous CRS by introducing a CCC in the form of a so-called Radio Enabler. Corresponding studies were also undertaken in the context of the ETSI Reconfigurable Radio Systems Technical Committee (ETSI RRS TC) [15], [16]. In recent years, a number of papers have been published detailing usage examples and advantages of such a channel; for example, [17] illustrates how a CPC may be exploited for orchestrating a heterogeneous indoor-environment, [18] introduces user-context dependent Virtual Connectivity Maps and details how the behavioural statistics of a radio node can be modeled based on Markov-models whose parameters can then be distributed via a cognitive channel, and the already mentioned [7] illustrates how such a channel is straightforwardly exploited for distribution and collection of radio measurements and other relevant parameters. As already noted, however, the set-up of such a channel still relies in most cases on a neighbour discovery phase. Solutions for neighbour discovery will be presented in Section III.

III. Neighbour discovery

Different classes of networks can be identified with respect to the issues posed in the neighbour discovery phase. A basic distinction can be made between single channel networks, where all devices share the same channel, and multiple channel networks, where each device can tune to different channels; the latter case is by far the most common one in current wireless networks. Cognitive networks can be seen as a special case of multiple channel networks, as will be discussed in detail later on in this Section.

In the following the case of two devices carrying on neighbour discovery will be considered. Under the assumption that a device is equipped with a single transceiver, and is thus only capable to listen and transmit on one channel at the time, performance of neighbour discovery is measured in this case by two parameters:

- Probability of selecting the same channel P_c
- Probability of successful discovery on same channel P_D

The probability of successful neighbour discovery P_{SND} can be defined as:

$$P_{SND} = P_c \cdot P_D \tag{1}$$

where P_c decreases as the time spent in a channel increases, while P_D decreases as the number of channels m increases. If the time required to span all channels is shorter, the average Time To Rendezvous (TTR) for a given P_D will be lower as well; on the other hand, less time on each channel will reduce P_D. The impact of the two probabilities defined above on the overall neighbour discovery performance can be shown by considering a simple random neighbour discovery scheme where each of the two devices cycles through three possible states:

- INQUIRY the devices sends packets of duration T_{packet};
- SCAN the device listens for INQUIRY packets;
- IDLE the device does not participate in neighbour discovery, as it is busy with other activities (e.g. sending traffic in a network it is already associated with, or entering in sleep to save energy).

In the considered scheme, a device spends a time $T_{channel}$ on each of N available channels, and a portion T_{idle} of each $T_{channel}$ is spent in IDLE state, while the remaining time is equally distributed, in average, between INQUIRY and SCAN states. Devices switch between channels every $T_{channel}$ seconds in a random fashion. The impact of the

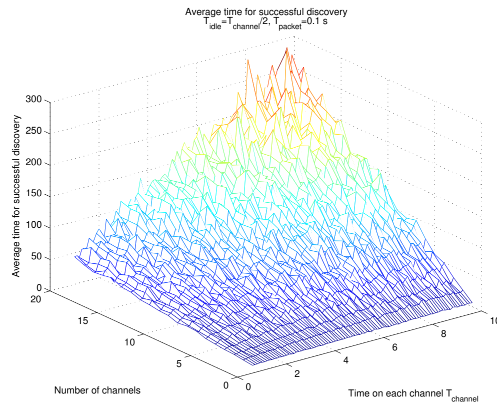

Fig. 1. Average time for successful discovery in the case $T_{idle} = T_{channel}/2$.

number of channels available to the devices as well as of the time spent on each channel, $T_{channel}$, is presented in Figure 1 for the case $T_{idle} = T_{channel}/2$. Figure 1 highlights that the average time required for succesful neighbour discovery increases with the number of channels, as well as with the time spent on each channel.

The efficiency of the neighbour discovery is also the result of decision regarding its impact on energy efficiency and network performance. Performance of the neighbour discovery algorithm can be in fact improved by reducing the time spent by each device in IDLE state, at the price of higher energy consumption and/or lower network performance, depending on the actual use reserved by devices to the time spent in IDLE state. An efficient solution for global network operation should thus optimize the amount of time and resources reserved to neighbour discovery, in order to guarantee the required performance for discovery without unnecessarily hinder other network operations or energy efficiency.

Cognitive networks can be seen as multiple channel networks, and as such share the issues presented above. Cognitive networks must however face additional challenges related to the coexistence with other radio systems:

- The available radio resource (i.e. available channels) varies over time due to activity of other radio systems;
- The available radio resource can be different for different terminals in the same network due to different geographic positions influencing the sensing results.

The presence of detection errors, in particular, may lead to significant degradation of neighbour discovery performance. In order to highlight the impact of sensing, one can refer to the simple neighbour discovery scheme introduced above, and extend it by taking into account the impact of sensing in the determination of the set of available channels by each of the two devices involved in the discovery.

Under the assumption that devices have no way to exchange information on the common available channels, they will search over potentially different sets as a result of individual

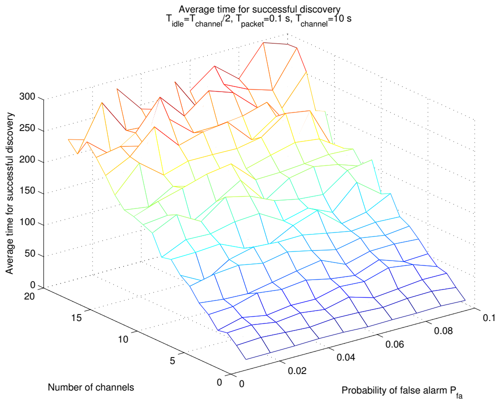

Fig. 2. Average time for successful discovery as a function of probability of false alarm and number of channels in the case $T_{idle} = T_{channel}/2$.

TABLE I
COMPARISON OF AMOUNT OF INFORMATION AND SYSTEM PROPERTIES REQUIRED FOR DIFFERENT NEIGHBOUR DISCOVERY MODELS (DRAWN FROM [2])

	Assisted	Roles	Shared	Individual	Free-for-all
Synchronization available	YES	YES			
Heterogeneous roles	YES	YES			
Number of radios	n	2	2	2	n
Common spectrum naming	YES	YES	YES		
Master controller	YES				
Wideband operation	YES				
Control channels	YES				
Fairness	YES	YES	YES	YES	
Common spectrum	YES	YES	YES		
Detection errors	NO	NO	NO	NO	
Malicious radios	NO	NO	NO	NO	

sensing decisions. The values of the probabilities of false alarm and detection characterizing the sensing module will thus influence the efficiency of the neighbour discovery process. Figure 2 presents the average time to successful neighbour discovery as a function of the number of channels and of the probability of false alarm, again for the case $T_{idle} = T_{channel}/2$. Figure 2 shows that the probability of false alarm has a significant impact on the time required to select the same signal, and a more dramatic effect can be observed by considering higher probabilities of false alarm.

The design of robust and efficient neighbour discovery schemes is thus of key importance in the effective deployment of cognitive networks. A key aspect in the design of such schemes is to determine the amount of information required for the scheme to operate. Under this aspect, the work in [2] provides an interesting classification of neighbour discovery schemes in term of underlying assumptions. The classification proposed in [2], based on a large set of parameters related to the amount of common information available to network devices, is summarized in Table I, where five different models of neighbour discovery schemes are identified, in increasing order of complexity, from *Assisted* to *Free-for-all*. Table I highlights that models taking into account detection errors are the most complex to address, as they are characterized by the minimum amount of common information between devices.

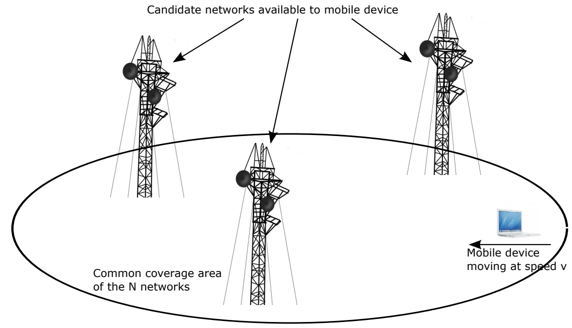

Fig. 3. Reference scenario considered in this work.

IV. Impact of Neighbour Discovery on Distributed Learning

The establishment of the common control channel at the basis of the information exchange required by the distributed learning process introduced in Section II will in most cases be the result of a neighbour discovery phase. In particular, the common control channel is used by mobile devices and networks to exchange the information required by a device to evaluate the conditional probabilities introduced in Section II, so to determine the best candidate network to achieve a given QoS for a given application.

Under ideal conditions, the neighbour discovery phase is assumed to be always successful, so that all devices and networks within radio coverage are able to communicate and exchange the context information needed for optimal network selection. In this case, it is shown in [19], for a scenario characterized by a device selecting between two candidate networks, that optimal selection based on context information leads to better performance than legacy selection schemes, in particular when one of the candidate networks shows a variation in the offered QoS.

The reference scenario is the one envisioned in Figure 3, where a mobile device enters an area where N candidate networks are available, and has a limited time T_{ND} to complete neighbour discovery and start communicating over the selected network. The overall time T for which the given set of networks will be available is determined by the ratio between the coverage range R of the networks and the speed of the mobile device v; it can be safely assumed that in order for the scenario to make sense, the network discovery time must be significantly lower than the total available time, that is $T_{ND}/T \ll 1$.

In order to assess the impact of imperfect neighbour discovery, one can model the optimal network selection scenario as a neighbour discovery problem where N+1 entities, given by the mobile device and the set of N candidate networks, try to complete discovery in order to establish a common channel and exchange the context knowledge. In the worst case, such a scenario is characterized by the need of all N+1 entities to reach reciprocal awareness and exchange information, each entity potentially adopting a different set of available channel

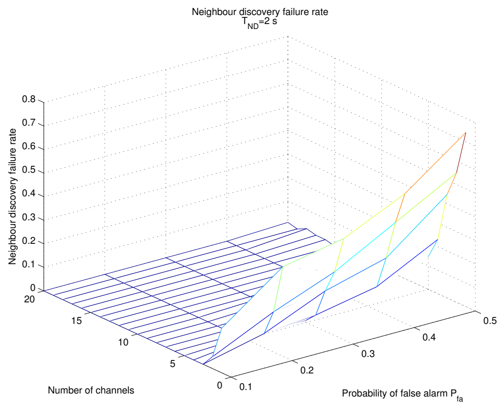

Fig. 4. Neighbour discovery failure rate as a function of probability of false alarm and number of channels in the case $T_{ND} = 2s$.

as a result of different propagation conditions and different sensing decisions. Such a worst case would fall in the *Free-for-all* category seen in Section III and introduced in [2] and would thus constitute a difficult neighbour discovery problem. Even in the more favourable case, when the device is only required to connect to any of the N networks, neighbour discovery could still prove challenging, in particular in the case of medium-to-high mobility and in presence of detection errors. As an example, Figure 4 shows the failure rate in neighbour discovery for the random algorithm introduced in Section III as a function of the probability of false alarm and of the total number of channels, assuming a device speed $v = 5m/s$, a coverage range $R = 1000m$, and imposing that $T_{ND}/T = 0.01$, leading to $T_{ND} = 2s$. Figure 4 highlights that when the number of channels is low, even low values of probability of false alarm can lead to significant failure rates. In the network selection problem this would translate in a device failing to receive context information regarding a network, potentially reducing the achievable performance.

V. Conclusion

This work focused on the interaction between neighbour discovery and a network selection scheme based on distributed learning of context information. Key issues related to neighbour discovery in multiple channel and cognitive wireless networks were introduced, and trade-offs between neighbour discovery performance and global network performance and energy efficiency were identified. Next, an optimal network selection algorithm based on context information exchanged and updated by means of distributed learning was introduced. The role of a common control channel in context information exchange was discussed, and ongoing activity regarding the definition of such a channel reviewed. In particular the need for a neighbour discovery phase in order to set-up such a channel was identified. Finally, the impact of neighbour discovery on the selection scheme was discussed by introducing a model for mapping the context information exchange to a neighbour discovery problem showing how failures in neighbour discovery may impact the performance of distributed learning, and calling for a joint performance evaluation, to be addressed in future work.

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