Cognitive Routing for Multi-hop Mobile Cognitive Radio Ad Hoc Networks

Jae-Joon Lee and Jaesung Lim

Abstract: **Mobility can lead to continual loss of data and service interruptions during communications in multi-hop cognitive radio networks. Mobility of primary users (PUs) or cognitive users (CUs) requires adjustment of multi-hop communications among CUs to avoid any interference to PUs. To provide durable and reliable data routing that ensures continuous network service, we propose mobility-aware cognitive routing (MCR) for multi-hop cognitive radio networks. MCR examines the risk level of each node against interference regions and selects the most reliable path for data delivery using a Markov predictor. Through simulation, we verify that the proposed scheme can avoid route destruction preemptively and achieve reliable data delivery.**

Index Terms: **Cognitive radio networks, mobility, routing.**

I. INTRODUCTION

Cognitive radio networks can increase licensed spectrum utilization and resolve congestion in the industrial, scientific, and medical (ISM) band [1]–[4]. Rapid increase in the use of mobile communication devices, such as smart phones, tablet PC, vehicular networks, tactical networks, and machine-to-machine/internet-of-things (M2M/IoT), leads to overcrowding in the ISM band. Wireless ad hoc networks of mobile communication devices need to be self-organized to ensure reliable data communication when dynamic changes occur in the network and its environments. The adjustment of CU to the dynamics of a network is important in cognitive radio networks to avoid interference with PUs. Further, cognitive radio technology is important in military applications, public safety, and mobile base stations. Military applications can especially take advantage of cognitive radio schemes to alleviate the problem of spectrum scarcity [5].

Communication of CUs should not interfere with active communications of PUs. In addition, data loss occurs when a CU experiences interference from PUs in a data delivery path using the same spectrum, resulting in service interruptions. Accordingly, when active PU spectrum use is detected, channel-switching of the existing path or re-establishment of new data delivery paths with nodes unaffected by interference must be carried out, following a routing protocol deployed in that network. When an available spectrum common to CUs that does not interfere with PUs is found through a spectrum sensing scheme, multi-hop ad hoc networks can take advantage of re-routing through alternate paths. Neither channel-switching through spectrum sensing nor path-switching through re-routing fully prevent data loss and service interruptions when active PU communication is detected during on-going communication among CUs. Mobility, especially, affects network performance significantly in spite of routing protocols' self-recovery process or spectrum sensing. A newly established route or switched channel can also be affected by interference owing to mobility. Route failure and recovery can be repeated because of the movement of either PUs or CUs. This repeated route failure and recovery results in continual service interruptions with data loss and resource waste.

To address this problem, we focus on a preemptive approach that discovers data delivery paths that can provide reliable communication without interruption and loss before active PU communication arrives. The main objective is to prevent route destruction to provide continuous data delivery without data loss owing to mobility of PUs or CUs. Therefore, we develop an adaptive routing scheme, which provides continuous and reliable service to users. The proposed scheme, mobility-aware cognitive routing (MCR), examines relative mobility characteristics of interference regions and obtains the risk level of a node indicating its reliability against interference. By using risk level information based on Markov prediction, MCR can provide reliable routes adaptively to avoid interference in advance.

The rest of the paper is organized as follows. Section II describes the impact of interference on routing and route recovery in mobile environments. Section III presents the proposed routing scheme that evaluates risk levels. Section IV presents the simulation results and Section V concludes the paper.

II. RELATED WORK

Routing in cognitive radio networks has been examined to provide reliable paths for efficient spectrum sharing among multiple communication devices [1]. Cesana *et al.* [3] have examined the issues focusing on the network layer in cognitive radio networks. A joint path and channel selection scheme for avoiding interference to PUs in cognitive network routing has been proposed in [6] and [7]. Opportunistic cognitive routing with spectrum sensing was investigated in [4]. This scheme uses location information and channel usage statistics in the local area for selecting the next hop relay. Route maintenance cost is investigated in [8]. Providing end-to-end multi-hop data delivery paths in cognitive radio networks requires route maintenance and incurs costs including signaling overhead, energy consumption, and service interruption. This work provides the minimum maintenance cost routing scheme among CUs, however, mobility is not considered in this scheme and service interruptions continue to occur, especially in mobile environments. OPERA [9] considers a mobile environment for cognitive radio ad hoc networks. OPERA evaluates end-to-end delay of a route by

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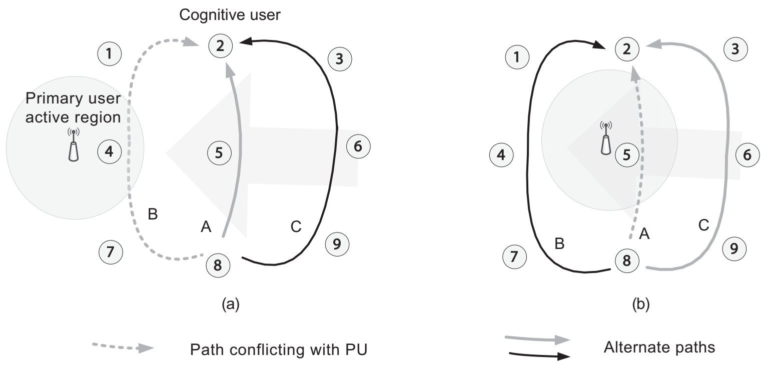


Fig. 1. Effect of route selection. There are three possible routes (A, B, and C) from node 8 to node 2, which is the destination node.

measuring the fraction of the time being interfered with PU, considering link availability due to node mobility. However, this method cannot avoid data loss and service interruptions due to interference in mobile environments either, because it depends on the current measurement of link availability, in contrast to our preemptive approach.

Interference, including jamming, can significantly degrade network performance. Shin *et al.* [10] analyzed the impact of WLAN and Bluetooth interference on the performance of IEEE 802.15.4 ZigBee. They obtained the packet error rate (PER) under the presence of interference and examined the distance between ZigBee and a single WLAN device to avoid high packet error. In [11], an extensive empirical study on the packet delivery performance of wireless sensor network devices in diverse environments was conducted, including coexistence with IEEE 802.11 WLAN. WLAN performance under diverse jamming schemes was analyzed in [12]. Jamming in sensor networks and defense strategies were discussed in [13]. A combination of the packet delivery ratio and signal strength can provide a good indication of jamming attacks. In addition, the spatial retreat method requiring relocation of mobile nodes was proposed for avoiding the jamming region. An effective jamming attack can use the link layer protocols to conserve jamming energy [14]. Multiple path routing can be used as a countermeasure for mobile jamming attacks [15]. However, multi-topologies also experience interference, route failure and repeated reconstruction in addition to the control overhead of maintaining multi-topologies. Flooding of data packets can result in service interruption as well as resource wastage.

Mobility prediction techniques are used to predict where a mobile device moves given available information regarding its previous movements. Many studies use a mobile user's previously visited locations. Location prediction is useful for cellular networks and access points to provide timely handoff and resource allocation for continuous service provision. Cellular networks predict a mobile device's location to reserve bandwidth in the next cell and admission control [16]. Several location prediction methods were compared with real experimental data in [17]. This study showed that a Markov predictor achieves the best location prediction. Prediction of a mobile device's connectivity is studied in [18]. Future movement of a mobile user is predicted by using the history of its past movements records. Client location is estimated and future network connectivity is predicted based on a Markov model.

III. IMPACT OF MOBILITY IN COGNITIVE AD HOC NETWORKING

When a subset of nodes in data delivery paths experiences interference in multi-hop wireless networks, data loss occurs and the quality of application service degrades. Many routing protocols use periodic exchange of a hello message to update the latest status of the network including neighbor status or topology information. Thus, routing protocols can recover a data delivery route by excluding unresponsive nodes.

Spectrum sensing techniques are used in cognitive radio networks to identify active PU communication to avoid interference with other PUs. If active PU communication is found in the spectrum that CUs have accessed, then CUs need to stop communication on that spectrum and find other spectrum gaps for communicating through the same links or other paths that do not interfere with active PUs. As discussed in [8], route maintenance for path switching or channel switching requires overhead. First, data loss occurs during periods between the arrival of a PU on on-going paths of CUs and re-establishment of new paths or channels that can avoid interference. Second, service is interrupted and delayed until routes are reconstructed. These are the significant problems for networking and application services. Third, available spectrum sensing and channel allocation process among CUs require control overhead, including communication among multiple CUs, as well as delay. These problems exist in static cognitive ad hoc networks.

When PUs are mobile or CUs move, route destruction and service interruption with data loss become more significant. These route failures and service interruptions can occur persistently despite route recovery. If a recovered route is close to a PU's active region or is in the path of an interference source's movement, the re-established route is likely to experience interference again. Route selection without consideration of mobile characteristics can result in significant performance degradation and wastage of network resources, owing to continual data loss, route reconstruction, and data retransmission.

Fig. 1 illustrates the effect of different route selections when CUs or PUs are mobile. Route A is the initial route from node 8 to node 2. As the interference source approaches node 5 owing to the mobility of either the interference source or node 5, node 5 in route A will be affected by the interference region; consequently, data loss will occur. In Fig. 1(a), if route C is used for data delivery before route A is destroyed by interference, the network can provide reliable data delivery continuously. In Fig. 1(b), considering the direction of the mobile interference source, route C is likely to be affected by the interference source soon. Thus, if the data delivery path is changed from route C to route B before the interference source moves to node 6, then no interruption occurs because of route destruction. It is clear that routing is significantly affected by mobility, and route selection should be adaptive to mobile environments to avoid any interruptions or loss.

IV. INTERFERENCE NOTIFICATION AND ROUTING

A. Detection and Notification

Spectrum sensing technologies for identifying active PU communication channels that CUs can interfere with have been studied extensively [2], [3], and [19]. CUs can detect the arrival or departure of a PU on the spectrum through a spectrum sensing mechanism for finding available channels. Spectrum sensing techniques are beyond the scope of this paper. The proposed MCR scheme can use any existing spectrum sensing technique. The focus of the proposed scheme is to provide stable multi-hop routing in mobile environments for cognitive ad hoc networks. The proposed scheme does not rely on full spectrum knowledge across an entire network and needs to identify only local spectrum availability. When a CU detects an active PU communication region, which is the area within a PU's communication range, it sends an interference notification (IN) message. Nodes in the interference region can send data and nodes outside the interference region can receive the IN message from a node inside the interference region. Detection of interference and transmission of the notification message can be performed in a manner similar to that described in [2] and [20].

The hop limit of an IN message is denoted as $IN_{\max}$, therefore, neighboring nodes with a hop distance from an interference region up to $IN_{\max}$ become aware of the occurrence of interference. The default value of $IN_{\max}$ is set to three in this paper, but a higher $IN_{\max}$ value can be used if the speed of mobility is higher. An IN message is periodically broadcasted as long as interference is being detected.

B. Risk Evaluation and Routing

The proximity and relative mobility characteristics of an interference source are important factors in predicting the future reliability of a path. MCR uses this information to achieve continuous and reliable data delivery without interruption of communication.

When an IN message is received, a node checks the minimum hop distance from the interference region to predict obtain the interference risk. Each node checks its distance from the nodes in the interference region. The proximity of node i is obtained as

$$d_i(t) = \min_{j \in F} dist_{ij}(t), \tag{1}$$

where F is the set of nodes affected by the interference and $dist_{ij}$ is the distance between nodes *i* and *j*. Then, each node calculates the risk level based on the proximity at time step t as follows:

$$r_i^{(D)}(t) = d_i^{-\alpha}(t), \tag{2}$$

where α is greater than or equal to one. As the distance from the interference increases, the risk level based on the proximity decreases. α determines the effect of proximity on the risk level. A higher value of α increases the gap between the risk levels of different distances from the PU interference region.

The closer the proximity of a node to an interference region, the higher is the risk of being interfered with in the near future. Hop distance or Euclidian distance can be used to measure proximity. In this paper, we use the hop distance from the nearest affected node as the proximity.

The risk level of a node indicates the possibility that the node will not provide reliable data communication in the future. Accordingly, a higher risk level indicates a greater chance that the node will be affected by an interference source. We use a Markov predictor (MP) to obtain the rish level based on mobility. Then, the risk level is applied to the cost of the inbound links of the node, and the minimum cost path from Dijkstra's algorithm is selected for routing.

V. PREDICTION FOR MOBILE COGNITIVE NETWORKS

A. Markov Predictor

The important factor in choosing a mobility prediction model is its suitability for a resource-constrained mobile communication device in wireless networks. In our scheme, each node should be able to perform the prediction operation in a distributed way to determine reliable paths. Markov models are well suited to this constraint because they use only limited past information for future prediction. Markov models have been widely studied and used for processing location prediction or next outcome prediction in any sequence [18], [21]–[23].

Markov predictors provide future outcome probabilities given past information. Each conditional probability of a future outcome is expressed as

$$P(X_{t+1} = x_{t+1} | X_t, X_{t-1}, \cdots, X_{t-k+1})$$

where X_t is a random variable at time t. k is the order of Markov predictors and determines the length of the past history information used to obtain future outcome probabilities. x_t is the context of the prediction model at time t. We express the state of the order-k Markov model as

$$S(t) = [X_{t-k+1}, X_{t-k+2}, \cdots, X_t]. \tag{3}$$

The conditional probability, $P(X_{t+1} = x_{t+1}|S(t))$, is estimated from the appearance count of x when the state is $S(t)$, $N(x_{t+1}, S(t))$, and the appearance count of that state, $N(S(t))$, as

$$P(X_{t+1} = x_{t+1}|S(t)) = \frac{N(x_{t+1}, S(t))}{N(S(t))}.$$

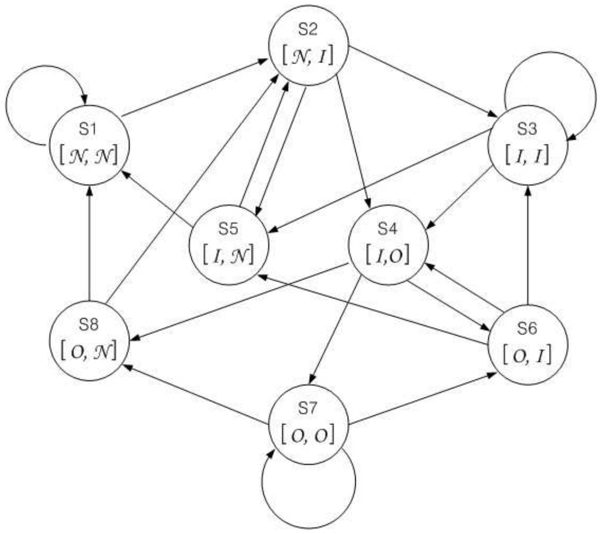


Fig. 2. State transitions of the proposed second-order Markov model for characterizing the movement of an interference region. Each state consists of two consecutive movements of the interference region.

B. Risk Level based on a Markov Predictor

To evaluate the risk level in the presence of communication interference in mobile environments, we examine the relative movement direction of an interference region against a node for the Markov model. We use three movement directions to describe the interference mobility status, $\mathcal{R}$, where $\mathcal{R} = \{\mathcal{N}, \mathcal{I}, \mathcal{O}\}$. Neutral ($\mathcal{N}$) status indicates that the distance from the interference region extends beyond the interference detection boundary. The interference detection boundary is determined by the IN message transmission range. Inward ($\mathcal{I}$) status indicates that the interference region is approaching the evaluating node. Outward ($\mathcal{O}$) status indicates that the interference region is moving away from the node.

The movement direction of an interference source is evaluated by each node and is used for the Markov predictor at each node. The proposed prediction model is different from other mobility prediction schemes that require specific location information, resulting in a significant increase in the space and time-complexity of prediction. The number of states required by the Markov predictor using these movement directions depends on the order of the Markov predictor. In this paper, we use a second-order Markov predictor, which has been found to be quite accurate [18], [22], and [23]. In our second-order Markov model, each state consists of movement directions including the current movement direction and the movement direction at the previous time step. The second-order model has eight states, S, are as follows.

$$\{[\mathcal{N},\mathcal{N}],[\mathcal{N},\mathcal{I}],[\mathcal{I},\mathcal{I}],[\mathcal{I},\mathcal{O}],[\mathcal{I},\mathcal{N}],[\mathcal{O},\mathcal{I}],[\mathcal{O},\mathcal{O}],[\mathcal{O},\mathcal{N}]\}$$

There is no state for $[\mathcal{N},\mathcal{O}]$ because the movement direction from Neutral to Outward is not possible. $[\mathcal{N},\mathcal{O}]$ indicates that the relative interference movement direction is from Neutral to Outward. Neutral ($\mathcal{N}$) means that the interference region is not detected within the detection boundary. Outward ($\mathcal{O}$) means that the previous distance from the interference region is shorter than the current status and both previous and current distances from the interference region are within the detection boundary. Thus, when the previous movement direction is out of detection range ($\mathcal{N}$), the next possible status is that the interference region is either coming ($\mathcal{I}$) or staying out of the detection boundary ($\mathcal{N}$). During the initialization phase, all nodes set the previous interference movement direction as $\mathcal{N}$. Thus, the initial state becomes either $[\mathcal{N},\mathcal{N}]$ or $[\mathcal{N},\mathcal{I}]$. Fig. 2 shows the state transitions of the proposed second-order Markov model. Each state consists of two consecutive mobility characteristics of the interference region.

Table 1. Sample of Markov prediction operation.

Node	$d_i(t-1)$	$d_i(t)$	$d_i(t+1)$	$S_i(t)$	$S_i(t+1)$
1	2	1	2	$[\mathcal{I},\mathcal{I}]$	$[\mathcal{I},\mathcal{O}]$
3	N/A (4)	3	2	$[\mathcal{N},\mathcal{I}]$	$[\mathcal{I},\mathcal{I}]$
4	1	0	1	$[\mathcal{I},\mathcal{I}]$	$[\mathcal{I},\mathcal{O}]$
5	2	1	0	$[\mathcal{I},\mathcal{I}]$	$[\mathcal{I},\mathcal{I}]$
6	3	2	1	$[\mathcal{I},\mathcal{I}]$	$[\mathcal{I},\mathcal{I}]$

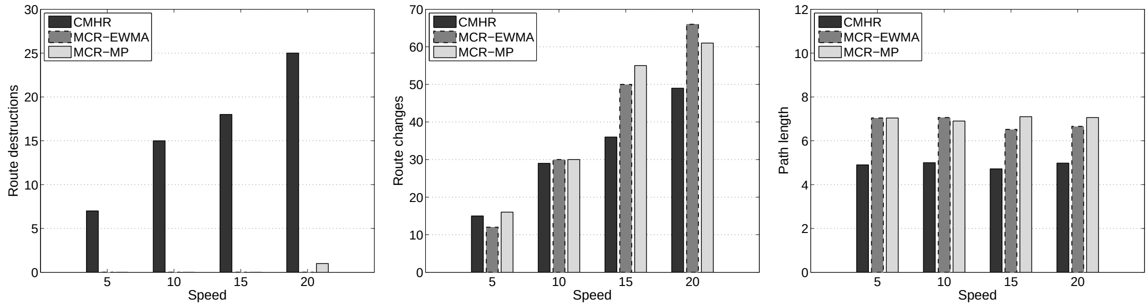
To provide an estimate of transition probabilities among states, each conditional probability $P(\mathcal{R}_{t+1}|S_i(t))$, where $S_i(t)$ is the Markov state of node i at time t as defined in (3), is updated whenever a transition occurs. The risk level from the Markov model is obtained as

$$r_i(t) = \sum_{j=S_i(t), k\in S} w_{jk} P_{jk}, \tag{4}$$

where P_{jk} is the transition probability from state j to state k. w_{jk} is the weight of P_{jk}, adjusting the degree of interference risk level for each state transition. $w_{jk} = 0, \text{if } k \in \{[\mathcal{R}_{\sqcup}, \mathcal{R}_{t+1}] | \mathcal{R}_{\sqcup+\infty} \neq \mathcal{I}\}$, because the risk level is determined by $P(\mathcal{R}_{\sqcup+\infty} = \mathcal{I}|S_i(t))$, which is the probability that the interference region will approach node i in the current Markov state. Thus, w_{jk} has non-zero positive value only for $P(\mathcal{R}_{\sqcup+\infty} = \mathcal{I}|S_i(t))$, and a different weight can be set based on the current status. w_{jk} has the largest value when the current status is $\mathcal{I}$.

C. Illustration of Markov Prediction

Table 1 illustrates the state transitions of each nodes in the sample network scenario in Fig. 1. This is an example illustrating the proposed Markov prediction scheme. We assume that Fig. 1(a) and (b) show the status at time t and $t+1$, respectively. Each CU can communicate directly with four adjacent nodes. For example, node 1 has bi-directional wireless links to node 2 and node 4. $d_i(t)$ is the interference proximity of node i at time t as in (1). The interference proximity and movement direction $\mathcal{R}$ at time $t-1$ are assumed to be as in this table. For example, the interference proximity of node 1 at time t becomes one from two at time $t-1$, indicating that the movement direction is $\mathcal{I}$. Thus, the state of node i at time t is set as $[\mathcal{I},\mathcal{I}]$, which consists of the previous interference movement direction and the current movement direction. At time $t+1$, as shown in Fig. 1(b), $d_1(t+1)$ becomes two from one at time t. Consequently, the movement direction is $\mathcal{O}$, and the state at time $t+1$ becomes $[\mathcal{I},\mathcal{O}]$. In the case of node 3, the interference movement direction is $\mathcal{N}$, because the distance from the interference region is



(a) (b) (c)

Fig. 3. Route destructions, route changes, and path length in CR-MHR and MCR in the case of constant speed and direction of a mobile interference region: (a) Route destructions, (b) route changes, and (c) path length.

outside of the detection limit ($IN_{\max}$), which is set three in this example. When a node is affected by the interference region, d_i becomes zero. Using this state and occurrences information, each CU estimates the transition probabilities among the states and obtains the risk level based on the Markov model as in (4).

D. Exponentially Weighted Moving Average

In addition to the Markov prediction scheme, we also evaluate interference aware prediction with the exponentially weighted moving average (EWMA) method for comparison. The EWMA method has been used widely for predicting a trend and smooth short-term fluctuation. The proposed EWMA scheme obtains the speed and direction of the PU interference region over time to evaluate the risk level of each CU for multi-hop routing.

We obtain the direction of the interference region from the change in the proximity similar to the MP scheme. In addition to the direction, the speed of the mobility is incorporated into the EWMA scheme as well. Each node examines the proximity and evaluates the velocity as $v_i(t) = \frac{d_i(t-\Delta t)-d_i(t)}{\Delta t}$, which provides both speed and direction information. While the absolute value indicates the speed, the plus and minus signs of the velocity indicates the direction of the interference region.

$$r_i(t) = \beta \text{sgn}(v_i(t))|v_t(t)|^{\gamma} - (1-\beta)r_i(t-1), \qquad (5)$$

where β is a positive value less than one and γ is greater than or equal to one. A higher value of β decreases dependency on the older observations. β can be set based on the mobility characteristics of a network. γ determines the effect of velocity on the risk level.

VI. SIMULATION RESULTS

We evaluate MCR with two risk level evaluation schemes, EWMA and MP, and compare it with a cognitive minimum hop routing (CMHR) scheme through simulation. CMHR finds the shortest path route consisting of CUs that are not interfering with a PU. Once the route experiences interference with a PU in mobile environments, CMHR finds a route that can avoid interference, similar to MCR schemes. Both MCR-EWMA and MCR-MP incorporate the risk level into the routing decision. In this computer simulation, we deploy 25 nodes in a grid topology. A sender and a receiver of CUs are located at each side of the network. The distance between adjacent nodes is set as 30 m, and the radio radius is set to allow a node to communicate directly with four adjacent nodes. The interference radius is set as 20 m. We examine five different speeds, and each simulation runtime is 300 s. In the first set of simulations, PU's active region moves between the sender and the receiver through the middle of the network. Two cases of mobility of the interference source are presented, constant speed and direction, and random speed and direction.

Fig. 3 shows the simulation results when the interference region moves with constant speed and direction. Fig. 3(a) presents the number of route destructions, which is the number of data delivery paths that experience interference owing to mobility during the simulations. As the speed of the interference region increases from 5 m/s to 20 m/s, the number of route destructions increases for CMHR. However, for MCR-EWMA and MCR-MP, data delivery paths hardly experiences interference throughout the simulation, regardless of the speed of the interference region. Because the recovered routes are affected repeatedly by the mobile interference source for CMHR, significant route destruction is observed. However, MCR provides consistently reliable routes by adapting to the mobile interference region, thereby preventing any interruptions and losses due to the active interference region.

Fig. 3(b) presents the number of route changes. Route reestablishments occur when nodes in the data delivery path are affected by interference or when a more optimal path based on a routing algorithm is found. As the interference region's speed increases, the route changes in MCR become larger than those of CMHR because of the dynamic adjustment of data delivery paths to the highly mobile environments following the MCR schemes. MCR-EWMA and MCR-MP show similarity in the number of route changes. When the speed reaches 20 m/s, the route changes in MCR-MP become smaller than those in MCR-EWMA. Though the number of route changes in MCR is greater than those of CMHR during high mobility, we note that MCR avoids interference preemptively, while CMHR experiences continual service interruptions during interference.

Fig. 3(c) shows the average path lengths between the source and the destination. The MCR schemes use longer paths than the CMHR scheme because MCR tends to select more reliable routes that are far from the interference region. However, route changes and path lengths are limited because MCR dynamically

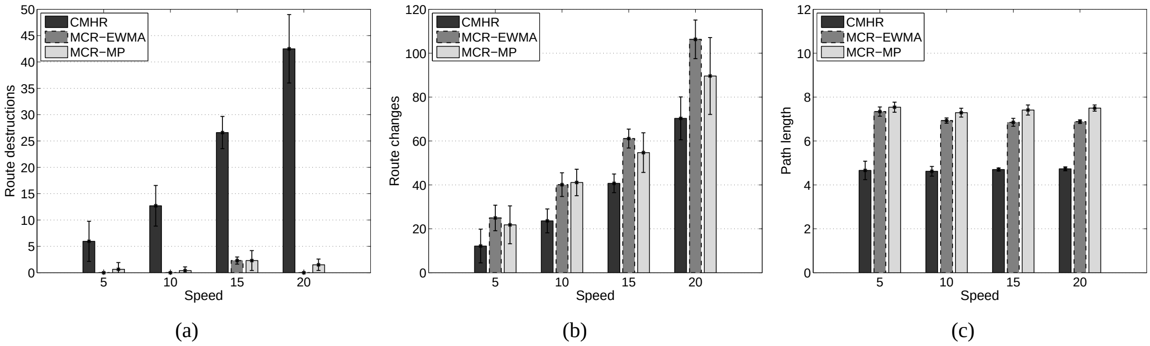


Fig. 4. Route destructions, route changes, and path length in CMHR and MCR in the case of random speed and direction of a mobile interference region: (a) Route destructions, (b) route changes, and (c) path length.

adjusts the path based on the proximity as well as the direction of the interference region. MCR-EWMA and MCR-MP show similar path lengths.

The simulation results when the interference region randomly changes its direction and speed are presented in Fig. 4. The simulation results of 30 runs for each of four different random speed selections are averaged. For example, the simulation with an average speed of 10 m/s allows the interference region to select its speed uniformly at randomly between zero and 20 m/s at each time step. Error-bars show standard deviations.

Fig. 4(a) shows the number of route destructions. Because the speed of the interference region can change sharply and the direction is random, the MCR schemes experience slight interruptions as the average speed increases. When we compare this result with the case of constant speed and direction in Fig. 3, much more severe route destructions occur in the case of random speed and direction. However, as compared to CMHR, MCR can provide much more reliable data delivery. Both MCR-EWMA and MCR-MP achieve reliable data delivery with almost no interference.

Fig. 4(b) shows the number of route changes. As compared to the case of constant speed and direction, more route changes are required for both CMHR and the MCR schemes owing to the random movements of the interference region. Especially, MCR-EWMA results in more route changes as compared to CMHR and MCR-MP, because MCR-EWMA tends to put high weight on the recent mobility characteristics, increasing route changes in the face of highly dynamic speed and direction of the interference region. MCR-MP achieves smaller route changes when compared to MCR-EWMA owing to the second-order prediction and training over time.

Fig. 4(c) presents a comparison of the average path lengths among three schemes, which are similar to the results of the case of constant speed and direction. The MCR schemes show greater path length than CMHR. However, both MCR schemes can achieve highly reliable data delivery among CUs.

The simulation results with mobile CUs are presented in Fig. 5. CUs have constant direction but change their speed randomly. The X-axis in the figure shows the average speed of CUs. Fig. 5(a) shows the number of route destructions. When compared to CMHR, MCR can achieve reliable data delivery by preemptively avoiding interference with a PU. MCR-MP can establish more reliable paths compared to MCR-EWMA. Fig. 5(b) shows the number of route changes. Overall, three schemes show similar route changes. Fig. 5(c) compares the average path lengths among three schemes. The MCR schemes show greater path lengths than CMHR.

Fig. 6 presents the simulation results of mobile CUs with random speed and random direction. As shown in Fig. 6(a), the MCR schemes can avoid route destruction significantly as compared to CMHR. However, when we compare this result with the constant direction case, the number of route destructions increases in both MCR schemes, owing to unpredictable movements of CUs. Fig. 6(b) shows the number of route changes and all three schemes show more route changes as compared to the case of constant direction. The average path lengths of three schemes are presented in Fig. 6(c), which shows results similar to those of constant direction in Fig. 5.

VII. CONCLUSION

Routing in multi-hop cognitive networks is significantly affected by mobility causing continual service interruptions and data loss. Our proposed MCR provides reliable paths adaptive to mobile environments preemptively. MCR successfully prevents route destructions when interference occurs with mobile PUs and CUs by utilizing mobility-aware prediction methods.

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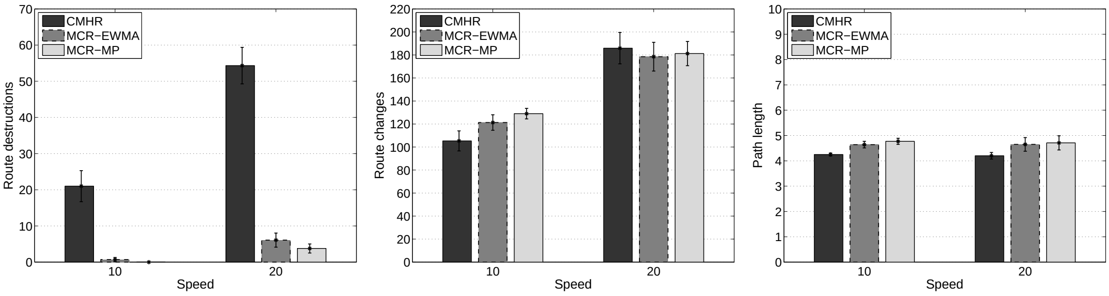
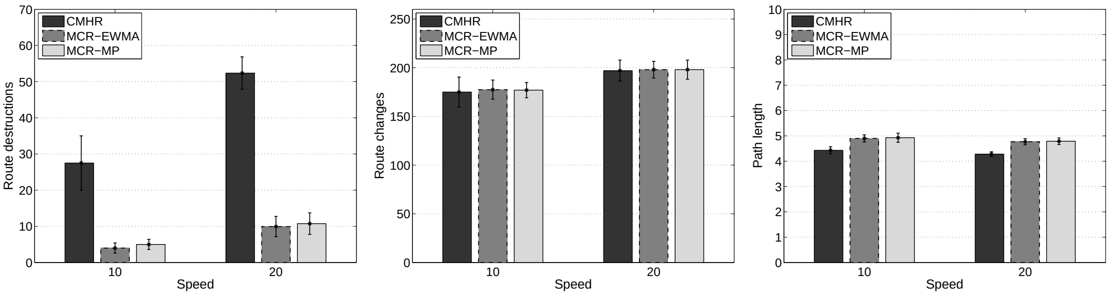


(a) (b) (c)

Fig. 5. Route destructions, route changes, and path length in CMHR and MCR in the case of random speed and constant direction of mobile CUs: (a) Route destructions, (b) route changes, and (c) path length.



(a) (b) (c)

Fig. 6. Route destructions, route changes, and path length in CMHR and MCR in the case of random speed and direction of mobile CUs: (a) Route destructions, (b) route changes, and (c) path length.

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