Context Discovery Mechanisms for Cognitive Radio

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Abstract— This paper addresses the estimation of different context parameters of a primary user network based on signal strength measurements obtained by a sensor network and without any prior knowledge of the antenna types used by primary transmitter or the propagation model. The obtained context information can be stored in a database like a Radio Environment Map (REM) and be used to decide the appropriate configuration of a secondary cognitive radio network. Proposed methodology is based on applying image processing over the set of measurements to identify the existing transmitters in the scenario and their parameters such as position, antenna pattern and propagation model.

I. Introduction

The current spectrum underutilization has motivated an important number of activities and initiatives in the regulatory, economic and research communities in searching for better spectrum management policies. The aim is to achieve a dynamic management of spectrum, in which one frequency band may be used by different operators in different instants of time and for different technologies, thanks to the reconfiguration capabilities of terminals and networks, according to cognitive mechanisms that allow them to interact, learn and take more appropriate decisions. Cognitive Radio (CR) and dynamic spectrum access paradigms have emerged as a promising solution to conciliate the current spectrum demand growth and its underutilization without changes to the existing legacy wireless systems [1][2]. CR enables much higher spectrum efficiency through opportunistic spectrum access. Therefore, it is an attractive technology for future wireless communications. The basic idea of CR is to allow secondary/unlicensed users (SUs) to access in an opportunistic and non-interfering manner some licensed bands temporarily unoccupied by primary/licensed users (PUs). The operating principle is to identify spatial and temporal spectrum gaps not occupied by PUs, place SU transmissions within such spaces and vacate the channel as soon as PUs return.

The different decisions that SUs have to take, such as the selection of the appropriate spectrum band to transmit, power level, modulation formats, etc. are highly dependent on the environment state in terms of PUs activity, transmitted power, etc. Much of the work on cognitive radios has been based on making inferences about that environmental state solely at the time of decision making, typically making use of sensing mechanisms to detect the presence or absence of the PU. However, any additional and temporally consistent long-term knowledge of the environment can be used to significantly improve the accuracy and performance of the decision-making process. Such information could include different context parameters of other transmitters in the area such as positions, propagation conditions, etc. usually assumed to be stored in a database-like system, locally or globally, typically coined under the term Radio Environment Map (REM) [3], as a comprehensive centralized map that identifies location and geo-spatial distribution of parameters like terrain, service availability, police requirements, etc. REM information can be updated with observations from CR nodes and disseminated throughout CR networks, providing the useful awareness of environmental status to assist the CR operation. Following a similar direction, the FCC established that for unlicensed operation using TV white spaces, secondary devices need to access a database to obtain information on the available channels at their location [4].

In addition to the detection of the presence or absence of a PU per frequency band, for which cooperative sensing and detection schemes have shown to decrease the false alarm and miss detection probabilities in the presence of fading effects, recently the possibility of spatial reuse of occupied bands in areas where the primary power is so low that could make that possible has received a growing interest. Finding these opportunities calls for ideally knowing the distribution of power in space and frequency of all the primary sources [5]. This problem has proved to be very ambitious, in particular when the context has to be discovered in terms of propagation parameters, including not only transmitters' positions and power, but also unknown propagation features like antenna radiation pattern, propagation factor, shadowing dispersion, etc. REM concepts go in this direction, although it is devised to be occasionally updated or corrected rather than acting in a near real time fashion due to the overheads and computational cost involved.

In [6] a massive sensor network is deployed aiming at estimating the antenna radiation pattern, positioning, transmitted power and propagation factor using received signal strength measurement. Different Maximum Likelihood (ML) approaches and associated grid search for the covered area are derived under different unknown parameters assuming a Gaussian radiation beam for the transmitters. Other approaches like [7] rely on an exhaustive ML approach considering just a low number of sensors. In this case the transmitted power and transmitter positioning are the parameters to be estimated by assuming a known propagation environment and omnidirectional antennas. This extends the normal situation extensively treated in node location in sensor networking where the transmitted power is known.

In this paper, we address the estimation of context parameters of the primary user network based on Received Signal Strength (RSS) measurements obtained by a sensor network. As a difference from prior works, no prior

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knowledge of the antenna types or the propagation model is considered. Proposed methodology is based on image processing techniques, extending prior work of the authors in [8] in which a positioning estimation method was presented, to include other context features like the antenna pattern and the propagation model. The proposed methodology targets to decrease the computer cost, so that it could be easily used to update REM information in near real time. The methodology is evaluated using a commercial planning tool that determines the RSS at the different points taking into consideration the uncertainties associated with the terrain as well as real antenna patterns.

This paper is organized as follows. Section II presents the problem formulation, while Section III discusses the different steps of the proposed methodology. Section IV presents the performance evaluation in specific scenarios and Section V summarizes the conclusions.

II. Problem Formulation

Let assume a generic scenario characterized by a number of primary transmitters operating at different frequencies and having different coverage areas. A secondary network will rely on the information measured by a number of sensors randomly scattered in the scenario that could be built-in e.g., mobile terminals, and the appropriate post-processing of this information, in order to estimate different context features of the primary network that could be stored in a REM, for further assistance in future decisions of the secondary network operation. It is assumed that the sensors cooperate with each other in a centralized manner, where a central entity plays the role to gather all sensing information from the sensors and to estimate the different context parameters.

A sensor measures the received power in a number of N specific frequencies in its geographical position. It is assumed that frequency f_i (i=1, 2,…N) is detected by the sensor at position (x,y) when the received power is above a given threshold $P_{th}(f_i)$. The value detected by a given sensor for each frequency is quantified to a set of 2^n values with quantization step Δ. Then, the sensor will send to the central entity this value encoded as a word of n bits.

The problem considered here consists in combining the different measurements at random positions, which represent a partial vision of the scenario, in order to get a full vision in which the primary transmitter networks are estimated, as shown in Fig. 1. It is worth mentioning that the considerations on the sensing process itself (such as errors in the process or the determination on which frequencies has to sense every sensor) and the means to report the sensing results are out of the scope of the paper.

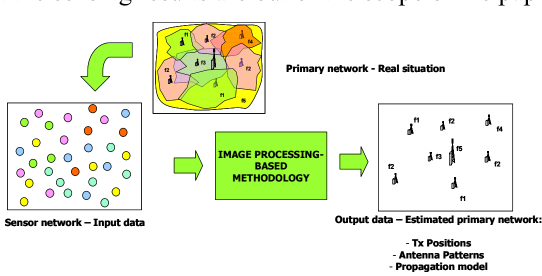

Fig. 1: General problem formulation

III. Proposed Methodology

The proposed methodology characterizes the radio environment by an image, where each pixel (i.e., a rectangular area of dimensions $\Delta x \times \Delta y$) contains the information of the RSS levels associated to the frequencies measured in this area. It is assumed that a pixel can only have the result of one sensor. Then, given that only the values of the pixels where a sensor is located are known, these values will be combined using image processing techniques in order to reconstruct the overall image and to discover context features such as transmitter positions, antenna patterns and directions and propagation model. In the following, the main steps of the procedure are listed as shown in Fig. 2.

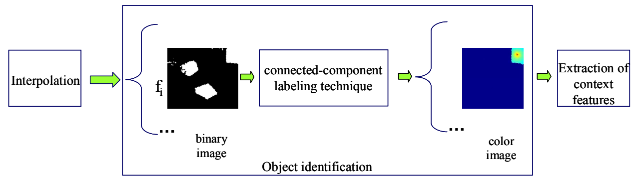

Fig. 2: Overall steps of the methodology

A. Interpolation

This is the first step intended to determine the RSS associated to those pixels without any sensor based on the pixels available. With the target of minimizing the computational complexity, the simplest nearest neighbor interpolation method is considered here, which selects for each position the value of the nearest sampling point. The value of the P(x,y) in every position without sensor can be interpolated as:

$$P(x,y) = \min_{d_k} P_k(x_k, y_k) \tag{1}$$

that is, the value of P(x, y) is simply obtained as the value measured by the closest sensor (i.e., the one with minimum distance d_k).

B. Object identification

This step targets the identification of the different transmitters existing in the scenario. This is done under the assumption that the area where a transmitter at frequency f_i is being detected can be considered as an "object" inside the image, so object identification techniques are applied. As shown in Fig. 2, the following steps are carried out.

- From the resulting interpolated image, a set of N binary images will be built, one per frequency f_i, whose pixels take the value 1 when frequency f_i is detected (i.e., it is above $P_{th}(f_i)$) and 0 otherwise. These images will be used as the basis to identify the different "objects".

- For each binary image (i.e., for each frequency f_i), an object identification mechanism following the so-called connected-component labeling technique [9] will be applied. It consists in scanning the image and making groups of adjacent pixels having the same value (4-connected pixels are assumed, meaning that pixels are adjacent if one of their four edge - sharing neighbors touch). Each group of pixels will be then an "object".

- In the next step, the binary images will be converted into color images, one per each object identified, using the quantified values from the received power at each frequency f_i after the interpolation.

C. Extraction of context features

For each of the objects identified in the previous step a set of context features are extracted, detailed as follows.

a) Transmitter position estimation

The highest received power will be measured in the pixels where the primary transmitter is located, then, a first estimate of the transmitter position will be the centroid of the pixels with the highest received power from each identified and retained "object". It should be mentioned that this estimation is appropriate in case that the transmitter uses an omnidirectional antennas. However, in case of having a directional antenna, this estimated position is biased as the quantified and retained maximum received power extends in a greater extent the pixels laying in the direction of the radiation pattern. In this situation, and once it is observed in the next sub-section that the antenna is directive, the estimation can be further refined as follows.

1.- Take as an intermediate estimation of the transmitter position the extreme point of the object formed with the pixels of maximum received power in the opposite direction of the maximum radiation pattern (point B in Fig. 3).

2.- Estimate antenna pattern and propagation model coefficient α as explained in next sub-sections.

3.- Estimate transmitter position by shifting the previous intermediate estimation (point B in Fig. 3) in the direction of the antenna by distance d_1. This distance is computed considering that the received power in points A and B of the figure, respectively, is equal, meaning that the following relationship holds:

$$\frac{G(\pi)}{d_1^{\alpha}} = \frac{1}{(d_2 - d_1)^{\alpha}} \tag{2}$$

where $G(\pi)$ is the value of the antenna radiation pattern in the back direction, α is the propagation coefficient and d_2 is the distance between the extreme points A and B in Fig. 3. From previous expression d_1 is easily obtained as:

$$d_1 = \frac{d_2 \cdot G(\pi)^{1/\alpha}}{1 + G(\pi)^{1/\alpha}} \tag{3}$$

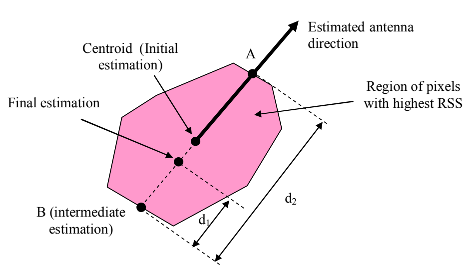

Fig. 3: Position estimation for directive antennas

b) Antenna orientation estimation

This step determines whether a transmitter corresponds to an omni-directional or a directive antenna and which is the orientation. It is done analyzing the values of the pixels corresponding to the received and quantized power after interpolation for each identified object. In particular, for a given distance d_i from the estimated transmitter position, the procedure computes first the difference between the maximum and minimum power for the different azimuth angles φ and averages it over a set of distances d_i:

$$\delta = \frac{1}{K}\sum_{i=1}^{K}\left(\max_{\varphi} P(d_i,\varphi) - \min_{\varphi} P(d_i,\varphi)\right) \tag{4}$$

where K is the number of distances $d_1,\ldots, d_K$ considered in the computation. In case δ is below a given threshold δ_{th} it is assumed that the antenna is omnidirectional, while on the contrary the antenna is assumed to be directive. In the latter case, the antenna direction ρ is estimated as the angle with maximum received power averaged over the different distance, which is:

$$\rho = \frac{1}{K}\sum_{i=1}^{K}\arg\max_{\varphi} P(d_i,\varphi) \tag{5}$$

c) Antenna pattern radiation estimation

One important context component relies in the radiation pattern of the primary transmitter's antenna. In practice, omnidirectional antennas can not be necessarily assumed. Usually, directional antennas are used, and even this radiation pattern can vary with smart antennas. So, in order to plan the deployment of a secondary network, it is a key issue to be aware of the actual radiation features of the primary system.

In this step, once transmitter position and direction ρ have been obtained, antenna's radiation pattern can be estimated for directional antennas based on the average over the distances of the received power for each azimuth angle φ, relative to the average for the antenna direction ρ:

$$G(\varphi) = \frac{1}{K}\sum_{i=1}^{K}\left(P(d_i,\varphi) - P(d_i,\rho)\right) \tag{6}$$

d) Propagation model estimation

The knowledge of the key propagation parameters could make more efficient the planning and deployment for a secondary system. The well-known radio signal propagation path-loss model is expressed as follows:

$$P_r(dBm) = P_0 - 10\alpha\log\left(\frac{d}{d_0}\right) \tag{7}$$

where P_r is received power, P_0 is received power at distance d_0 (typically 1m), α is the path loss exponent, and d is the distance between the transmitter and receiver. Based on the prior estimation of the transmitter position, and making a linear regression analysis with the available sensors, it is possible to obtain an estimate of parameters α and P_0 (assuming d_0 = 1m). Here also a differentiation has to be done between the case of directive and omnidirectional antennas. Specifically, for directive antennas, given that the received power is affected by the antenna radiation pattern, a correction factor should be applied to the received power before doing regression analysis, simply by subtracting the value of the radiation pattern $G(\varphi)$ in the corresponding direction.

It should be noted that the regression analysis will also provide an estimation of the shadowing standard deviation σ as the standard deviation error of the regression.

The regression analysis can also be used to discard those objects identified in step B that do not actually correspond to transmitters but are due to effects such as shadowing or detection noise. In particular, the regression analysis should reveal a clear correlation between distance (to the estimated transmitter position) and the received power for all the identified objects, translating into reasonable values of α (typically between 2 and 5). When no clear correlation with the distance is found (e.g. a negative value of α or a very low value) this will correspond to an object that is not actually a transmitter.

IV. RESULTS

In the following the proposed methodology is evaluated in different scenarios.

A. Scenario with omnidirectional antennas

In this part, it is evaluated a cellular scenario with a 5 frequency reuse pattern (f_1, f_2, f_3, f_4, f_5). The total scenario size is 10 km x 10 km, the pixel size is $\Delta x = \Delta y = 20$ m, and there are 21 primary transmitters in a suburban area. EIRP (Equivalent Isotropic Radiated Power) is 40 dBm. Propagation losses as a function of distance d are computed using a planning tool in a real environment, without any additional shadowing losses. Power threshold $P_{th}(f_i)$ is -85 dBm for all frequencies. The quantization step is $\Delta = 3.28$ dB and n = 5 bits are used to encode the RSS measurements.

Fig. 4 plots the average error in the transmitter positioning for different sensor densities. Vertical lines show the standard deviation among the different transmitters. As expected, the mean error improves when increasing the sensor density. It can be observed that with sensor densities in the order of 50 sensors/km^2 it is possible to obtain errors around 50 m.

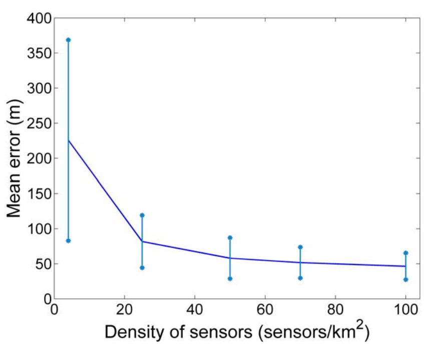

Fig. 4: Mean positioning error as a function of the sensor density

The correlation between distance and received power for the available sensors was examined for each transmitter detected. Fig. 5 plots the average received power (corresponding to one transmitter) measured by sensors according to the distance between each of the sensors and the transmitter, for D = 100 sensors/km^2. The estimated received power as a function of the distance obtained from linear regression is given by:

$$P = 53.65 - 30.62 \times \log(d) \tag{8}$$

In turn, in a scenario with sensor density D = 50 sensors/km^2, the estimated received power as a function of the distance obtained from linear regression is given by:

$$P = 56.70 - 31.66 \times \log(d) \tag{9}$$

Based on the propagation model used by the planning tool, expected received power should be in the order of $P(dBm) = 48.16 - 35.22 \times \log d(m)$ which should be taken only as a reference, since there can be additional losses due to diffraction and also there is some heterogeneity in the scenario so that different propagation expressions depend on each region type. As it can be observed, the relative error in the propagation factor α is around 13% for D = 100 sensors/km^2, and around 10% for D = 50 sensors/km^2, while the relative error in the received power at d = 1 m, P_0, is 11% for D = 100 sensors/km^2, and increases up to 17% for D = 50 sensors/km^2.

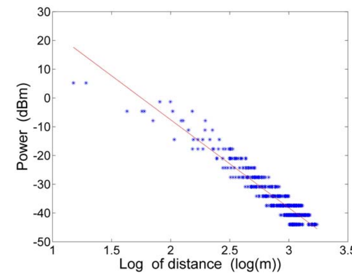

Fig. 5: Linear regression of the received power as a function of distance, for D = 100 sensors/km^2.

B. Scenario with directive antennas

In this scenario, three transmitters are considered, each one equipped with a directive antenna pointing in three different directions. Total scenario size is 3780 m x 3780 m, the pixel size is $\Delta x = \Delta y = 20$ m. The EIRP is 57.15 dBm, and based on the propagation model used by the planning tool in the area of the transmitter, the expected received power at distance d(m) should be approximately P(dBm) = 53.98 – 35.2log(d(m)).

Fig. 6 presents the mean error and standard deviation of the final position estimation based on Fig. 3, for different values of sensor density D. Similarly, Fig. 7 presents the mean error and standard deviation in the antenna's direction estimation. Results were averaged for the three transmitters over 10 realizations of sensors distribution, and vertical lines represent the standard deviation of the error in the different measurements. Errors are reduced as the density of sensors increases. It should be noted that the average error in the estimation of the antenna direction is very close to zero and the standard deviation decreases when increasing the sensor density.

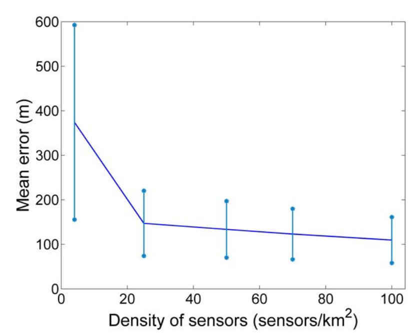

Fig. 6: Mean error and standard deviation (represented as vertical lines) in transmitter position estimation for different sensor densities.

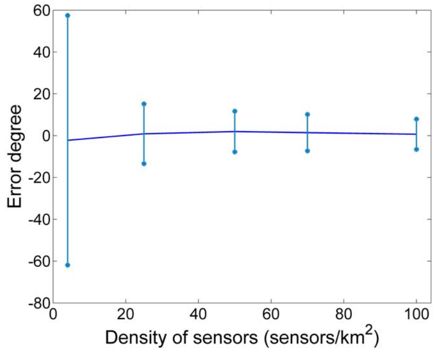

Fig. 7: Mean error and standard deviation (represented as vertical lines) in antenna's direction estimation, for different sensor densities.

When considering a sensor density D = 50 sensors/km^2 the estimated propagation model based on regression analysis leads to:

$$P = 49.04 - 35.93 \times \log(d) \quad (10)$$

As it can be observed, the error in the propagation α is only 2 %, while the error in P_0 is 9 %, similar to the previous scenario with omnidirectional antennas. The higher accuracy of the directive antenna case compared with the omnidirectional situation could be justified by the lower terrain heterogeneity associated to the area covered by a narrower antenna beam.

Finally, the estimated radiation pattern of the primary transmitter antenna is presented in Fig. 8 for the case D = 50 sensors/km^2. It can be observed how the estimated radiation pattern follows quite adequately the original radiation pattern, particularly in the main lobe, and differences with respect to the real pattern mainly appear in the back side of the antenna. For the case D = 50 sensors/km^2, the beamwidth at -3 dB is detected to be 75.04º, a value 10.3º higher than the beamwidth of the considered antenna.

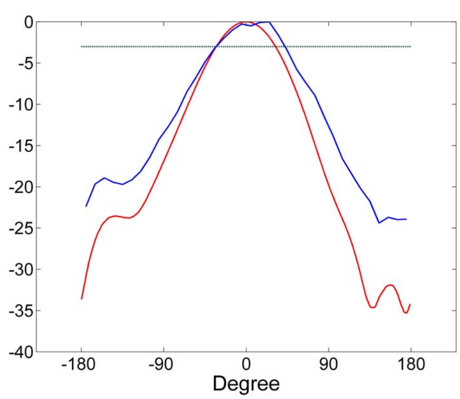

Fig. 8: Horizontal radiation pattern of the primary transmitter's antenna, for the case D = 50 sensors/km^2, red – the original radiation pattern, blue – the estimated radiation pattern

V. Conclusions

This paper has presented a methodology to address the estimation of different context parameters of a primary user network based on RSS measurements obtained by a sensor network and without any prior knowledge of the antenna types used by primary transmitter or the propagation model. Methodology is based on considering the set of RSS measurements in different positions as an image and identifying the objects which are associated to the different transmitters, and their corresponding features. The obtained context features are intended to be stored in a database like a REM so that they can be used in the configuration of the transmission parameters for a secondary network. Thanks to the simplicity of the proposed methodology it could be easily implemented while still providing an acceptable accuracy in context features such as antenna pattern or propagation model, particularly in the case of directive antennas. Methodology has been tested in different scenarios with both omnidirectional and directive antennas under data obtained from a planning tool. The analysis of parameter sensitivity and the inclusion of the shadowing effects considering real measurements in different scenarios are left for future work.

Acknowledgements

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