Impact of Mobility Prediction on the Performance of Cognitive Radio Networks

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***Abstract*—Wireless technology has enabled the development of increasingly diverse applications and devices resulting in an exponential growth in usage and services. These advancements made the radio frequency spectrum a scarce resource, and consequently, its efficient use is of the ultimate importance. To cope with the growing demand, network design focused on increasing the spectral efficiency by making use of advancement in Cognitive Radio technology. Cognitive Radio can reduce the spectrum shortage problem by enabling unlicensed users equipped with Cognitive Radios to reuse and share the licensed spectrum bands. Using the fact that a Cognitive Radio is capable of sensing the environmental conditions and automatically adapting its operating parameters in order to enhance network performance, we would like to make use of its knowledge to predict the mobility of Cognitive Radio users to improve the overall performance of the Cognitive Radio network. This study makes novel use of mobility prediction techniques to enhance reliability, bandwidth efficiency and scalability of the cognitive radio networks. Firstly, prediction techniques are evaluated and compared for prediction accuracy. Secondly, routing protocol reliability, efficiency and scalability performances are evaluated under different prediction techniques. Simulation results verify the performance improvements even with moderate accuracy predictors. Results clearly show that hybrid Markov CDF prediction performs the best. When compared with no prediction it significantly improves average reliability and efficiency by 11% and 8%, respectively.**

***Index Terms*—cognitive radio networks, mobility prediction, performance, Markov, CDF, reliability, bandwidth efficiency, scalability**

I. Introduction

In recent years, there is a shortage of unlicensed spectrum as a consequence of increased demand and strict allocation policies, such as spectrum reserved for the industrial, scientific and medical (ISM) radio bands. There are increasing number of applications and devices that solely depends on the availability of the unlicensed bands. Such applications and devices make the unlicensed bands over crowded, on the other hand, experimental studies have shown that the major portion of the licensed (primary) bands (channels) are under utilized [1]. To ensure future growth of wireless services, it is necessary to increase the efficient usage of these channels. Cognitive Radio (CR) [2] networks have emerged as a promising networking technology that aims at achieving these goals through applying distributed reasoning and learning across the protocol stack and throughout the environment. A CR has a cognitive process that can perceive current network and environmental conditions, and then plan, decide and act on those conditions. The CR can learn from these adaptations and use them to make future decisions such as changing transmission parameters dynamically, all while taking into account end-to-end goals.

The main components of Cognitive Radio Network (CRN) can be classified into two groups: the licensed (primary) network and the CR (secondary or unlicensed) network. The licensed network is referred to as an existing network, where the primary users have licenses issued by the government licensing authorities to operate in certain spectrum bands. Due to their priority in spectrum access, the operations of primary users must not be affected by unlicensed users. The CR network does not have and require a license to operate in a desired band and may overlay with the primary networks. As illustrated in used in Fig. 1, the CR users have the opportunity to access their own CR base stations if they have, on both licensed and unlicensed spectrum bands. Since all interactions occur inside the CR network, their spectrum sharing policy can be independent of that of the primary network. The CR users can also access one of the licensed network's base stations through the licensed band. For this type of access roaming must be enabled. Another access type for a CR user is communicating with other CR users through an ad hoc connection on both licensed and unlicensed spectrum bands.

In multi-hop mobile cognitive radio ad hoc networks, the CR nodes sense spectrum and identify available frequency bands, named as Spectrum OPportunities (SOP) or white holes [3], then select one candidate from SOP via a predetermined policy, which will not cause harmful interference to the licensed nodes. Based on the sensed information, CR users access the licensed band opportunistically when no primary users are using that channel and vacate the channel immediately upon primary user activity detection. Using these unoccupied channels provides a more effective way to increase the overall network capacity. Many issues remain to be resolved before mobile cognitive radio ad hoc networks can be efficiently deployed and a number of these issues are related to performance. Furthermore performance is also significantly dependent on the node mobility in ad hoc networks. Mobility is one of the most important factors in wireless systems

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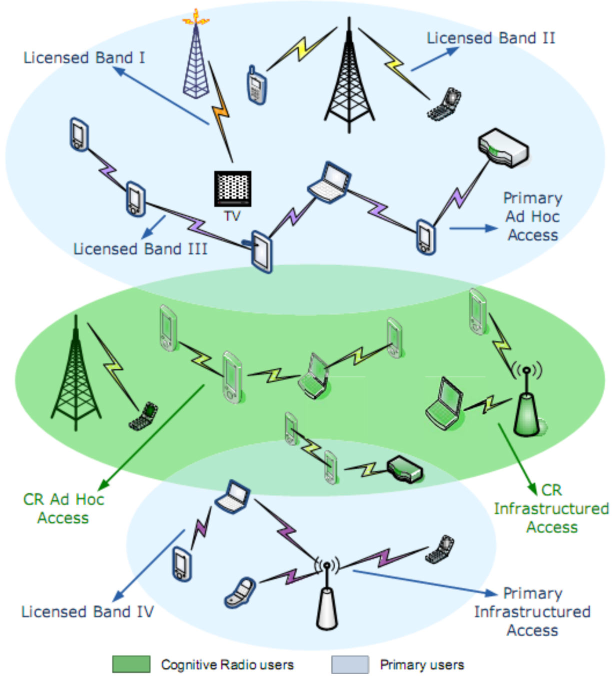

Fig. 1. An illustration of a cognitive radio network (Primary and CR users share the same geographic area).

because it affects numerous network characteristics, such as network capacity, connectivity, coverage, routing, etc. [4], [5]. The mobility of nodes coupled with the transient nature of cognitive radios due to primary node activity often results in a highly dynamic network behavior. Despite its importance, however, mobility is still largely unexplored in the context of dynamic spectrum access. At the most fundamental level, quality of service can only be provided if the system is able to maintain connectivity effectively within the cognitive radio users without causing any harmful interference to the primary users, even when the CR user frequently changes its physical location or switches different frequencies due to primary user activity. It is possible to maintain connectivity and guarantee QoS to the cognitive radio users if the system knows, prior to the CR users or primary user's movements and their time. With the help of this information, CR users can determine if there are enough resources available along the path for the lifetime of the connection. If such is the case, the CR users can plan in anticipation of the demands, and take appropriate steps such as setting up end-to-end routes, reserving resource along these routes, and planning quick frequency switching between the involved CR users. To achieve this objective, an effective prediction method is needed. Therefore, a series of predictors that reflect possible dependencies across time and space while benefiting from either individual or group mobility behaviors has been evaluated.

The remaining part of the paper is organized as follows. Details of the predictors is given in Section II. The simulation and performance analysis is presented in Section III. Finally, summary of the study and future research directions are provided in Section IV.

II. Prediction Mechanisms

Firstly, mobility prediction methods that can predict the time of the next movement of CR or primary users, which can be used in tandem with a predictor that predicts the next location (of which many have been proposed in the literature such as [6]) is introduced. After that, integrated approaches that jointly predict the time and location is considered. A predictor examines a movement history, which is a record of client position and velocity. Three fundamentally different types of predictors are considered: Markov predictors, moving-average predictors, and CDF predictors [7]. Some of these may be used to predict the movement time only, while some can predict both time and destination. Each of these predictors can be trained on either the history of movements by a single individual, or the history of movements by all users. Whether trained with "individual" or "aggregate" data, the predictor is used in the same way. In addition to these three types of predictors, a Static Neighbor Graph predictor is also included for comparison.

In quantifying the utility of the past in predicting the future, a formal problem definition is needed. Let $\sum$ be an alphabet, consisting of a finite number of symbols $s_1, s_2, ..., s_{|\Sigma|}$, where $|.|$ stands for the length/cardinality of its argument. A predictor accumulates sequences of the type $a_i = \alpha_i^1, \alpha_i^2, ..., \alpha_i^{n_i}$, where $\alpha_i^j \in \sum, \forall i, j$ and n_i denotes the number of symbols comprising ai. Without loss of generality, we can assume that all the knowledge of the predictor consists of a single sequence $a = \alpha^1, \alpha^2, ..., \alpha^{n_i}$. Based on a, the predictor's goal is to construct a model that assigns probabilities for any future outcome given "some" past.

First, we define the three basic predictor types followed by the Neighbor predictor.

1) *Markov family predictor:*The order-k Markov predictor takes a sequence of symbols $(a_1, a_2, ..., a_n)$ as a history string, and tries to predict the next symbol from the current context, that is, the sequence of the k most recent symbols in the history $(a_{n-k+1}, ..., a_n)$. Consider history $H = a_1 a_2 ... a_n$, and let substring $H(i, j) = a_i a_{i+1} ... a_j$ for any $1 \leq i \leq j \leq n$. Let X be a random variable symbol. Let $X(i, j)$ be a string $X_i X_{i+1} ... X_j$ representing the sequence of discrete random variates $X_i, X_{i+1}, ..., X_j$ for any $1 \leq i \leq j \leq n$. Define the context $c = H(n-k+1, n)$. Let A be the set of all possible symbols. If X has order-k stationary Markov distribution [8], for all $a \in A$ and $i \in 1, ..., n-k$, its distribution satisfies $P(X_{n+1} = a \mid X(1, n) = H)$
$= P(X_{n+1} = a \mid X(n-k+1, n) = c)$
$= P(X_{i+k+1} = a \mid X(i+1, i+k) = c)$.
At any given time, we can estimate the transition probability to a using current history H and current context c of most recent k symbols as

$$P(X_{n+1} = a \mid H) \approx \hat{P}(X_{n+1} = a \mid H) = \frac{N(ca, H)}{N(c, H)}. \tag{1}$$

where $N(s', s)$ denotes the number of times the substring s' occurs in the string s. The Markov predictor returns the most likely next symbol as its output:

$$X_{n+1} = argmax_{\alpha \in A}(P(X_{n+1} = \alpha)). \tag{2}$$

Also the $O(k)$ fallback Markov predictor is defined, which falls back to an $O(k-1)$ Markov predictor whenever the $O(k)$ predictor is unable to make a prediction, which occurs whenever $N(c, H)$ is zero, that is, whenever the current context has never been seen before. We also define the "order- 0" Markov predictor, which always outputs the symbol that occurs most frequently in the history H.

2) *Moving-average predictor:* Moving averages are commonly used to predict a trend in a sequence of values. The order-k moving-average predictor takes a sequence of values and predicts that the next value of the sequence is the average of the last k values in the sequence. Consider a history H of values $v_1, v_2, ..., v_n$. The order-k moving-average predictor estimates the next value to be

$$v_{n+1} = \frac{1}{k}\sum_{i=1}^{k} v_{n-i+1}. \tag{3}$$

3) *CDF predictor:* Rather than attempting to predict the next symbol or value in a sequence, this predictor works with inequalities. Specifically, it produces the probability that the next value is less than (or greater than) a given value. It does so by computing the observed cumulative distribution function (CDF) of the historic values, and using the CDF to measure the probability of a given value appearing in the distribution. Consider a history H of values $v_1, v_2, ..., v_n$. Suppose V is the random variate, which outputs the actual values in H, and P is its distribution. The CDF predictor computes the observed CDF function of V from the histogram, that is,

$$CDF(V < v) = \frac{1}{n}\sum_{i=1}^{n} I(v_i < v). \tag{4}$$

where I is the indicator function. In a similar fashion, we can compute the probability of values occurring in range $a \leq V < b$ by simply computing $P(a \leq V < b) \approx (CDF(V < b) - CDF(V < a))$.

4) *Static neighbor graph predictor:* We also used a simple "straw-man" predictor, the Static Neighbor Graph Predictor, to compare with mentioned predictors. Using users' current neighbor locations as the prediction is an obvious way to pre- dict future locations. If the network topology does not change quickly over time, a location predictor can use precollected topology information to predict the user's mobility. A directed graph representing transition history is constructed as follows: when we observe a user move from an location i to another location j, if the edge (i, j) is not in the graph, we will add the directed edge to the graph and set the weight of this edge to 1; if the edge (i, j) is in the graph, we add 1 to the weight of the edge. At the end, we have a directed graph with weighted edges and normalize the weights so that $\forall i, \Sigma_j w_{ij} = 1$, where w_{ij} is the weight on edge (i, j). When a prediction is requested, the predictor finds the user's current location i in the graph, and returns a list (j, w_{ij}) for all edges (i, j) originating at i.

A. Prediction Stage

We now show how to apply the first three techniques to predict the duration of the current stay and the likelihood of movement to any other location. Some applications need an estimate of the time (or, equivalently, the duration of the stay at the current location); other applications are more concerned about knowing whether the movement will happen "soon" and if so, the destination of the movement.

To predict the time of movement, one can look for patterns in the residence times rather than the absolute time of the movement. We apply all three predictors, i.e. Markov, moving-average, and CDF to predict the next duration. We use the Markov predictor by considering the history $H = d_1, d_2, ..., d_n$ of previous durations, again quantized into intervals of size Δt. Each quantized duration bucket is thus a symbol in A. We use the moving-average predictor as follows.Consider again the history $H = d_1, d_2, ..., d_n$ of previous durations; there is no need to quantize the times as we did above. Then by Equation 3 the order-k moving-average estimate of the residence time at the current location is

$$d_{n+1} = \frac{1}{k}\sum_{i=1}^{k} d_{n-i+1}. \tag{5}$$

Similarly, we do not need to quantize the duration to apply CDF predictor. Consider again history $H = d_1, d_2, ..., d_n$ of previous durations, we estimate a value of d such that with probability p the duration will be less than d. We define the CDF by counting the fraction of durations shorter than a given time:

$$CDF(t) = \frac{1}{n}\sum_{i=1}^{n} I(d_i < t)$$

, where $I()$ is the indicator function. We can interpolate to predict that the user will stay shorter than $d = (t_l + t_h)/2$, where t_l is the minimum t that satisfies $CDF(t) \geq p$, and t_h is the maximum t that satisfies $CDF(t) \leq p$. The predictor parameter p expresses the desired confidence in the result.

We can apply each predictor to the history observed in any location as well as to the history observed only at the current location to make them "location-independent" and "location-dependent" predictors respectively. We can also apply the predictors to each users history (individual predictors) or apply them to all users' history (aggregate predictors).

B. Joint Location and Time Prediction

The knowledge of time and destination of the next movement will give great advantage to the network if used appropriately. In this case the goal is to predict, for every destination, the probability that a movement will occur within

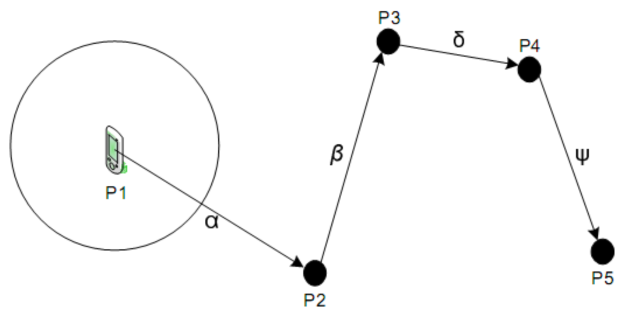

Fig. 2. An illustration of the modified waypoint model, shown as CR user is at waypoint P1.

the next Δt period, conditioned on the current location and the duration of the visit so far. Our approach is to use the combination of the Markov location predictor and the CDF time predictor. Consider a users movement history $H = (t_1, a_1), (t_2, a_2), ..., (t_n, a_n)$, in which t_i is the time that the user arrived at location a_i. From H we extract the location history $L = a_1, a_2, ..., a_n$, and from L the order-k location context $c = L(n-k+1, n) = a_{n-k+1}, ..., a_{n-1}, a_n$. We then search the history L for instances of the context c. We need to examine the destinations that follow each such instance, and in particular to examine the duration of the visit preceding each of those destinations, to be able to predict the duration in the current context. So, we need to extract the set of durations for each possible destination x:

$$D_x = d_i | d_i = t_{i+1} - t_i \tag{6}$$

where $L(i-k+1, i+1) = cx$. From each duration set D_x, we use the CDF predictor in Section II-3 to compute the conditional probability $P_x(t \leq d < t + \Delta t | c, t)$ that the user will move to location x within Δt seconds after the current elapsed residence time t. We can also use the $O(k)$ Markov predictor to compute the probability $P(x)$ of every possible next location x with Equation 1. Therefore, the probability of the user moving to each of the possible locations x within the next Δt seconds, given the current context c at the current elapsed residence time t, is P

$$P(c|c,t) = P(x).P_x(t \leq d < t + \Delta t | c, t). \tag{7}$$

This predictor is always conditioned on the current location context. As described above, the predictor builds per-user tables, but it is equally possible to build aggregate tables from all users' movement histories.

III. Performance Evaluation

A proper evaluation of predictors and their effect requires meaningful performance metrics. With no doubt, one of the metrics should be accuracy, defined as the ratio between the number of correct predictions and the number of all predictions. We investigate the effect of prediction accuracy on routing protocol performance when mobility prediction is used. Our goal is to determine the enhancement's dependency on the accuracy of mobility prediction. We simulated RACON: a routing protocol for mobile cognitive radio networks [9]. The conditions that we varied in this scenario are (i) accuracy of node position in meters, (ii) frequency of direction changes, and (iii) waypoint distance in the random waypoint mobility model. Extensive simulations are implemented in ns2 [10]. The primary users activities are modeled by using the exponential ON-OFF process. In the general case, the primary user activity results in a spectral overlap with the CR channels. On the contrary, as CR user moves further away from the primary user's transmission frequency, spectral overlap reduces significantly. During the simulation the following default communication pattern is used. Each source node generates and transmits constant bit rate (CBR) traffic and each message is 1KB in length. Simulations are performed in random multi-hop network topologies, in which, 150 CR nodes and 50 primary users are distributed in an area of 1000 x 1500 m2. The coverage range of the primary on its occupied channel is 250m and the transmission range of the CR user is set at 180m. The CR and primary node locations are randomly chosen in each run and an average of 50 trial runs is used for a data point. A modified version of the random waypoint model is used in simulations. Random waypoint mobility model randomly selects successive destination location points for the node to travel to. Mobile node moves there with a speed uniformly distributed between 0-10 m/s. Upon reaching a destination point, a new target location is selected and the whole process is repeated again. When a destination position is reached, a mobile CR user can either pause for a random period of time before moving towards the new waypoint again or not pause at all randomly. In this experiment, we make modifications to the waypoint model by limiting the waypoint distance (i.e., distance between two successive random destinations) to T_m as shown in Fig. 2. Therefore, when mobile CR node N reaches waypoint P_1, a new waypoint P_2 is selected with a new distance. This process is repeated when P_3 is reached, and so on. Since mobile CR node N changes its direction each time a new waypoint is reached, decreasing the waypoint distance will increase the randomness of the mobility pattern. On one end of the spectrum, a very large waypoint distance will result in a straight line trajectory mobility model. The other extreme of having a very small waypoint distance will result in a Brownian-motion like pattern.

For all scenarios that we simulated, the metrics of interest are:

- **Packet delivery ratio:** The number of data packets received by destinations over the number of data packets supposed to be received by destination nodes.
- **Number of total packets transmitted per data packet delivered:** The number of all packets (i.e., data and control packets) transmitted divided by the number of data packet delivered to destinations. This measure shows the efficiency in terms of channel access and is very important in cognitive radio ad hoc networks.

The simulation results demonstrate that Markov family predictor has better accuracy as can be seen in Table I. Our exper-

TABLE I
ACCURACY OF THE PREDICTORS

Predictor	Accuracy	Mean error rate
Markov	91	.195
Moving Average	84	.264
CDF	87	.238
Neighbor graph	87	.218

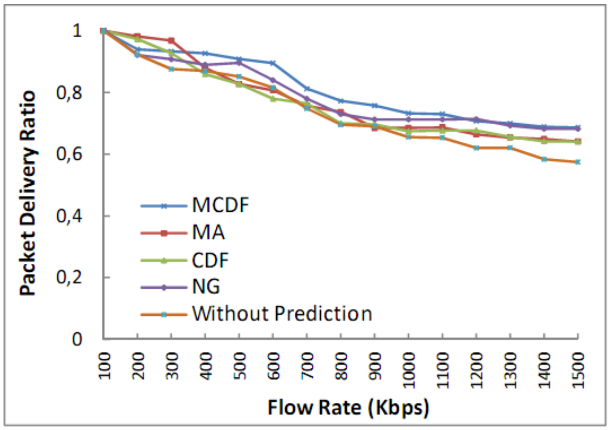

Fig. 3. The packet delivery ratio with increasing flow rate.

iments with predictors showed that CDF and neighbor graph predictor have nearly the same performance. Accordingly, we used the combination of the Markov location predictor and the CDF time predictor to get a better overall performance.

The packet delivery ratio as a function of flow rate is shown in Fig. 3. We can see from Fig. 3 that as flow rate increases, the routing effectiveness degrades. However with the help of mobility prediction, there is a significant performance improvement compared to without mobility prediction. Using mobility prediction to perform re-routing or local repair prior to route disconnection and to send data over more stable routes minimized packet losses. As can be seen, Markov family predictor combined with CDF predictor performs better than the other predictors.

The number of total packets (i.e., control packets, data packets) transmitted per data packet delivered is presented in Fig. 4. We have mentioned previously that this measure indicates the channel access efficiency. From Fig. 4, we can see that the numbers for Markov family predictor combined with CDF remain relatively constant. As expected without prediction has the highest ratio. We can conclude that using prediction is more scalable in terms of number of flows.

IV. CONCLUSION

Effective delivery of data packets while minimizing connection disruption is crucial in cognitive radio ad hoc networks. In this study, the use of mobility prediction to anticipate connection breaks due to primary user activity or mobility and perform rerouting or local repair prior to route breaks is investigated. Mobility prediction mechanism was applied to a recent and representative of the cognitive radio ad hoc routing family,

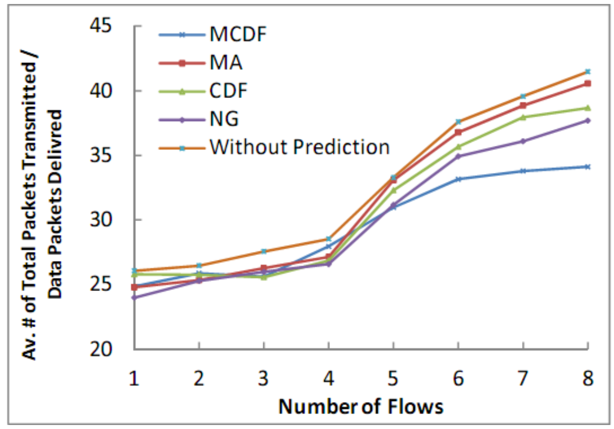

Fig. 4. The number of total packets transmitted per data packet delivered as a function of number of flows.

namely RACON: a routing protocol for mobile cognitive radio networks. Through an implementation in the ns2 simulator, it is shown that with mobility prediction enhancements, more data packets were delivered to destinations while the control packets were utilized more efficiently. Routes that are the most stable (i.e., do not become invalid due to primary user activity or mobility) and stay connected longest are chosen by utilizing the mobility prediction. Simulation results indicates that even with moderate accuracy predictors, the overall performance is improved nearly 10%. These results are very encouraging and open the way to further research in several directions.

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