REM Based Approach for Hidden Node Detection and Avoidance in Cognitive Radio Networks

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Abstract—This paper examines the benefit of using a Radio Environment Map (REM) exploiting measurement based signal level prediction as a means to detect and avoid the hidden node problem within wireless networks. Practical implementation considerations are taken into account, such as support for multi-Radio Access Technology (RAT) deployments, unknown transmit power levels, radio measurement inaccuracies and propagation anomalies (such as fading), which can reduce the reliability of REM based predictions. The approach considered within this paper manages to overcome these limitations and the expected performance is assessed in a representative deployment scenario. The novelty of the proposed approach lies in the ability to combine measurements to perform signal localization and a predicted signal space model using measurements taken by a grid of sensors. The model is then used for prediction of hidden node conditions and can be exploited in existing and future networks employing carrier sensing based medium access control or dynamic frequency re-use, or to other radio interference and cognitive radio related problems.

Keywords—cognitive radio; dynamic resource management

I. INTRODUCTION

It is well known that frequency re-use partitioning and dynamic spectrum sharing are attractive ways of improving resource utilisation in wireless networks (see [1]). However, in dynamic environments it is also difficult to ensure that interference is not harmful to other transmissions. Hence, techniques must be used to predict or avoid interference from neighbouring transmissions using radio measurements to determine the path-losses. Measurement combining provides the means to either improve the performance, in terms of reliability and accuracy of predictions, using different heterogeneous Measurement Capable Devices (MCDs). This is particularly attractive in complex radio deployments such as multi-RAT or cognitive radio (i.e. secondary spectrum exploitation) scenarios in which incomplete or inadequate sets of measurements are available. It is also useful for scenarios in which a network coverage or performance is optimised during normal operation or within the planning process by predicting the performance or interference levels that would occur in alternative configurations by exploiting the radio signal space information. However, unfortunately it is difficult to accurately predict the propagation environment between terminal devices due to propagation anomalies such as shadow and multi-path fading. These effects render predictions a difficult and challenging problem when there is no direct communication between the devices in question.

A possible solution to these issues can be by exploiting the recently introduced REM concept, which provides an integrated database of multi-domain environmental information and prior knowledge for cognitive radios. There are two main ways in which we consider that the REM approach can be beneficial, compared to prior technology specific environment mapping approaches (such as defined in [2]). Firstly, by combining information about the radio environment from measurements of different radio technologies, and secondly by providing compensation for unknown characteristics, such as transmitted power or received signal strength measurement and localization inaccuracies. These benefits can support the goal of predicting hidden nodes with sufficient confidence in existing and future radio deployments.

The hidden node problem is a classic issue with radio systems that opportunistically share the same spectral resources and can result in significant performance degradation. The reason for the degradation is due to the fact that an interfering node (or node pair) may be unaware that they are causing interference to another transmission, which is normally an essential prerequisite for radio coexistence etiquettes. For instance, to give a concrete example, a Zigbee sensor network node may degrade the performance of a WiFi network (sharing the same channel) considerably without being aware it is doing so and so will continue to operate on the same channel and cause interference. Therefore, it is important when considering spectrum sharing for the hidden node problem to be addressed. Two ways of overcoming this problem are possible, firstly, by proactive prediction of the hidden node occurrence or likely occurrences and secondly by reactive detection, and notification or indication, of the interference caused by the hidden nodes. Both approaches have implications, for proactive prediction the issue is to do with how reliably and what overhead is involved in making predictions and in the case of reactive approaches the issue is how much interference (and degradation) can be sustained before the culprit is identified and agreement on a universally supported indication mechanism.

Scenarios that are difficult for hidden node prediction and detection are mobile or indoor scenarios in which shadowing and other fading phenomena make it hard to determine if a hidden node problem is likely or does exist due to the dynamic nature of measurements. This problem is made harder by consideration of cognitive radio techniques which opportunistically utilise different RAT and frequency bands and hence do not exhibit predictable characteristics. To solve this problem requires measurements of the various radio
signals and interference. The hypothesis that we consider with this approach is that intelligently combining many measurements and using REM prediction approaches can assist resource management based on hidden node detection and avoidance.

Previous related work has considered the problem of joint localization and transmitter power estimation [3] of single transmitters using Maximum Likelihood (ML) techniques and this has also been extended to the multiple transmitter case [4]. This previous work analytically determines the best MCD placement strategy assuming independent Gaussian signal fading rather than correlated shadow fading caused by obstructions in the environment. The potential benefit that our proposed REM approach provides is the ability to attempt to predict the correlated spatial distribution of propagation environment (such as shadow fading) that can be exploited when determining the location and transmitter power levels within a constrained environment (i.e. indoors). The REM approach that we consider exploits MCD measurements in order to make predictions about the radio environment (both in terms of spectrum usage and radio propagation anomalies such as fading) in order to predict the best channels to utilise without needing to try each possible combination or make statistical assumptions (and hence ML approach) regarding fading. In order to determine a REM model, many approaches utilise an absolute location reference and mobile MCD (i.e. measurements correlated with absolute geographic location using GPS [5]). In our considered approach the MCD measurements are taken at fixed points on a grid of MCD devices (i.e. static MCD deployment), which could either be at the access point or base station locations or using an MCD overlay network.

II. HIDDEN NODE PROBLEM

A. Background

A typical way of avoiding the hidden node problem is to utilise request to send / clear to send handshakes before each transmission and deferring the transmission when a hidden node is active. However, such an approach is not possible in multi-RAT scenarios in which the interferer is not transmitting using the same technology as the potential hidden node. It is also undesirable to utilise these countermeasures as they introduce a high overhead and indeterminate latency and imply the need to try out different channel combinations in order to find the best channel sharing solutions. This is why such techniques are not normally used in practice. Also, such an approach does not guarantee that some nodes or node pairs (i.e. the interferers) are aware that a problem exists (i.e. this pair is still able to continue without significant impact). Therefore, it becomes much more important to accurately predict these occurrences prior to causing any interference. Hence this optimization is concerned with using REM to detect potential hidden nodes and then to initiate an appropriate virtual channel re-allocation to avoid the interference that would otherwise be caused.

The first step is to formally define the meaning of a hidden node; which is that two nodes transmit on the same channel at the same time (resource) and cannot detect each other’s transmission, but one of the intended recipients suffers a signal to interference (i.e. ratio of signals) that is less than a required margin. Therefore, the necessary constraints in order to avoid (i.e. exclude) hidden nodes are fourfold; first determine whether the wanted and interference signal levels under comparison are on the same channel, then whether the signal strength of a potential interferer at the intended receiver position is within a specified margin of the wanted signal, which would result in unacceptable interference. Next the time of the two measurements must be within the same epoch, which can be specified according to the temporal resolution required. Finally, whether the interferer can detect this wanted signal based on a sensing threshold (i.e. such that the transmitter is unable to detect the interferer given the specified sensing threshold T).

The hidden node in this derivation assumes that the signal strength sensing level (detection threshold), given by the value of T, is known and optionally also configurable. When received signals are below this level it is assumed that it is not possible for the interference signal to be detected and hence a hidden node is possible. Therefore, the process of using REM to predict the occurrence of hidden nodes and to avoid hidden nodes depends largely on the ability to predict the radio environment including transmitter location and transmitter power levels. The overall process is illustrated in Figure 1 and the first step in the process is for MCDs to measure the real signal levels and load (activity) on the available channels. The second step is the combination of the signal load and channel availability in order to determine the REM estimation given assumptions about possible channel reallocations. Next is the REM estimation of the transmitter locations and transmitter power of the wanted and interference signal sources to make predictions about the resulting interference signal strengths received at the intended signal receiver positions. Then the hidden nodes (terminals) are determined using this context information based on REM prediction. The hidden node policy rules are then evaluated assuming the real and also virtual (i.e. potential future) channel allocations.

On detection of a hidden node condition the relevant channel “virtual hand over” (VHO) is initiated, in order to select the best alternative channel (i.e. the one with lowest activity in the vicinity), and the whole process repeated. In this manner the number of hidden nodes is reduced until none exist or the maximum number of iterations is reached and the channel load is evenly distributed geographical. In most frequency re-use schemes and cognitive radio scenarios there are a fixed number of channels (resources) available and this has an impact on the VHO scheme. It is assumed that there is at least one alternative that can be selected for each node. Also, it is assumed that the channel activity is measured by the MCD in terms of channel occupancy ratio, which is defined as the proportion of the time there is deemed to be a transmission signal above the threshold (T).
B. REM Approach

The main rationale for the REM concept is to permit the radio environment to be predicted with minimal measurements. Transmitter localization is therefore a key aspect for REM formation, which must also consider the propagation anomalies such as shadow fading caused by objects in the environment. In fact for dynamic REMs the rapid localization of mobile transmitters is the most challenging problem, especially when there are large numbers of obstructions causing shadow fading. Previous approaches, such as the ML estimation technique described in [3], assume that the transmitter \((x,y)\) coordinates are determined by the most likely candidate location (i.e. the candidate exhibiting least estimated transmit power difference errors) using the minimization expression:

\[
\text{arg min}_{(x_T,y_T)} \sum_{i=1}^{N} \left( \ln(p_i d_{i,T}^\alpha) - \frac{\sum_{j=1}^{N} \ln(p_j d_{j,T}^\alpha)}{N} \right)^2
\]

where \(p_i = e^{x_i}\) and \(z = (z_1, z_2, ..., z_N)\) represents the log of the received power measured at each of the \(N\) MCD and \(d\) represents the distance from the candidate transmitter location to the corresponding MCD and \(\alpha\) is the estimated path-loss exponent with \((x_T, y_T)\) being the candidate coordinates.

The rationale with this approach is to find the most likely, out of the candidate locations, based on examination of the variance in signal estimation errors of all the candidates with respect to the estimated mean transmitted signal level. Further to this the deviation is assumed to be caused by an independent Gaussian signal fading component combined with the ambiguity due to regular MCD placement. A drawback with this approach is that the two processes that give rise to the location errors (which are signal fading and candidate transmit power ambiguity) are combined into one ML estimate. Therefore, it is implied that the fading is not correlated with candidate locations and are independent random processes. It is consequently proposed that the only way to avoid ambiguity in candidate transmitter locations is by using increased numbers of a random MCD placement, as regular MCD placements give rise to at least two alternative locations, which cannot be compensated for. However, these assumptions do not consider the fact that the Gaussian fading assumption is not valid in radio environments with correlated shadow fading. For instance, when the shadowing is strongly correlated with transmitter location the ML approach assumptions do not necessarily provide improved location accuracy and will not minimize nearer to the true location. In our approach, the transmit power ambiguity can be overcome even with correlated shadow fading by combining orthogonal measurements using pairs of relative values that uniquely resolve the transmitter location, provided that the transmitter lies within the designated coverage area, or is otherwise shielded from external transmitters.

The individual measurements taken by the MCDs are then combined to make predictions about the transmitted power and hence a prediction of interference. The first step is to utilise relative signal references to eliminate uncertainty (i.e. lack of knowledge) about the transmitter power level and therefore localise the potential interfering transmitters with respect to the MCDs. The problem is addressed by combining pairs of relative MCD measurements on different orthogonal axes. This knowledge is then used to generate the REM model to estimate radio interference levels at the intended receiver locations. The REM results can be used within resource management processes such as configuration optimization, handover triggering or channel assignment by predicting the hidden nodes.

![Figure 1: Iterative hidden node avoidance algorithm](image1)

![Figure 2: Relative signal space geometric calculation of coordinates](image2)
The approach in Figure 2 shows the method of computation of signal related coordinates (in two dimensions) using relative signal strengths measured at MCDs (i.e. with no knowledge of transmitter power assumed). The MCDs are grid aligned with equal separation, given by c. The centre MCD (0,0) is chosen to be the one with the highest measured signal level (i.e. such that a < b and a < d). The ambiguity in the y dimension can be resolved by a single extra orthogonal measurement to determine which side of the MCD axis the transmitter lies. For non-linear MCD arrangements the computation becomes harder, but is not considered further in this paper. For the case of square grid aligned MCDs the axis can be rotated about the centre (0,0) point in order to obtain further estimates of the coordinates (x,y) with only two extra MCD. Also, localization to a three dimensional mapping can occur with at least one (ideally two) additional orthogonal measurement points on the third axis if necessary. The different candidate coordinates provided by each set of three MCD measurement triples are computed (using the first axis reference i.e. with subscript 1) as follows:

\[ a = \sqrt{x_1^2 + y_1^2} \quad \text{and} \quad b = \sqrt{y_1^2 + (c - x_1)^2} \]

Assuming \( b/a = r \)

\[ r^2 = \frac{y_1^2 + (c - x_1)^2}{y_1^2 + x_1^2} \]

Assuming \( d/a = s \)

\[ s^2 = \frac{y_1^2 + (c + x_1)^2}{y_1^2 + x_1^2} \]

\[ x_1 = \frac{c(s^2 - r^2)}{2(s^2 + r^2 - 2)} \]  

\[ y_1 = \pm \frac{c^2 + 2cx_1}{s^2 - 1} - x_1^2 \]  

where \( r \) and \( s \) are defined as the ratio of signal strengths for the positive and negative MCD pair (i.e. \( e^{2\theta_1}/e^{2\theta_2} = e^{(2\theta_1-\pi)} \) and \( e^{2\theta_1}/e^{2\theta_2} = e^{(2\theta_2-\pi)} \) respectively).

Now if this axis is rotated and two more MCD measurements points used (i.e. orthogonal to the first axis with the same central MCD) the candidate coordinates are given in the same way as in (1) and (2) by the expressions (3) and (4) respectively.

\[ y_2 = \frac{c(u^2-r^2)}{2(t^2 + u^2 - 2)} \]

\[ x_2 = \pm \frac{c^2 + 2cy_2}{t^2 - 1} - y_2^2 \]

where \( t \) and \( u \) represent the ratio of signal strength measurements for the two additional MCD on the second axis (i.e. \( e^{\theta_1}/e^{\theta_2} = e^{(\theta_1-\pi)} \) and \( e^{\theta_1}/e^{\theta_2} = e^{(\theta_2-\pi)} \) respectively).

Hence the overall coordinates are given by combining the candidates derived from (1), (2), (3) and (4) in the following way:

\[ x_1 = \frac{c(s^2 - r^2)}{2(r^2 + s^2 - 2)} \quad \text{and} \quad y_1 = \frac{c^2 + 2cx_1}{s^2 - 1} - x_1^2 \quad \text{iff} \quad y_2 \geq 0 \]

\[ \text{otherwise} \quad y_1 = -\frac{c^2 + 2cx_1}{s^2 - 1} - x_1^2 \]

and

\[ y_2 = \frac{c(u^2 - t^2)}{2(t^2 + u^2 - 2)} \quad \text{and} \quad x_2 = -\frac{c^2 + 2cy_2}{u^2 - 1} - y_2^2 \quad \text{iff} \quad x_1 \geq 0 \]

\[ \text{otherwise} \quad x_2 = -\frac{c^2 + 2cy_2}{u^2 - 1} - y_2^2 \]

Finally the most likely transmitter (x,y) coordinate is computed as the midpoint between candidates rather than attempting to select one candidate over the other.

\[ x = \frac{(x_1 + x_2)}{2} \quad \text{and} \quad y = \frac{(y_1 + y_2)}{2} \]

The REM can now make use of the transmitter coordinates in order to estimate transmitter power and path loss and hence interference levels. A conservative approach is used for transmitter power estimation, which takes into account the maximum difference between candidate estimates. This is given by the following expression:

\[ P_T = \ln\left(\frac{p_0(x^2 + y^2)^{a/2}}{p_0}\right) \]

where the estimated error in power \( p_T = p_0w^{a/2} \) and

\[ w = \max\left\{\frac{\max_i(x - x_i)^2}{\max_j(y - y_j)^2}\right\} \]

Next the coordinates (x,y) of the potential interferer and potential victim are used together with the predicted transmit power \( P_T \) to determine whether a hidden node condition exists.

C. Evaluation Methodology

In order to assess the performance of a REM based approach to predicting and avoiding hidden nodes we firstly have to make assumptions about the deployment and topology. The key factor affecting the performance of REM is the shadowing and multi-path fading characteristics of the radio environment. Therefore, to determine the impact that this has on prediction performance we consider the detection of hidden nodes in the presence of these propagation anomalies. It is possible to eliminate or at least reduce the effects of multi-
path fading by considering averaging of measurements over longer timescales and over different channels/sub-channels (if possible), therefore shadow fading is of most interest for evaluation purposes. The deployment layout that we consider for the evaluation is based on considering five hundred random node placements (transmitter locations) within a symmetrical grid of thirty six MCD with uniform separation (i.e. c). The REM uses the MCD measurements corresponding to each transmitter node location in order to predict the potential occurrence of hidden nodes. The REM predictions are then used to initiate a virtual handover (i.e. reconfiguration) to another channel in order to avoid the hidden node condition.

III. RESULTS

A. Localization

The results that we obtained are firstly to estimate the transmitter (node) localization prediction error, in the presence of shadow fading caused by fixed obstructions (causing correlated shadowing), and secondly the performance of the hidden node avoidance algorithm. The prediction errors are summarised in Figure 3 and are obtained with the randomly placed fixed obstructions. Each obstruction is on average \(c/4\) units long (uniformly distributed between 0 and \(c/2\)) and are either horizontally (x axis) or vertically (y axis) aligned and cause a cumulative shadowing attenuation of 5dB each. Three cases are considered, the first is when the transmitter location is estimated by the candidate coordinate \((x_1,y_2)\), secondly when the average \((x,y)\) is used and thirdly when the ML candidate coordinate is taken. The other assumptions that are made within this first comparison are that the MCD signal strength measurement precision is to within 1dB. Clearly if dynamic power control techniques are used this would also impact on the accuracy of the REM prediction, but if the measurement epoch is sufficiently chosen this is not an issue.

The results shown in Figure 3 suggests that as more obstructions are placed in the environment (i.e. increased shadowing) then the error in localization increases (as expected), to around \(0.3c\) for the average candidate \((x,y)\) coordinate. In contrast the ML candidate exhibits much higher error of up to \(0.8c\) due to the inability to select the correct candidates. Also, clearly at higher densities the averaged candidate coordinate \((x,y)\) provides the lowest error although this is not the case when there are no obstructions.

Next we consider the evaluation of the hidden node avoidance algorithm in the presence of obstructions. Two cases are considered, with the first case assuming that ten orthogonal channels are available, and hence there is a good probability of selecting a non-interfering channel. In this case the signal strength margin (i.e. the ratio between the interference and wanted signals) used within the algorithm has two possible values (-3dB or -10dB). The second case considers that all devices share only two channels, and in this case the obstruction density and the signal strength threshold \(T\) are varied.

B. Hidden node avoidance

Figure 4 shows the overall convergence performance of the hidden node detection and avoidance algorithm. It illustrates that when the sensing threshold is at an appropriate level the convergence occurs after 10 or 20 iterations (for 40 and 80 obstructions respectively), and for a higher threshold
more iterations are required. Another observation is that the signal margin has an impact on convergence. This can be explained by the fact that a high margin implies that for a hidden node condition to exist a greater difference is required between the wanted and interfering signals, which is less likely particularly at low obstruction density. The other important observation is that most triggers are associated with a few nodes near to the obstructions and where the distance between hidden node and victim node is greatest. In the second case the results indicate the implication of increasing T, which is to significantly increase the occurrence of hidden node conditions and the convergence time of the algorithm. Therefore, a trade-off exists to select appropriate T values that maximize the overall performance considering both hidden node detection and the impact on system throughput.

C. Hidden node impact

Next we consider the impact of hidden nodes on performance in order to evaluate the overall benefit of REM based detection and avoidance. As the impact is mostly in terms of indeterminate latency, we consider the data transmission latency distribution as the performance measure for comparison. A simulation model is used which assumes a typical binary exponential collision avoidance algorithm (such as utilised in 802.11), but we also take into account the impact of not being able to detect collision (i.e. the case when hidden nodes cannot be detected by carrier sensing). An inverse exponential packet inter-arrival distribution is assumed.

The results in Figure 5 illustrate the variation of latency distribution with both loading and also the placement of random obstructions in the environment. The impact of even a relatively low obstruction density is a significant decrease in observed latency performance. This cannot easily be compensated for by reducing load if a high probability of low latency is required. For instance, reducing load to 0.55 still results in significantly worse performance than a load of 0.83 when no obstructions are present. Hence, it is essential for good latency performance to detect and avoid the hidden nodes. Reducing the T level, and hence the carrier sensing sensitivity, is an alternative method to achieve this goal, but this increases the cost and also may reduce the accuracy of the sensing due to becoming increasingly close to the thermal noise floor. For instance, assuming reducing the sensing T by 10dB leads to a false detection rate of (20%), would negate the benefit as shown in Figure 6. However, if the sensitivity could be increased with a 10% failure rate then the degradation is less severe at 4ms or more.

Figure 5: Latency cdf Distribution for Different Normalized Loads

Figure 6: Latency cdf Distribution with False Sensing Rates (%)
IV. CONCLUSIONS

The use of REM for measurement based prediction for detection and avoidance of hidden nodes has a high potential value in radio network optimisation as the performance degradation that occurs can be severe. It is especially disruptive when deterministic or bounded latency and reliability are required within opportunistic, multi-RAT or cognitive radio deployment environments. The evaluation that has been performed on the REM prediction approach illustrates the ability to compensate for unknown transmitter power and propagation anomalies such as correlated shadow fading, which have a significant impact on predictions even with relatively few obstructions and using low cost commercial measurement devices. Therefore, it is essential that the REM prediction approaches exploit the ability to combine measurements made using different references in an intelligent manner. Doing so not only improves the ability of REM to make interference predictions, but can do so without the need for deploying large numbers of MCDs to take excessive additional or more complex measurements (which would otherwise incur extra complexity and power consumption). The proposed approach has been shown to exhibit attractive characteristics, in particular the good localization accuracy without knowledge of transmitter power level and fast convergence with knowledge of (and optionally with the ability to configure) the sensing threshold T. With this approach the best combination of sensing and proactive hidden node detection and avoidance can be selected.

Augmenting the proposed MCD based signal strength measurements with angle of arrival or time difference of arrival techniques could be an interesting and beneficial extension not only for localising transmitter nodes, but also for locating obstructions. Therefore, when fast convergence for elimination of hidden nodes, with minimal disruption, is required combining these different techniques could prove to be highly beneficial.

Further work is also necessary to validate the assumptions made regarding correlated shadow fading and also to apply the REM prediction approach to other interference related problems such as dynamic channel selection and coexistence scenarios, for which similar conclusions can be expected. Performance evaluations are also being conducted in real system deployments to evaluate different ways of resolving multiple simultaneous transmitters.

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