Meta-Routing: Synergistic Merging of Message Routing and Link Maintenance

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Meta-Routing: Synergistic Merging of Message Routing and Link Maintenance

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by
Mustafa A. Ayad

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Advisor: Dr. Richard Voyles
Abstract

The maintenance of network connectivity is essential for effective and efficient mobile team operations. Achieving robust mobile ad hoc networks (MANETs) connectivity requires a capable link maintenance mechanism especially if the network experiences expected intermittent connectivity due to a hostile environment. One applicable example of such network scenarios is multi-robot exploration for urban search and rescue (USAR). With the proliferation of these robotic networks, communication problems such as the link maintenance problem are subject to be raised quickly. Although various routing protocols for wireless ad hoc networks have been proposed, they solve the problems of message routing and link maintenance separately, resulting in additional overhead costs and long latency in network communication. Traditional routing protocols discover existing links, connect these links, find the best path and minimize the path cost. The limitation of previous routing protocols motivates us to develop a new concept of routing mechanism for a robotic network. This routing mechanism is named Meta-Routing. Meta-Routing expands current routing protocols to include not only the normal routing of packets, but also the maintenance of links in mobile agent scenarios. Thus, Meta-Routing minimizes the communication path cost and the overhead cost, the latter of which results from discovering a route, repairing a link or establishing a new communication path between nodes.

This dissertation presents a method to achieve Meta-Routing by controlling robot motion based on the radio frequency (RF) environment recognition method and gradi-
ent descent method. Mobile robot controlled motion can effectively improve network performance by driving robots to favorable locations with strong links. Moreover, the gradient descent method is used in driving the robots into the direction of favorable positions for maximizing broken or failing links and maintaining network connectivity.

The main accomplished goals of this thesis are summarized as follows: firstly, the Meta-Routing protocol, which integrates link maintenance into the normal message routing protocol cost function; secondly, the dissertation examines the unification of the syntax of message routing protocol and the link maintenance process through physical configuration of mobile network nodes by controlling their movement in the field; finally, the dissertation demonstrates that the utilization of the RF environment recognition and classification method improves route repair estimation for achieving link maintenance in the presented Meta-Routing protocol. The numerical experimental results demonstrate promising RF environment recognition and node controlled motion results, as well as confirm their abilities in robot movement control for link maintenance and reduction of the total path cost.
First and foremost, I would like to express my gratitude to my graduate advisor Professor Richard M. Voyles for being an excellent teacher as well as mentor to me from the beginning of my graduate school experience. His tremendous knowledge, patience, teaching, and support have inspired me to keep working hard. On an intellectual level, I learned much from Richards’ research visions, of which he has an endless supply, and his ability to put them in context. He can connect even the most mundane ideas to worthwhile pursuits, and conversely, break down hard research problems into small, manageable pieces. On a personal level, he patiently pushed and pulled and guided me through problems I was convinced I could not do. I am very thankful and I express my gratitude to co-advisor Professor Jun Jason Zhang for his time, advise and support to serve on my dissertation committee. I would like to express my appreciation to Professor Mohammed H. Mahoor for his help, support and take time to be on my committee. Also, I thank and express my gratitude to all the staff of the department of Electrical and Computer Engineering, for being always helpful and resourceful. I would like to thank my parents, parents-in-law, my brothers and my sisters. Finally, I would like to dedicate this dissertation to my beloved wife Hsna Kazam, and my children, Mohamed, Elyas, Alaa and Ayat. I hope I can make it up to them for all the time they sacrificed to help me to be devoted to my study.
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Chapter 1

Introduction

1.1 Motivation and Challenges

Most wireless communication networks operate in harsh environments, which may result in signal attenuation and multipath interferences [1]. A typical example of such harsh environments is a collapsed building, where a team of small robots need to work together to perform tasks that are difficult to achieve for a single robot or humans in such a hostile environment [2,3]. Figure 1.1 demonstrates the scenario of a collapsed structure and a team of USAR robots that communicate together to transmit data from the source to the destination. A fundamental problem for this robot network is how to maintain a robust communication path from the source to the destination such that message delivery is guaranteed. These robots are moving, and they are not able to transmit data directly from the furthest location in the network topology all the way to the destination. Also, these robots perform multiple tasks based on their capabilities, including searching for survivors, building and maintaining communication networks, and transmitting data from all peripheral areas of the network back to the base station.
Figure 1.1: Robotic network in a collapsed structure.

Conventionally, building and maintaining communication networks, and routing information packets are handled separately. In general, robot teams potentially provide solutions to surveillance, monitoring, and search and rescue operations, eliminating the need for human intervention in hazardous areas [4]. However, robots have limited mobility capabilities, energy availability, communication range, and computation capabilities due to their sizes and power constraints [5]. As a result of these constraints, system resources must be reasonably distributed across multiple robots,
which work together to achieve a mission. In a robot team, each small robot is equipped with limited sensing and processing capabilities for its mission, such as mapping the surroundings, providing feedback for human operators, or carrying sensors for the mission. Therefore, reliable communication between small robots is essential for their successful operations to explore the environment. For this reason, recovering wireless network communication strategies is needed for these environments where a robot can easily lose connection with the rest of the team [6]. Consequently, maintaining network connectivity becomes an essential requirement to obtain sufficient network capacity. In this context, signal strength measurements between nodes in the network can be employed to manage communication links to ensure network connectivity for each of mobile nodes. With the advancement of robotic network usage, mobile robots appearing in the communication field want to cooperate in an *ad hoc* manner without requiring any prior communication infrastructure. As a result, the concept of controlled motion has arisen in robotic networks. The concept of controlled motion is intrinsically tied to the capability of the nodes to move to favorable positions for maintaining network connectivity [7]. Controlled motion is one proposed solution to the link maintenance problem. The link maintenance problem concerns repairing broken or failing links in the network while maintaining the task of routing messages. Although various routing protocols for wireless *ad hoc* networks have been proposed, these protocols only consider message routing without control over the node movement to maintain network links; also the route discovery phase in these protocol schemes incurs communication latency in the network. In addition, most routing protocols are developed to handle static networks, which require the protocol to treat link maintenance and message routing as two separate problems. Traditional routing protocols are concerned with discovering existing links in the network, con-
necting these links together to create communication paths, then choosing the best path among the created communication paths. The routing protocols choose a best path by minimize the path cost between two chosen nodes, which is the sum of the cost of each link in the path. The routing protocols do not attempt to create new links in the network, they only discover new links that might arise.

To unify message routing and link maintenance we are motivated to develop a new class of routing and control protocol, by enhancing the existing routing protocols. We modify and improve the performance of routing protocols by imposing link repair as an alternative to the route discovery process and incorporating it into the cost structure of selecting a route. We call this enhanced routing technique Meta-Routing, because it integrates normal routing of packets and maintenance of physical links in a mobile agent environment.

Like conventional routing protocols, Meta-Routing attempts to figure out the best communication path between nodes by attributing path cost. However, Meta-Routing computes path cost not only from the cost of each communication link as in conventional routing, but includes the overhead costs of discovering and maintaining links.

For example, consider the network in figure 1.2. In this network, both nodes C and D are moving; node C is moving out of range while node D tries to move within the range of node C. However, node C can not know that node D is within its range until it executes the discovery procedure, which incurs an overhead cost $C_{Rd}$ with likelihood of success, $L_{Rd}$ as in Figure 1.2 (a). But the network can also move node B to stay in range of C, which incurs overhead cost $C_{Mov}$ with likelihood of success, $L_{Mov}$ as in Figure 1.2 (b). This simplest of examples illustrates both the opportunity of Meta-Routing and the challenges of Meta-Routing. The opportunity of Meta-Routing is obvious, as it is easy to invent scenarios in which the cost of movement is lower
than the cost of new link discovery or when no new links are present. The challenges are in estimating the costs of these actions as well as the likelihood of success.

This dissertation not only introduces the concept of Meta-Routing, but also addresses the difficult challenge of estimating overhead costs and likelihoods. A simple way to achieve this involves the estimation of gradients in the RF signal strength measurements as a function of motion. But this dissertation also explores the much more powerful technique of in-situ mapping of RF obstacles in the environment for real-world scenarios. By mapping and predictively recognizing common primitive types of RF obstacles, the estimation of cost is dramatically improved. In this dissertation, the RF environment recognition method is employed to recognize hostile environments containing RF obstacles for achieving Meta-Routing.

Figure 1.2: (a) Node C moves out of range of node D (b) Node B moves within the range of node C.

In summary, the following research work is for robotic network maintaining connectivity while robots are executing tasks. A new routing mechanism is introduced to improve the existing routing protocols - such as reactive, proactive and hybrid protocols - which incorporates the route repair algorithm directly into the routing protocol cost function as an alternative to the route discovery algorithm. In addition, the controlled motion algorithm based on RF environment recognition method and the gradient descent method is developed to achieve Meta-Routing.
1.2 Background

1.2.1 Routing Protocols

Routing protocols perform an extremely essential role in the implementation of mobile ad hoc networks (MANETs). Thus, routing is the process of discovering the path with the lowest cost in a network along which to send information packets. Routing protocols deal with finding existing communication links and placing these links together to form a lower path cost. Due to the nature of MANETs, it is a crucial task to find a path from the source node to the destination node to achieve communication among a highly interconnected network of communicating nodes as shown in Figure 1.3. Message routing protocols involve two activities: determining optimal routing paths with lower costs and transferring data packets [8]. Message routing protocols use a number of metrics to compute a lower path cost for routing the packets to their destination. These metrics are standard measurements such as the number of hops, speed of the path, packet loss, latency (delay), path reliability and path bandwidth. Message routing algorithms use these metrics to determine the optimal paths for transmitting packets to their destination.

1.2.1.1 Routing Problem

The routing problem arises when a node attempts to find an unknown path to another node: not only is the path unknown, but the complexity of the path is also unknown. For example, Figure 1.4 shows that node A attempts to connect to node B, but the path between them is undefined, and the network between node A and node B is unknown. In other words, not knowing the path between communicating nodes nor the complexity of the path are the key points of the routing problem.
Figure 1.3: An interconnected network of communicating nodes.

1.2.2 Message Routing in ad hoc Networks

A wireless ad hoc network is a collection of mobile communication devices forming a network without any supporting infrastructure. Mobile nodes in the communication network must have the ability to discover nearby nodes. Due to the limited transmission range of wireless network nodes, multiple network hops may be used when one node needs to exchange data with another across the network. MANETs are wireless networks consisting of mobile nodes, which are characterized by their decentralized organization and the high volatility of the network topology. Therefore, MANETs are most suitable for applications with multi-robot systems. The USAR scenarios are one example of such applications [9] as in Figure 1.1. In these systems, the mobile robots are communication nodes that provide robust communication infrastructures and network connectivity.
Figure 1.4: Node A cannot communicate directly to node B, but it might have an indirect path.

1.2.3 Link Maintenance Problem

Link maintenance aims to preserve effective communication between a node and its neighbors by varying their operational characteristics. For most cases in RF communication, *effective* communication means that the signal to noise (S/N) ratio is above some communication threshold. However, the bottom line is that the robot can send messages to a neighbor. There are many reasons that cause changes in the S/N ratio and lead to adjustment of a node’s operational characteristics. For example, in a static cell phone network, the mobile phone can not move by itself, but it can increase its output power to increase the S/N ratio to regain communication with the base station. Another example, if it is raining, the mobile phone must increase its output power to lift up the S/N ratio above some threshold to maintain communication with the base station. In addition, tuning the antenna either by changing the direction of the antenna or manipulating the parameters characteristics of the antenna will vary the operating characteristics of a node. In summary, the solutions for a link maintenance problem in wireless networks are summarized as follows:
1. Adjust the output power of a node (e.g. cellular phone network).

2. Adjust the antenna direction (e.g. NASA Deep Space Network).

3. Move an existing node to a position to recover signal.

4. Move a new node from the base station to a position to recover signal.

In our case with mobile robots if one robot moves too far from the base station and causes a decreased $S/N$ ratio, then we will instruct the robot to move to a position in the transmission range to communicate with other robots or the base station. Thus, the $S/N$ ratio goes down below some threshold when the robot is too far; consequently, the robot must move back into the communication signal coverage. These are all examples of how the node can adjust its operating characteristics to maintain link quality above the noise threshold. In this dissertation, we are going to focus on the movement of robots throughout the environment while not adjusting the output power, which is appropriated for static nodes.

1.2.4 Routing Protocol and Route Discovery Phase

Unlike most existing approaches in literature, we are working to combine both problems, message routing and link maintenance, into one unified framework. A prior student in our lab has developed a novel routing protocol called the LSP, but we are also working on tasks, which are performed by robots. Hence, these tasks require communications among mobile robots. Consequently, we have to work on the link maintenance problem too. Conventionally, we have been working on both problems independently. Because we are working on both problems simultaneously, we have the knowledge that helps us to maintain and merge the two problems as
one. In some scenarios, with the LSP if the battery dies in one node, the node loses the communication completely. On the other hand, in static networks, like the Internet, we only have to fix the node or the broken link. When facing a loss of communication signals, most routing protocols start the discovery protocol phase. The routing protocols try to find another node that might appear on the network. Routing protocols always start to run node discovery phases, but it takes a long time to discover a new node to keep the network connectivity; whereas, controlling the movement of some nodes into a strong signal place to regain the communication between nodes becomes more effective in some cases as shown in Figure 1.5(b). As a result, it is, in some cases, quicker to move one node into a more optimal position than to perform the route discovery phase to find another node in the network as shown in Figure 1.5(c).

1.2.5 Controlled Motion of Mobile Nodes

Node controlled motion is a form of mobility where mobile nodes are moving to favorable places in the field. Thus, the communication among network nodes is regained or improved. In Figure 1.5 (a), two robots are moving. They want to talk to each other, but as they move, they lose communication. Hence, robot 1 and robot 2 can not communicate any more with each other. Robot 1 can communicate with the base station directly, but robot 2 no longer communicates with the base station. To improve the communication again between the two robots, we have to perform one of two steps. The first option is to move robot 1 or robot 2 back through a free locomotion into some positions so that they can maintain communication between each other and the base station directly as in Figure 1.5 (b). The second option is to discover a new robot to act as a bridge between robots to regain communication.
Therefore, another robot should be moving from the base station into place, so robot 3 is moved into a position that allows robot 2 to regain communication again with the base station in Figure 1.5(c). That is how we can control the movement of robots to repair the broken links.

Performing tasks and maintaining connectivity is problematic because it is a multi-objective optimization problem that we have to deal with simultaneously. The reason these robots are moving is because they have some search objective. If it is a worthy desire to keep the communication, then they will stay close to the base station. Therefore, it is necessary to understand that what is driving the robots to move is the task. Hence, they have other duties to perform simultaneously with the task; maintaining the network, and exchanging data. Accordingly, robots have different objectives to perform at the same time, and that is what makes the problem more complicated. Thus, there is a reason for the robots to move, which is the task, and there is a reason for them to create a network, which is to transmit information packets. Therefore, it

Figure 1.5: Two robots are in (a) lost communication and in (b) move back to regain communication in (c) communicated to the base station through a third robot.
is a balancing act to perform the task effectively when at the same time communicating data and maintaining links. The link maintenance problem requires a balance between the movement of the robots to maintain the links connectivity and their movement to accomplish the tasks. This reason made the researchers traditionally break the mentioned problems down into separate parts. They have been separating them into the message routing problem and the link maintenance problem.

1.3 Dissertation Objectives and Contributions

Wired networks have many limitations with respect to the practical implementation of large networks due to the maintenance cost of the large infrastructures of the network. Although wireless networks have enormous advantages over wired networks, they have limitations due to the high cost of maintaining infrastructure. In critical scenarios such as disasters, military attacks, floods and earthquakes, the network infrastructure may break down. To overcome these limitations, many researchers have worked on mobile ad hoc networks, where the mobility of nodes is an essential characteristic of MANETs. Other important features of this network type are the abilities to interact with a sudden change of network topologies. Most routing protocols for MANETs are designed to handle the routing message and link maintenance problems independently. They use route discovery to find new nodes in the network when links get broken. Route discovery often takes a long time in a practical medium based approach where there is a conflict involved. There are many situations over low-level protocols for which a self-mobile node can improve a network faster or at lower cost than the traditional discovery process for new nodes. Based on this observation, we have come up with the idea of combining self-mobile link maintenance with a tradi-
tional routing protocol to obtain an optimal decision to create an effective reduction of data delivery latency by including link repair as another tool in the routing protocol. The key point in this thesis is based on the fact that if self-mobile nodes exist in the network, in some cases, it is faster to relocate a node rather than discovering an unknown node.

The discovery phase in routing protocols is time-varying, consumes a large amount of energy and bandwidth, and incurs latency that affects the network throughput. The main observation from our work in protocols and RF mapping is that higher network performance can be achieved from link repair rather than running a node discovery phase in some cases. Motivated by this observation, we end up with the idea of combining the self-mobile link maintenance with a normal routing protocol to make it effective by reducing discovery latency, which in turn improves the throughput of the network.

In this dissertation, the Meta-Routing protocol is presented as a new concept of mobile robot and *ad hoc* network infrastructure management, which is not only introduced as a packet routing scheme, but also as a new strategy of maintaining communication links. Therefore, the main contributions of this dissertation are summarized as follows:

1. Meta-Routing, which incorporates link maintenance directly into the routing protocols cost function as an alternative to route discovery for robust network connectivity. The advantages of the integration help in achieving robust network connectivity and minimizing the overhead cost results from different link maintenance methods. Meta-Routing aims to reduce the total path cost compared to the standard routing protocols.
2. Development of a novel RF environment recognition method (RF mapping) to enhance route repair cost estimation and reduces overhead costs, which results from other link maintenance methods.

3. The introduction of hypothesized nodes into the augmented connection graph that implements a unified syntax of the message routing protocol and the link maintenance mechanism that allows the overhead costs of routing to be merged with the direct link costs of routing.

1.4 Dissertation Outline

The remainder of this dissertation is organized as follows. In Chapter two, the related work in terms of routing protocols and maintaining connectivity is presented. Chapter three discusses in detail the concept, insightful scenario, achievement, path costs and the design of the Meta-Routing protocol. Chapter four presents the details of node movements and the advantages of controlled mobility of nodes in Meta-Routing. Chapter five presents and explains the gradient algorithm for node movement, different gradient scenarios, experimental results and the importance of gradient and node movement based on RF classification. The Details of RF mapping or RF environment recognition method for cost estimation improvement is presented in chapter six. Chapter seven explains the details of the link maintenance based on the Hidden Markov Model results. Chapter eight explains the robot controlled motion algorithm for connectivity maintenance and discusses the cost estimate results of robot controlled motion and route discovery methods. Finally chapter nine presents the conclusions, contributions and the directions for future works.
Chapter 2

Literature Review

Mobile ad hoc networks are used in many applications such as search and rescue scenarios, where communication routes are multi-hop, and the network of robots communicate via radio frequency. Routing protocols in mobile ad hoc networks are a challenging concern. Traditionally, an ad hoc protocol is a convention or standard that controls how to route information packets between nodes in a mobile ad hoc network [10]. In the following sections, we will present some routing protocols in more detail in terms of message routing, route discovery, and link maintenance.

2.1 Routing Protocols in MANETs

One of the fundamental challenges in the design of MANETs in a multi-hop environment is the design of dynamic routing protocols. These routing protocols can efficiently build routes to deliver data packets between mobile nodes. They do that with lowest communication overhead while ensuring high throughput and low end-to-end delay. Many researchers proposed routing protocols for different types of wireless networks. Researchers traditionally classify these routing protocols as proactive, re-
active and hybrid as in Figure 2.1. Routing protocols can also be classified as link state protocols (LS) or distance-vector protocols (DV) [11]. LS routing protocols keep a copy of the network topology and costs for all known network links. DV routing protocols keep only information about next hops to adjacent neighbors and costs for paths to all known destinations. LS routing protocols are more reliable, easier to debug and consume less bandwidth than DV protocols [12]. LS protocols generate larger routing overhead control than DV.

In the existing routing protocols for ad hoc networks, route discovery is represented in a single network search, using some message flooding and referred as a single step route discovery [13]. In this context route discovery is equivalent to perform a single network search, therefore, the distinction between the route discovery algorithm and the search process is not necessary. In general, the routing protocols for MANETs can be classified as proactive or reactive based on how route discovery algorithm is initiated [14].
2.1.1 Proactive Protocols

Proactive protocols are also referred as table driven protocols. In these protocols, each node preserves routing information to every other node in the communication network. The routing information is usually kept in number of different routing tables. These tables are periodically updated as a result of the changes in network topology [15]. These protocols are different in ways to update, detect and store the routing information. Some of these protocols are: destination sequenced distance vectored (DSDV) [16], optimized link state routing (OLSR) [17], distributed Bellman-Ford (DBF) [18], wireless routing protocol (WRP) and cluster head gateway switch routing (CHGS) [19]. In this category, protocols such as DSDV and OLSR attempt to preserve up to date routing information among any node pair in the network [20]. Each mobile node is required to periodically discover and maintain routes to every possible destination in the network. Periodic routing information updates and update results from broken links are exchanged in proactive routing protocols. Periodic routing information can result in a large routing control overhead in high mobility networks. Thus, these protocols suffer from excessive routing control overhead. Therefore, these routing protocols are not scalable in MANETs, which have limited bandwidth and whose topologies are highly volatile.

2.1.1.1 DSDV Protocol

DSDV routing protocol is a proactive, table-driven routing protocol for mobile ad hoc networks. DSDV uses the hop count as a metric in route selection. DSDV is one of the most well known table-driven routing algorithms for MANETs [21]. In DSDV, each mobile node preserves a routing table. The routing table contains a list of all available destinations, the next hop to each destination and a sequence number
generated by the destination node. The nodes transmit packets using stored routing tables in each mobile node. Each node updates the routing table periodically or when significant new information is available [22]. The node performs this to preserve the consistency of the routing table with the dynamic topology changes in the network. DSDV uses the sequence number to identify stale routes from new ones and thus avoid loop formation. Therefore, the routing table update occurs both in time-driven and event-driven process. The routing table update can be sent in two ways either a full dump or an incremental update. In a full dump, the node sends the entire routing table to the neighbors and spans several packets [21]. In an incremental update, the entries of the routing table that has a metric change since the last update is sent, and those entries must fit into a packet. If there is enough space in the incremental update packet, then the entries whose sequence number has changed may be included in the packet. When the network is stable, incremental update is sent to avoid additional traffic. In a rapidly changing network, incremental packets can grow large. Therefore,
full dumps will be more frequent [22]. For example, Figure 2.2 shows the routing table of node A in this network [23]. The routing table contains details of all possible paths node A can reach, the next hop, number of hops and sequence number.

One of the main purposes of DSDV is to address the looping problem of the normal DV routing protocol and to make the DV routing more suitable for ad hoc networks. However, DSDV arises route oscillation, which results from the criteria of route updates. At the same time, DSDV does not solve the common problem of all DV routing protocols, the unidirectional links problem [22].

2.1.2 Reactive Protocols

Reactive protocols are also referred as on-demand protocols, which are designed to reduce communication overhead by maintaining information for active routes only, at the expense of delays due to route discovery. This means that routes are determined and maintained for the nodes that require data transmission to known destinations. The route discovery is achieved by flooding a route request through the network. Some examples of the reactive protocols are dynamic source routing (DSR) [24], the temporary ordered routing algorithm (TORA) [25] and the ad hoc on demand distance vector routing protocol (AODV) [26].

2.1.2.1 AODV Protocol

In the on-demand routing protocols, such AODV and DSR, routes are discovered when they are needed. Each node maintains a route to a destination pair without the use of periodic exchanges of routing table or knowledge of a whole network topology. AODV combines the features of DSDV and DSR protocols [27]. However, AODV maintains routes in a distribution fashion, as routing table entries. The AODV keeps
routing table entries in the form of destination, next hop, and distance. AODV incorporates timer-based routing table entries for a destination in each node [28].

2.1.2.2 Route Discovery Mechanism in AODV

In AODV routing, when a source node has data to transmit packet information to a new destination node, it transmits a route request (RREQ) packet for that destination to its neighbors. The RREQ packet contains the address of the destination node, sequence number of the destination node, broadcasting sequence number, sequence number of the source node, and address of previous hop count. When an intermediate node receives RREQ packet, if it has a route node in its routing table to the destination, it forwards route reply (RREP) packet by reverse routing. The RREP contains the address of the source node, address of the destination node, hop count and life time of the link. The RREP is unicasted in hop by hop fashion to the source [29]. When the source receives the RREP, it records a new route in its routing table to the
destination and begins sending packets as shown in Figure 2.3. If the source receives multiple route replies, the route with the shortest hop count and highest destination number is chosen. The highest destination number means the latest information about the destination route. If the source node does not receive any RREP packet before the RREQ timer expires, it broadcasts a new RREQ with an increased time to live (TTL) value. This technique called expanding ring search [30] continues until either a RREP is received or a RREQ with the maximum TTL value is broadcasted. Broadcasting a RREQ with the maximum TTL value is referred to as a network-wide search since the RREQ is disseminated throughout the MANET. If a source performs a network-wide search without receiving any corresponding RREP, it may try again to find a route to the destination, up to a maximum of (RREQ − RETRIES) times after which the session is aborted [29]. In case a link break is detected the node at the upstream of the route broken would broadcast RERR, which contains the address and sequence number of unreachable nodes to the neighbor nodes. As the route error propagates towards the source, each intermediate node invalidates routes to unreachable destinations. When the source node receives the RERR, it invalidates the route and reinitiates route discovery.

The limitation of AODV is that it generates a large number of control packets while performing the route discovery in the regular AODV routing protocol, which increases the congestion in the route. Thus, the routing overhead increases with the increase in the number of control packets generated and effects the network bandwidth. Finally, the delay in the transfer of packets increases.
2.1.3 Hybrid Protocols

More recently, hybrid routing protocols have emerged to address more complicated communication network situations. These protocols combine the merits of proactive and reactive routing protocols with additional features such as reducing routing information. Protocols in this category are: The zone resolution protocol (ZRP) [31], SHARP [32] and the locally selectable protocol (LSP) [2,4].

2.1.3.1 ZRP Protocol

ZRP was the first hybrid routing protocol that combines a proactive and a reactive routing protocol [31]. ZRP was proposed to minimize the control overhead caused by proactive protocols and minimize the route discovery latency in reactive protocols. ZRP defines a routing zone around each node that consists of k-neighborhood (e.g. K=3). In ZRP, all nodes located in hop distance from a source node belongs to the routing zone of that node. ZRP is formed by two sub-protocols. Firstly, a proactive routing protocol called Intra-zone Routing Protocol (IARP), which is applied inside routing zones. Secondly, a reactive routing protocol called Inter-zone Routing Protocol (IERP), which is applied between routing zones, respectively. When a route to a destination node is located in the local zone established from the proactive routing table of the source node by IARP protocol, and if the source and destination are in the same zone, then the packet can be delivered to the destination node immediately [33]. Most of the existing proactive routing protocols can be used efficiently as the IARP protocol for ZRP protocol. For routes outside the local zone, route discovery occurs reactively. The source node transmits a route request to all of its border nodes that contain its own address, a unique sequence number and the destination node address. Border nodes are nodes that represent the maximum number of hops away from the
source node into the defined local zone [33]. The border nodes keep aware of their local zone for the destination node. If the requested node is not a member of this local zone, then the node inserts its address to the request packet and then it forwards the packet to all its border nodes [34]. If the destination node is one member of the local zone of the source node, the destination sends a route reply on the reverse path back to the source node. The source node uses the path saved in the reply packet then it sends data packets to the destination node.

Figure 2.4: ZRP routing protocol.

Consider the simple network in Fig 2.4. The source node $S$ has a packet to send to the destination node $X$. The radius of the zone is $r = 2$. The source node uses the routing table provided by the IARP protocol, to make sure that the destination node is located in its routing zone. Since the destination zone is not in its local zone, a route request packet is generated using IERP protocol. The request transmits to the peripheral nodes (blue nodes in the figure). Each of these nodes searches its routing table for the destination node information.
In summary, in ZRP, the network zone radius must be configured by the administrator prior to deploying the network. The routing zone radius provides the performance of the ZRP. As the mobility of nodes in ZRP increases, link formation and breakage increase, and this make the preserved routing information invalid. Therefore, control traffic consumes more time and bandwidth than the time and the bandwidth consumed in data traffic. ZRP decreases the size of the proactive zone as mobility and, correspondingly, the frequency of link-failures increase. ZRP dynamically takes advantage of proactive discovery with a nodes local neighborhood and reactive discovery between these neighborhoods. ZRP keeps the focus on interest areas by adjusting the radius of the covered area. ZRP may have extra overhead results from adjusting the zone radius size and handling of two different routing protocols simultaneously. ZRP would be adequate as the size of mobile ad hoc networks becomes large. This protocol tries to separate the control adaptation of the routing layer for different areas and minimize packet overhead. However, they might not be appropriate small scale sensor networks, such as wireless video sensor networks (WVSNs) for USAR.

2.1.3.2 LSP Routing Protocol

Locally selectable protocol is a hybrid routing protocol, whose main objective is that it infrequently applies a proactive routing protocol to the global network in order to periodically keep all routing information at the top level of the hierarchical network. If a critical error on the path occurs during transmission, it uses a reactive protocol to locally provide a solution to the path failure and to update the routing table on demand [3]. By updating the global table infrequently and hierarchically, the LSP routing protocol minimizes the overhead of tracking volatile links through irrelevant changes. While by updating the local links opportunistically, the LSP minimizes
the latency by keeping a reasonable search. The proactive routing protocol used by LSP is the cluster head gateway switched routing protocol (CHGS). CHGS is a hierarchical protocol which is chosen due to the capability of being into the Bluetooth piconet structure as shown in Figure 2.5. Furthermore, the hierarchical nature of the CHGS protocol reduces connection overhead, which is critical in highly volatile network configurations. The reactive routing protocol in LSP is the AODV routing protocol as shown in Figure 2.6. The LSP flowchart is shown in Figure 2.7(a).

![Figure 2.5: The cluster-head gateway switch (CHGS) routing protocol.](image)

Cluster heads in CHGS maintain routing information for a group of in-range slave nodes. As a result, the routing table generated by CHGS is smaller compared to other proactive routing protocols such as DSDV. The reduced routing table only contains routes information between the cluster heads and a list of slave nodes that are associated with each cluster head. LSP utilizes the AODV routing protocol as a locally reactive response to routing failures. When a failure in an effective route occurs an alternate route, after consulting the proactive routing table, is chosen. If an alternate route exists, nodes are “un-parked” as needed and the routing of packets
resumes. If no alternate route exists, AODV initiates route discovery to find a new route to maintain transmission.

In summary LSP protocol has the following novel features:

1. The LSP combines the proactive and the reactive strategies to reduce latency and achieve a short routing path for better network performance.

2. The LSP can be implemented on top of the Bluetooth MAC/transport layer due to its high raw bandwidth.

3. The LSP is suitable for sparse, highly volatile wireless video sensor networks (WVSNs) for small robots in USAR applications.

4. The LSP, with its marriage to the Bluetooth transport layer, fills the important and critical gap shown in Figure 2.7(b).
Figure 2.7: (a) Flow chart of the LSP protocol (b) volatility, power consumption and bandwidth of different networks.

2.1.4 Limitations of Existing ad hoc Routing Protocols

Most ad hoc protocols mentioned in previous sections do not have any control of the node movement in the network or the potential for connectivity maintenance. Proactive protocols preserve routing information to every other node in the network to guarantee network connectivity. Maintaining large routing tables causes more overhead in the network which leads to consumption of more bandwidth. Reactive protocols perform route discovery to discover new nodes in the network to maintain the network connectivity. Reactive protocols do not maintain routing information or routing activity at the network nodes when there is no communication. The route discovery in reactive protocols often causes latency in the network. The aforementioned types of protocols address message routing problems separate from the link maintenance problems.
2.2 Related Work in Maintaining Connectivity

In recent years, communication network properties such as connectivity and signal strength measurements have been used to maintain the quality of connectivity of the network [35]. There is growing interests in developing robot networks that can explore, discover and respond to the surrounding environments. The robotic network should conduct its tasks while exploring the environment and maintaining network communication to ensure the acquisition and delivery of the required data [36]. Mobile robotic communication networks have evolved from a transmission medium of data to smart sensor networks used to discover surrounding environments. Therefore, properties such as received signal strength and maintaining connectivity are used to maintain the quality of communication links as well as network communication. As a result of this, there is some significant literature on maintaining network connectivity.

In [37], the authors incorporated radio signal strength information into the exploration algorithm by locally sampling the signal strength and estimating the 2-D gradient. The authors determined the gradient of a mobile robot with respect to a stationary signal source. In [38], the authors considered a scenario for exploiting the 2-D gradient within a cooperating sensor network to localize and navigate to a fixed radio source. The authors in [37] and [38] determined the 2-D gradient where one robot move with respect to a fixed signal source while we are considering the 4-D gradient for two mobile robots.

In [39], the authors considered the scenario where a robot needs to maximize the amount of information it sends to a base station as it moves along a predefined trajectory. The authors proposed a probabilistic wireless channel assessment framework to allow the robot to adapt its velocity, motion energy, and transmission power along its trajectory. In [40], the authors focused on developing tools that allowed for online
estimation and mapping of received radio signal strength. Specifically, they considered the simplest scenario where there is a base station at an unknown location and the base station transmits to one or more mobile robots.

In [41], the authors’ approach entailed the automated construction of a radio map for a partially known urban environment which can then be used to deploy a team of robots and the corresponding control algorithm that will drive the team to achieve designated targets while maintaining satisfying communication link quality. The authors proposed reactive controllers for link maintenance. These controllers can be combined with the information collected from the radio signal strength maps. The reactive controllers allow the robots to adapt to changes in actual signal strength. Therefore, their approach uses radio connectivity maps for planning and low level reactive controllers that respond to changes in actual signal strength. Although their reactive controller acts as a scenario-independent support that allows for the deployment of a robot team to any location and maintains the connectivity among robots, they did not address the routing problem in conjunction with the link maintenance problem. Hence, they tried to solve the problem of maintaining connectivity independently.

In [5], the authors conferred about the experimental justification of a distributed algorithm that sustain the connectivity of a team of robots. The authors were certain that the algorithm requires only limited local information and communication between robots. They did this to determine additions or deletions of network links through distributed consensus and market based auctions. Although the simulation and the experimental results demonstrated the effectiveness of the algorithm to guarantee connectivity in a team of robots, the approach addresses the maintaining connectivity problem independently; however, they did not address the routing problem. The
authors of [42] suggested a distributed feedback control framework that imposes no restriction on the network structure other than the desired connectivity specification. In [43], a measure of local connectivity of a network is introduced that under certain conditions is sufficient for global connectivity. Furthermore, Distributed repair for adjacent neighbor links in stabilization development is addressed in [44]. To overcome environment interference, the authors of [45] considered the problem of controlling a team of robots to ensure end-to-end communication. The authors proposed two different performance metrics, point-to-point signal strength and data throughput, to observe the network connectivity of the system. Even ad hoc communication protocols pose difficult challenges during multi-robot experimentation as in [46]. In [47], a controllability framework for state-dependent dynamic graphs is developed while the authors in [1] proposed a method for utilizing multi-path fading by controlling the robot according to radio signal strength. In [48], the authors considered estimating the distance variations of a wireless channel based on a small number of signal strength measurements in a robotic network. Their work can be utilized for communication-aware motion planning in robotic networks, where a prediction of the link qualities is required.

The aforementioned connectivity conservation methods use methodologies, including reactive controllers for link maintenance, distributed algorithm that preserves the connectivity and artificial potential field. However, all of these treat the problem of maintaining connectivity without taking the routing problems into consideration.
2.3 Summary

In this chapter, we have presented an overview for mobile ad hoc routing protocols. Routing is the process of selecting communication paths in a network along which message packets are sent. In MANETs, mobile nodes communicate with each other using multihop wireless links. There is no stationary infrastructure where each node in the network performs as a router. Each node forwards received packets for other nodes. An important challenge in the design of MANETs is the development of efficient dynamic routing protocols. These protocols can efficiently find routes between the communicating nodes. The routing protocol must be aware to a high degree of node mobility that causes changes to the network topology drastically and unpredictably. These protocols are classified as proactive, reactive, and hybrid routing protocols. In proactive routing protocols, each node in the network has one or more routing tables. These tables contain the latest information of the routes to any other node in the network. Various table-driven protocols differ in how the information propagates through all nodes in the network when the topology changes. The proactive routing protocols maintain each and every node’s entries in the routing table. Therefore, they are not suitable for larger networks. Maintaining large routing tables causes more overhead in the network, which leads to an increase in the consumption of more bandwidth. Reactive routing is also known as on-demand routing protocol. Reactive protocols do not keep routing table information or routing activity at the network nodes when there is no communication existing. If a node wants to send a packet to another node, then this protocol searches for the route in an on-demand manner and establishes the connection in order to transmit and receive the packet. The route discovery occurs by flooding the route request packets throughout the network. Hybrid routing protocols combine the advantages of proactive and reactive
routing protocols by overcoming their shortcomings. All these protocol types react to the message routing separate from the link connectivity problems that occur with repairing or creating new links. In addition, we have presented a variety of literature with respect to link maintenance and maintaining connectivity that treats the message routing problem separately.
Chapter 3

Meta-Routing Protocol

3.1 Introduction

One of the most significant challenges in mobile ad hoc networks is the maintenance of network infrastructure, especially in critical scenarios in which the normal infrastructure may be damaged or unreliable, such as military attacks, flood, earthquake, etc. We also noted in mobile ad hoc networks that the mobility of nodes is an important property that results in dynamical changes of network topologies [9]. As a result, the routing strategies in MANETs are essential for maintaining network communication capacity. Many protocols for MANETs have been designed and developed to handle routing message and link maintenance problems. However, most of the routing protocols treat these two problems separately. In these protocols, route discovery is commonly used to discover new nodes in the network. They run route discovery when existing links fail, which usually takes a long time in practice when contentions are involved. Also, we have realized that if network nodes are mobile, healing the network by node relocation is usually faster than discovering a new node.
From the aforementioned motivations, challenges and facts, we propose the idea of integrating the node link maintenance, which is a route repair, and the message routing protocol problem. Therefore, our goal is to incorporate the controlled motion of mobile nodes into the routing protocol to repair links and maintain network connectivity and to create what we call Meta-Routing protocol.

3.2 Meta-Routing Main Concept

Routing protocols are concerned with finding the best path to transmit the message packets among nodes. The "best path" is determined by considering the cost of links that establish a communication path and considerable research has been directed toward improving estimates of the link costs. Network researchers consider message routing of information packets separately from link maintenance process, which is the idea of creating links and keeping these links. Meta-Routing combines the concept of message routing of information packets, which is finding the lowest path cost, and link maintenance, which is creating and improving paths (a path consists of links). Therefore, Meta-Routing is the integration of logical message routing and physical link maintenance for the overall goal: getting information packets from node $A$ to node $B$, (see Figure 3.1), at the lowest total cost.

![Figure 3.1: Two nodes transmit packets.](image-url)
Algorithmically, Meta-Routing takes existing methods of computing path cost and augments them with the costs of overhead and maintenance to develop a more comprehensive cost metric. Meta-Routing includes links cost, route discovery cost and link tuning / adjustment cost as in Figure 3.2. Meta-Routing is applicable to the entire gamut of link maintenance mechanisms available, including controlled motion of nodes, transmit power adjustment, antenna pointing, and other forms of antenna tuning that varies the operating characteristics of nodes. Regardless of the array of maintenance options available, if the costs and likelihood of success can be quantified, the mechanism can be incorporated into the paradigm.

![Figure 3.2: Meta-Routing cost diagram.](image)

### 3.2.1 Meta-Routing Insight

A very specific scenario involving of two crawler robots moving in an unknown environment, communicating and exchanging messages packets provided the insight
from which Meta-Routing was born (see Figure 3.3 (a)). While these robots are exploring an unknown environment and exchanging message packets, they approach a Faraday cage-like obstacle. As they move forward, the communication signal strength goes down until communication is lost. The robots can not communicate anymore as a result of the RF obstacle effects on the communication signal as shown in Figure 3.3 (b).

![Figure 3.3: Two crawler robots in an unknown environment, robots are (a) maintain signal (b) signal lost.](image)

To reestablish communication between the two crawler robots, there are two choices: discover a new node that might re-connect the route, or move existing nodes to re-connect the route. The first choice is to discover a new node by the network to act as a bridge between the two nodes that lost the communication. This action requires performing the route discovery phase to find an intermediate node which acts as a bridge as shown in Figure 3.4(a). In our work with LSP over Bluetooth [2], this process costs up to 39 seconds in the simulation experiment as shown in Figure 3.5. On the other hand, we realized that turning the robot around and crawling backwards
Figure 3.4: (a) Discovering a new node (b) controlling motion of an existing node.

to regain signal was significantly faster (lower cost). Therefore, physically moving the
nodes to regain the communication route is significantly lower cost than node discov-
ery, in this case! Furthermore, node discovery is highly uncertain. If no new node is
present, the cost is wasted.

3.3 Meta-Routing Achievement

Meta-Routing merges the concept of message routing, which is finding the best
path and link maintenance, which is creating and improving communication paths
(a path consists of links). Meta-Routing efficiently combines these two approaches
through an enhancement of the cost structure. The new cost includes both the direct
communication cost of the links, plus any overhead costs of establishing the existence
of those links.

Meta-routing is best illustrated when a link disappears somewhere in the middle
of the network and no known alternate route exists. In other words, the path that
Figure 3.5: Controlling motion of an existing node and discovering a new node cost estimation comparison.

Routing protocol thought is the best path, it is now broken. Therefore, there is a subproblem; instead of going from node $A$ to node $B$, it is going from node $C$ to node $B$. Therefore, the routing protocol does not know what the path is, and now we are going to compute both the complete cost to that path (not only the individual links), but also what is going to cost us to find a path or create a new path or strengthen an existing path. Thus, this is what Meta-Routing is about. As a result, we are not going to change the basic routing protocols; we could use proactive, reactive or hybrid protocols. The point is we are going to show how we are going to integrate link maintenance into a standard routing protocol.

One of the advantages of the Meta-Routing approach is that we are going to include the cost of moving a node in the cost function of estimating the lowest total path cost. Therefore, all links are strong enough to have a path from node $A$ to node $C$ then to node $B$. The cost of strengthening links is related to the overhead cost of the node movement, which takes time and energy to move the node. In summary,
using node movement and computing the gradient while robots are moving, is one way that lead to achieve the Meta-Routing protocol.

3.4 Routing Protocol Path Cost

The total communication cost of a path includes the sum of each link cost that constitute the complete path from the source to the destination. Routing protocols focus on the minimum cost of a communication path, which is the minimum cost of links for that path. They had not taken the consideration of the overhead cost results from route discovery latency of the new node in the communication network when a link failed. Therefore, route discovery is about finding what communication paths exist so that the lowest-cost path can be chosen. For example, when reactive protocols are used, a source node usually starts a timer, $T_W$, after sending out a $RREQ$ message, to wait for the $RREP$s messages [49]. The $T_W$ is the total latency (overhead cost) results from route discovery, and it is summarized in the equation as

$$T_W = (T_{Req} + T_{Rep}) + T_{SL}$$  \hspace{1cm} (3.1)

Where $T_{Req}$ is the time it takes for the first $RREQ$ message to traverse from the source node to the destination node; $T_{Rep}$ is the time it takes for the first $RREP$ message to traverse from the destination node back to the source node; $T_{SL}$ is the extra waiting time after receiving the first $RREQ$ or $RREP$, namely, the soft latency. For source selection reactive protocols, $T_{SL}$ happens at the source side, and after $T_{Rep}$; for the destination selection reactive protocols, $T_{SL}$ happens at the destination side and before $T_{Rep}$ [49]. In addition, note that the hard latency, $T_{HD}$, is the sum of $T_{Req}$ request and $T_{Rep}$. 

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For example in Figure 3.6, if node 1 needs to communicate and forward a packet of messages to node 8, then node 1 has to sent a request message $RREQ$ to its neighbors and then the neighbors transmit to other nodes until the source receives a response message $RREP$. Figure 3.6 shows the present set of links to make a connection to node 8. The set of links are $(1, 2), (2, 6), (6, 8), (1, 3), (3, 5), (5, 7), (1, 4), (4, 5), (5, 7), (7, 8)$. The set of paths available are $path_1$, which is among nodes $(1, 2, 6, 8)$, $path_2$, which is among nodes $(1, 3, 5, 7, 8)$, and $path_3$, which is among nodes $(1, 4, 5, 7, 8)$. The cost of $path_1$ equals $2 + 1 + 3 = 6$ and the number of hops are 3. The cost of $path_2$ equals $1 + 2 + 3 + 5 = 11$ and the number of hops are 4. The cost of $path_3$ equals $1 + 1 + 3 + 5 = 10$, and the number of hops are 4. Therefore, $path_1$ is the best path among the available paths in terms of number of hops and distance weights.
3.5 Simple Meta-Routing Scenario

In Figure 3.7 (a), node A is communicating with node C. There are two possible routes: \( A - B - C \) and \( A - D - B - C \). The lower cost route is \( A - B - C \). In this scenario, we assume that node C wants to move to the right as the arrow indicates, but node D is also moving in the direction of its arrow as shown in Figure 3.7 (a). As a result of this movement, node C has moved out of range of node B, but node D has moved into the range of node C; consequently, node C and node D can communicate with each other but they don’t know it yet. (The link between nodes C and D is not established until the link discovery protocol is initiated.) Furthermore, node B can not communicate with node C as shown in Figure 3.7 (b).

![Diagram showing nodes A, B, C, and D in two configurations. In the first configuration, node C is to the right of node B, and node D is to the left of node C. In the second configuration, node C has moved closer to node B, and node D is no longer within range of node C.]

Figure 3.7: (a) Node C and node D are moving in the direction of the arrows (b) Node C moves out of range of node B, but node D has moved in such a manner that it is within range of node C.
For this scenario, there are two possible solutions for maintaining communication between the mobile nodes. First, when node $C$ moves out of range of node $B$, node $B$ triggers the route discovery algorithm to find a new link to node $C$, and this is what traditional routing protocols do. Therefore, node $B$ can communicate to node $C$ through node $D$ because node $D$ and node $C$ are within range and can communicate with each other as shown in Figure 3.8 (a). Second, node $B$ can be moved along with node $C$ (at half speed), so node $B$ will remain in range of nodes $A$ and $C$ and then maintain links as shown in Figure 3.8 (b). This is exactly what link maintenance does for the connectivity maintenance of the network.

Figure 3.8: (a) Node $D$ is in range of node $C$ (b) Node $B$ moves toward node $C$. 
3.6 Meta-Routing and the Conventional Routing Paradigm

Traditional routing protocols find paths (a series of links) in a connection graph, then they choose the lowest cost path along which to send information packets. Traditional routing protocols trigger an automatic route discovery when there is not a direct path to the destination as shown in Figure 3.8 (a). In Meta-Routing protocol, we are going to augment the graph with hypothesized nodes, and that will be our trigger to find paths in the augmented graph and compute the cost function for each path. Hypothesized nodes augmented in a graph are shown in Figure 3.9, where $\phi_D$ represents the route discovery hypothesized node and $\phi_B$ represents the controlled motion hypothesized node.

![Meta-Routing augmented graph with hypothesized nodes, $\phi_B$ and $\phi_D$.](image)

Figure 3.9: Meta-Routing augmented graph with hypothesized nodes, $\phi_B$ and $\phi_D$. 

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3.7 Meta-Routing Protocol Path Cost

Figure 3.9 results from augmenting two hypothesized nodes \( \phi_B \) and \( \phi_D \), which are virtual nodes, into the traditional routing protocol graph of Figure 3.7. The resulting graph in Figure 3.9 represents the Meta-Routing augmented graph, where \( \phi_D \) represents the route discovery hypothesized node (virtual node), which results from running the route discovery algorithm by node \( B \) to communicate with node \( C \), and \( \phi_B \) represents the controlled motion hypothesized node (virtual node), which results from moving node \( B \) to the position shown in Figure 3.9, so that node \( B \) can communicate with node \( A \) and \( C \). Because both nodes \( \phi_B \) and \( \phi_D \) are hypothesized, they are uncertain. Hence, it is appropriate to consider their likelihoods of success of route discovery \( L_{Rd} \) and controlled motion \( L_{Mov} \). Meta-Routing protocol total path cost represents the sum of the message routing protocol cost, which is the minimum links cost of a communication path \( (C_{Ls}) \), and the link maintenance path cost, which is the minimum overhead cost to find the path \( (C_{Oh}) \). In fact, Meta-Routing estimates the overhead cost of the route discovery \( (C_{Rd}) \) and the overhead cost of node movement \( (C_{Mov}) \). Meta-Routing chooses the best total cost estimate, which represents the lowest total path cost. In case that the lowest overhead cost estimate is the cost of node movement, Meta-Routing uses the controlled motion algorithm when signal strength goes below some threshold and a link failure occurs. The controlled motion algorithm moves communicating nodes in the field to a favorable position to regain a strong communication signal. The controlled motion algorithm performs this to reduce the overhead cost that results from route discovery. Thus, the total path cost \( (C_{T_{meta}}) \) is the sum of the node movement cost, which is the time and energy costs to move a node and the minimum links cost (communication cost), which is the shortest path or a path with less hop count number. On the other hand, when the node
movement cost is higher than the discovery cost of a new node, Meta-Routing total path cost will be the sum of the minimum communication links cost and the route discovery cost. Therefore, Meta-Routing lowest total path cost is the sum of minimum communication cost of links and the minimum overhead cost as in Equation 3.2.

\[ C_{T_{meta}} = \Sigma C_{Ls} + \Sigma C_{Oh} \]  

(3.2)

The graph in Figure 3.9 shows two hypothesized nodes to create links from node A to node C, which is \( \phi_B \), and from node B to node C, which is \( \phi_D \). Traditional protocols trigger route discovery automatically when a link failure occurs. On the other hand, Meta-Routing goes to hypothesis mode to trigger the optimal cost choice based on the cost function and likelihood of success for discovery, \( L_{Rd} \) or likelihood of success for movement, \( L_{Mov} \). According to this, two hypotheses are discussed below.

### 3.7.1 First Hypothesis \( H_1 \) : Link Discovery

In Figure 3.10, a hypothesized node \( \phi_D \) is inserted between node B and node C. Therefore, the cost change of the link between node A and node B, \( \Delta C_{AB} \), is equal to 0 because node B does not move. Without loss of generality, we assume that the communication cost between the hypothesized node \( \phi_D \) and node C is equal to 1. As a result, the Meta-Routing total cost of the first hypothesis \( H_1 \) is given by Equation 3.3.

\[ C_{T_{meta}}(H_1) = C_{AB} + \Delta C_{AB} + C_{B\phi_D} + C_{\phi_D C} + C_{Rd} \]  

(3.3)

Where \( C_{AB} \) is the communication cost between node A and node B, \( \Delta C_{AB} = 0 \), \( C_{B\phi_D} \) is the communication cost between node B and hypothesized node \( \phi_D \), \( C_{\phi_D C} \) is
the communication cost between hypothesized node $\phi_D$ and node $C$ and the overhead cost, which is the route discovery cost, $C_{Rd}$. $C_{Rd}$ is the overhead cost that node $B$ takes to discover the hypothesized node $\phi_D$.

To ensure that node $B$ can find another node when it runs the route discovery process, we need to compute the likelihood of success, $L_{Rd}$, and then divide the route discovery overhead cost by the $L_{Rd}$; and that is a way to normalize that cost, because we do not know that node $B$ is going to find another node. Therefore, the Equation 3.3 is enhanced as in Equation 3.4.

$$C_{T_{meta}}(H_1) = C_{AB} + \Delta C_{AB} + C_{B\phi_D} + C_{\phi_D C} + C_{Rd}/L_{Rd}$$

(3.4)

### 3.7.2 Second Hypothesis $H_2$: Controlled Motion

In Figure 3.11, a hypothesized node $\phi_B$ is moved between node $A$ and node $C$. Therefore, the cost change of the link between node $A$ and hypothesized node $\phi_B$, $\Delta C_{A\phi_B}$, is not equal to 0 because node $B$ moves. Without loss of generality, we assume that the communication cost between the hypothesized node $\phi_B$ and node $C$ is equal to 1. As a result, the Meta-Routing total cost of the second hypothesis $H_2$ is given by Equation 3.5.
\[ \Delta C_{A\phi} \neq 0 \]

Figure 3.11: Hypothesized path for controlled motion of a node.

\[ C_{T_{meta}}(H_2) = C_{A\phi B} + \Delta C_{A\phi B} + C_{\phi B C} + C_{Mov} \]  \hspace{1cm} (3.5)

Where \( C_{A\phi B} \) is the communication cost between node \( A \) and node \( \phi_B \), \( \Delta C_{A\phi B} \) is the cost change between node \( A \) and node \( \phi_B \), \( C_{\phi B C} \) is the communication cost between hypothesized node \( \phi_B \) and node \( C \), and the overhead cost, which is the movement cost, \( C_{Mov} \). \( C_{Mov} \) is the overhead cost that node \( B \) takes to move to the position of the hypothesized node \( \phi_B \).

We have to compute the likelihood of success, \( L_{Mov} \), when we control node \( B \) movement so that it will move in the right direction and not lose a connection with node \( A \). In fact, there are some likelihoods of success to guarantee link repair when we move node \( B \), so we have to consider the \( L_{Mov} \). Therefore, we divide overhead cost of movement by likelihood of success, \( L_{Mov} \), to normalize the cost. Consequently, Equation 3.5 is enhanced as in Equation 3.6.

\[ C_{T_{meta}}(H_2) = C_{A\phi B} + \Delta C_{A\phi B} + C_{\phi B C} + C_{Mov}/L_{Mov} \]  \hspace{1cm} (3.6)
In summary, after computing $C_{T_{meta}}(H_1)$ and $C_{T_{meta}}(H_2)$, Meta-Routing will choose the lowest total cost and decide whether to control the movement of a node to repair a link or discover a new node to maintain the network connectivity.

### 3.7.3 Meta-routing Hypothesis Generation

The novelty of Meta-Routing is in creating hypothesized graphs. Therefore, Meta-Routing is about hypothesizing new graphs and then applying the traditional routing protocols to the hypothesized graphs to choose the lowest path cost. Thus, Meta-Routing injects new hypothesized nodes to the graph to create different communication paths. The hypothesized node could represent discovering a route, increasing the power, tuning an antenna or moving a node as shown in Figure 3.12. Consequently, Meta-Routing can trigger any hypothesized option using all types of link maintenance for all networks.

![Figure 3.12: Meta-routing hypothesis generation graph.](image)

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3.8 Design the Meta-Routing Protocol

The first proposed research is the design of Meta-Routing protocol. The Meta-Routing combines routing protocol strategies such as proactive, reactive and hybrid, and link maintenance approaches. One of its features is the ability of node controlled motion for achieving network connectivity maintenance. We believe that higher network performance can be achieved from the combination of routing protocol and link repair rather than running the node discovery phase. Motivated by this expectation, we propose the idea of combining the node controlled motion-based link maintenance with the routing protocol to achieve more effective connectivity and improve the network performance. We intended to incorporate link maintenance into the routing protocol to achieve Meta-Routing as shown in Figure 3.13.

Figure 3.13: The block diagram of Meta-Routing protocol for mobile ad hoc network.
In a normal network situation, the Meta-Routing works and acts as a traditional routing protocol. Therefore, it infrequently applies a message routing protocol to the local network in order to transmit packet messages between nodes in the communication network. Meta-Routing computes the route repair and the route discovery cost functions and the likelihood of success for route repair and route discovery, for achieving robust network connectivity and minimizing the path overhead cost. The Meta-Routing protocol triggers the hypothesis generation process when a critical error occurs on the communication path during message transmission and computes the cost function. Meta-Routing runs the route repair algorithm or the route discovery algorithm to maintain the network connectivity. It decides the route discovery or the route repair algorithm based on the estimated total path cost produced by the cost function and the likelihood of success for route repair, $L_{Mov}$ and route discovery, $L_{Rd}$.

The Meta-Routing protocol will perform the route repair algorithm for link maintenance if the total path cost to repair a broken link is lower than the total path cost to discover a route, and the $L_{Mov}$ is higher than that of route discovery. Otherwise, Meta-routing performs the route discovery process. In summary, estimating the cost function and the likelihood of success are extremely essential to decide whether the route repair or the route discovery algorithm will be executed. Figure 3.14 shows the flowchart for the Meta-Routing protocol.
3.9 Summary

In this chapter, we have presented a new routing mechanism called Meta-Routing. Meta-Routing integrates the normal routing of message packets and the maintenance of physical links in a mobile network environment. Meta-Routing takes existing methods of computing communication path costs and augments them with the costs of over-
head and maintenance to develop a more comprehensive cost metric. Meta-Routing is applicable to the entire types of link maintenance mechanisms available, including controlled motion of nodes, transmit power adjustment, antenna pointing, and other forms of antenna tuning that varies the operating characteristics of nodes. Regardless of the array of maintenance options available, if the communication costs and likelihood of success can be quantified, the mechanism can be incorporated into the Meta-Routing paradigm. Normally, conventional routing protocols find paths in a graph. They trigger an automatic route discovery when there is no path to the destination. On the other side, Meta-Routing protocol augments the routing graph with hypothesized nodes to create different hypothesized paths. Afterwards, Meta-Routing computes the cost function and likelihood of success for each hypothesized path. Meta-Routing triggers the lowest path cost according to the computed cost function and likelihood of success of each path. Therefore, the Meta-Routing total path cost is the sum of minimum communication cost of links and the minimum overhead cost. The novelty of Meta-Routing is in creating hypothesized graphs. Consequently, Meta-Routing is about hypothesizing new graphs and then applying the traditional protocols to these hypothesized graphs to choose the lowest path cost.
Chapter 4

Meta-Routing Node Movement

In the recent past, numerous works studied the effects of mobility in *ad hoc* networks. Often, a device’s mobility has been regarded as having a negative impact that causes link failure, disconnections, and high network latency. Movement of nodes can potentially be used to improve performance of the network. Nowadays the concept of controlled node motion has emerged. The controlled node motion is intended as a new network dimension allowing to drive nodes to a favorable position in the field. It does this in order to achieve some common objectives and maintain network connectivity. In our dissertation, Meta-Routing relies on controlled node motion in order to increase the communication links quality and maximize the broken communication links. Meta-Routing performs controlled node motion and move nodes to proper coverage positions to reduce the total path cost by computing the cost function and likelihood of success of the path resulted from the movement. Therefore, Meta-Routing challenges to minimize the overhead cost, which effects the total path cost between communicating nodes.
4.1 Details of Movements in Meta-Routing

The combination of controlled node motion with wireless networks greatly expands the application space of both robots and distributed wireless sensor networks; such an extensive system can enable seamless integration between the digital and physical worlds. However, there are a number of issues in both robotic and wireless sensor network fields that need research, and their integration generates additional challenges. A mobile \textit{ad hoc} network is a self configuring network of mobile nodes connected by wireless links that generates an arbitrary topology. In fact, technical devices, such as mobile robots, can facilitate personal assistance. A mobile robot requires a sensing system in order to control the path of movement and the surrounding environment. The robot can be equipped with sensors for detecting distances and obstacles. The nodes are free to move randomly. Thus, the network’s wireless topology may be unpredictable and may change rapidly. Minimal configuration, rapid deployment and lack of a central governing authority make \textit{ad hoc} networks, suitable for emergency situations such as natural disasters, military conflicts, etc. [50]. MANETs are used in various applications with high volatility and node configuration. Varying robots’ characteristics and mobility has a significant impact on the performance of the routing protocols such as DSDV and AODV. The performance of any wireless protocol depends on the duration time of interconnections between any two nodes transmitting information packets. It also depends on the duration time of interconnections among nodes of a data path containing \( n \) number of nodes [50]. The nodes’ mobility affects the average number of connected paths, which in turn affects the routing protocol performance.
4.2 Advantages of Node Controlled Motion

The network elements of robotic sensor networks are strongly tied to the surrounding physical environment. The robotic nodes’ resource requirements change dynamically as the environment changes in space and time [52]. It is useful to adjust physically the configuration of the network nodes at run time to adjust to the external effects. Therefore, physical reconfiguration through controlled and coordinated nodes movement should improve the network performance. Traditional applications have considered node mobility as a source of an extra overhead for which the network must adapt, possibly at a loss of performance. Even when mobility has been considered useful for the network, control over mobility is assumed to stay outside the network [52]. The network protocols in those cases are affecting nodes mobility. The advantages of node controlled motion are summarized as follows:

4.2.1 Network Topology Adaptation

Controlled node Mobility provides a level of control on the network topology which is difficult to emulate using other mechanisms. This gives us the following advantages:

**Run Time Adaptation:** The evolution of the environment changes the sensor data generation and the resultant traffic patterns in the network over time. Adjusting protocol parameters such as coding rates or initiating new routes along the existing topology may not allow the network to meet the new traffic requirements. Physical mobility control of nodes is required, in these situations, to adapt to the run time dynamics of network topology changes as a result of environment changes [52].
**Robot Deployment:** Initial deployment becomes a difficult problem to solve. A priori knowledge of the external environment where the robotic network is being deployed is necessary. A priori knowledge is typically unavailable and can be learned over a period of time. Additionally, an optimal physical topology is difficult to create at the time of robot deployment [52]. However, controlled node motion can drive robots to favorable positions that help them maintain there connectivity.

### 4.2.2 Network Capacity Improvement

Controlled mobility leads to increased traffic capacity. Controlled mobility can achieve the capacity increase for arbitrary and finite network topologies, which effect, the following:

**Channel Capacity:** The data carrying capacity of a wireless network which increases when node control mobility is used. With controlled mobility, data capacity increases even with bounded delay [52].

**Energy Capacity:** The energy capacity of the network can be improved in certain situations where mobile elements can be used to aggregate data from several nodes and hence carry a sufficiently large amount of data to offset the energy cost of physically moving the node [52].

### 4.3 Movement in Meta-Routing

One important goal of Meta-Routing is to repair failed or broken links in an adverse environment. In fact, there is a variety of locations that will satisfy the criteria of a good quality link. Robots do not necessarily know where they are, nor know when...
they last had a strong link signal. Therefore, Robots could just go back to a known location, however, it is problematic, because this requires having an accurate location. Robots need to know exactly where that place was and where they are now, which could mean that there may have been an error as they moved along. Therefore, moving robots back is harder than it sounds because of air propagation and incidents where robots do not know where they were, and they do not know where they are now. Robots tried to move back to a wrong position from another wrong position and may be getting further away from the correct position. In fact, there is a work from Gini [53] that demonstrates that the random walk is often better than moving back due to the uncertainty of where back is, and so moving in the reverse direction is one option, but it is sometimes dangerous.

![Figure 4.1: Different movement modes.](image)

Meta-Routing uses movement back through a free locomotion when the robots signal strength goes down, and the robots start to lose communication signal. In typical scenarios, the robot would take the shortest straight line path to reach the
destination. However, this leads to unsuitable signal strength gradient estimates because the sampling locations cannot be co-linear. Therefore, rather than travel in straight line trajectories, the robot introduces gentle oscillations to its path (see Figure 4.1). This makes the gradient estimate more powerful than traveling in a straight line at the cost of greater distance traveled.

4.4 Meta-Routing based on Link Maintenance

Meta-routing protocol can be used for variety of wireless communication link maintenance options such as discovering a new route, tuning an antenna or controlling node movement. Despite of the array of link maintenance options available for wireless communication, if the communication costs and likelihood of success can be quantified, the mechanism can be incorporated into the Meta-Routing mechanism. Traditionally, conventional routing protocols generate an automatic route discovery when there is no path to the destination. Meta-Routing protocol augments hypothesized nodes into the routing graph, and it triggers the lowest cost path in the augmented graph by computing the cost function and likelihood of success for each path.

In this dissertation, we will focus on controlled motion of mobile nodes in experimental fields. Therefore, Meta-routing protocol uses controlled node motion as one option to achieve link maintenance to maintain network connectivity while the network performs assigned tasks in a harsh environment. The controlled motion of the mobile robots is achieved by driving the robots to favorable link positions where they can maintain their connectivity. Therefore, this will lead us to develop a routing control mechanism to control the node movement. This control mechanism requires the knowledge about the direction of where the node should move while it is performs
it task. One way to achieve this is to use gradient descent method. The gradient method is used to determine the direction of movement of the mobile node in the field towards the strongest RF signal strength to maintain the network connectivity (detailed in the next chapters).

To reduce the total path cost estimate, the node controlled motion algorithm should utilize the knowledge that is learned from the RF environment recognition based on the RF signal strength measurements. Therefore, this will guide us to explore the relationship between different known RF obstacle types and their impact on RF signal strength measurements for the overall goal, which is minimizing the the Meta-Routing total path cost. The information learned from the RF environment could be employed as the features for identifying the RF obstacle type, size and the resulting RF environment. Once the robot identifies the RF environment type and size, the node controlled motion algorithm will drive the robot towards a favorable position predicted by the RF environment recognition method. Then, by applying the gradient method, which is used to extract the multi-dimensional gradient of the RF signals, a decision is made on the direction and control of the robots’ motion (detailed in the next chapter). The main steps of the node controlled motion algorithm can be summarized as

1. Move robots to a favorable position in the field where they can gain strong RF signal strength to maintain their network connectivity.

2. Apply the gradient descent method to make a decision on the direction of the robot motion in the experimental field.

3. Utilize the knowledge learned from RF environment recognition method, to identify the RF obstacle type and size.
As mentioned in this chapter, robots will move back through a free locomotion when the signal strength goes below some threshold and a communication error occurs. The details of gradient method that used to drive robots to the strongest signal strength are discussed in details, in chapter five. The RF environment recognition method (RF mapping) that used to identify different RF obstacle types and sizes is detailed in chapters six and seven. Finally, chapter eight connects node movement, RF mapping, and gradient descent method into a controlled node motion algorithm to achieve Meta-Routing protocol for the overall goal minimizing the total path cost through minimizing the overhead cost to maintain this path.

4.5 Summary

In this chapter, we have presented the effects of node mobility in the robotic networks. The mobility of robots in the network has been regarded as a negative impact that causes link failure and poor network connectivity. However, mobility of robots can be used to improve the network performance. With the growth of robotic networks, the node motion control emerges, which drives robots to strong positions in the field to maintain connectivity. The mobile nodes in ad hoc are free to move through a free locomotion and randomly. Thus, the network wireless topology may be unpredictable and may change rapidly. As a result, varying nodes’ mobility has a significant impact on the performance of the routing protocol. The nodes’ mobility affects the average number of connected paths, which is in turn affect the routing protocol performance. In Meta-Routing, we chose the freeway movement back through a free locomotion when the robots’ signal strength goes down, and the robots start to lose communication signal. The robots introduce gentle oscillation to their paths.
to compute the gradient rather than moving in straight lines. Meta-Routing relies on node controlled movement in order to minimize the total path cost, increase the communication links quality and maximize the broken communication links. Meta-Routing achieves lowest total path cost based on the computation of the cost function and likelihood of success of a path in the augmented hypothesized graph.
Chapter 5

Gradient Descent for Intelligent Controlled Motion

An important part of Meta-Routing is the ability to move in an intelligent fashion that actually maintains the communication links. No assumption is made, initially, on the locations of RF obstacles or RF 'dead zones.' Planned motions must be inferred from RF signal strength measurements.

5.1 Gradient Descent

The gradient of a scalar field is a vector field that points in the direction of the greatest rate of increase of the scalar field, and whose magnitude is that rate of increase [54]. Simply, the variation in space of any quantity can be represented graphically by a slope [54]. The gradient represents the steepness and direction of that slope. Gradient descent is popular for most extensive optimization problems because it is easy to implement, and each iteration is reduced. Its major drawback is that it can take a long time to converge [55]. In the other hand, hill climbing is an approach that
analogous to steepest descent, which used for large discrete problems, where the space of states is involving combinations [55]. Even though the name of the approach is hill climbing, but it can be applied to either minimization or maximization problems. Hill climbing attempts to maximize or minimize a target function \( f(x) \), where \( x \) is a vector of continuous and/or discrete values. At each iteration, hill climbing will customize a single element in \( x \) and determine whether the change improves the value of \( f(x) \) (Note that this differs from gradient descent methods, which adjust all of the values in \( x \) at each iteration according to the gradient of the hill) [56].

5.2 Online Computation of the RF Signal Gradient

In this work, a simple gradient approach is used. Therefore, the gradient descent is used to reduce the error on the signal strength because the robots estimate the signal strength gradient while they are moving. The gradient descent method helps to achieve Meta-Routing protocol. The gradient method is applied in a way that helps in minimizing the total path cost function, and increasing the likelihood of success of controlling the direction and the robots’ motion.

In the gradient estimation experiments, a simple scenario was started where two mobile robots transmitted and received RF signals, respectively. The sensor measures RF signal strength at the receiver location. The two robots were separated by distance \( d \) along the \( x \)-direction as shown in Figure 6.1 (b). The signal strength \( S_l^{(j)}(k) \) at time \( k \) for the \( l \)th trajectory in the presence of RF obstacle type \( j \) can be measured according to Equation 6.2 as defined in section 6.2.

The multi-dimensional gradient of the RF signal strength measurements is estimated to determine the direction of the signal strength, which is used to control
robots’ movements to maintain the network connectivity. The gradient process has a significant impact on the performance of the Meta-Routing protocol. Gradient method allows the robot to move in the direction of the strong RF signal strength; consequently, it affects the cost function of computing the total lowest path. On the same time, the likelihood of success, $L_{Mov}$, to move robots in the direction of communication coverage, becomes high. Therefore, gradient descent method affects the overhead cost, $C_{Mov}$, which is a part of the total path cost of Meta-Routing protocol. Thus, robots will move to strong signal positions for maintaining communication instead of hitting random directions to maintain their connectivity. In summary, gradient method has a significant impact on $C_{Mov}$ and $L_{Mov}$, which affects the overhead cost, and eventually affects the total path cost of Meta-Routing.
5.3 Gradient Descent Formulation

As the robots move in the RF environment with line of sight between each other, the signal strength $S_l^{(j)}(k)$ remains stable. However, if a conductive RF obstacle appears in the experiment field, the $S_l^{(j)}(k)$ is subject to change as the robots move around the RF obstacle.

In this scenario, the RF signal strength measurements, $S_l^{(j)}(k)$, resulted from the two moving robots are measured and recorded for each $(x_k^{(i)}, y_k^{(i)})$, $i = 1, 2$ at time $k$. We then extract the gradient vector of the RF signal strength corresponding to known trajectories. The gradient vector of the signal strength at time $k$ for the $l$th trajectory is defined as

$$
\nabla S_l^{(j)}(k) = \begin{bmatrix}
\frac{\partial S_l^{(j)}(k)}{\partial x_k^{(1)}} & \frac{\partial S_l^{(j)}(k)}{\partial y_k^{(1)}} & \frac{\partial S_l^{(j)}(k)}{\partial x_k^{(2)}} & \frac{\partial S_l^{(j)}(k)}{\partial y_k^{(2)}}
\end{bmatrix}^T
$$

We compute the signal strength gradient using the trajectories as shown in Figure 5.1 where we assume robot 1 and robot 2 are located at positions $(x_k^{(1)}, y_k^{(1)})$ and $(x_k^{(2)}, y_k^{(2)})$ at time $k$, respectively. If only one robot moves at a time and the other stays still, the gradient can be calculated using the following method. Figure 5.1 shows the step wise trajectories of the two robots for calculating the gradient vector. During time $k$ and $k + 1$, robot 1 moves along trajectory segment 1, so $x_{k+1}^{(1)} = x_k^{(1)} + \Delta x$, $y_{k+1}^{(1)} = y_k^{(1)}$, $x_{k+1}^{(2)} = x_k^{(2)}$, $y_{k+1}^{(2)} = y_k^{(2)}$, and the gradient element $\frac{\partial S_l^{(j)}(k)}{\partial x_k^{(1)}}$ is calculated as

$$
\frac{\partial S_l^{(j)}(k)}{\partial x_k^{(1)}} \approx \frac{\Delta S_l^{(j)}(k)}{\Delta x_k^{(1)}} = \frac{S_l^{(j)}(k+1) - S_l^{(j)}(k)}{x_{k+1}^{(1)} - x_k^{(1)}} = \frac{S_l^{(j)}(k+1) - S_l^{(j)}(k)}{\Delta x}
$$
During time $k + 1$ and $k + 2$, robot 2 moves along trajectory segment 2, so $x_{k+2}^{(1)} = x_{k+1}^{(1)} + \Delta x$, $y_{k+2}^{(1)} = y_{k+1}^{(1)}$, $x_{k+2}^{(2)} = x_{k+1}^{(2)} + \Delta x$, $y_{k+2}^{(2)} = y_{k+1}^{(2)}$, and the gradient element is calculated as

$$\frac{\partial S_l^{(j)}(k)}{\partial x_k^{(2)}} \approx \frac{\Delta S_l^{(j)}(k + 1)}{\Delta x_k^{(2)}} = \frac{S_l^{(j)}(k + 2) - S_l^{(j)}(k + 1)}{x_{k+2}^{(2)} - x_{k+1}^{(2)}} = \frac{S_l^{(j)}(k + 2) - S_l^{(j)}(k + 1)}{\Delta x}$$ (5.3)

During time $k + 2$ and $k + 3$, robot 1 moves along trajectory segment 3, so $x_{k+3}^{(1)} = x_{k+2}^{(1)} + \Delta y$, $x_{k+3}^{(2)} = x_{k+2}^{(2)} + \Delta y$, $y_{k+3}^{(1)} = y_{k+2}^{(1)} + \Delta y$, $y_{k+3}^{(2)} = y_{k+2}^{(2)} + \Delta y$, and the gradient element $\frac{\partial S_l^{(j)}(k)}{\partial y_k^{(1)}}$ is calculated as

$$\frac{\partial S_l^{(j)}(k)}{\partial y_k^{(1)}} \approx \frac{\Delta S_l^{(j)}(k + 1)}{\Delta y_{k+2}^{(1)}} = \frac{S_l^{(j)}(k + 3) - S_l^{(j)}(k + 2)}{y_{k+3}^{(1)} - y_{k+2}^{(1)}} = \frac{S_l^{(j)}(k + 3) - S_l^{(j)}(k + 2)}{\Delta y}$$ (5.4)

During time $k + 3$ and $k + 4$, robot 2 moves along trajectory segment 4, so $x_{k+4}^{(1)} = x_{k+3}^{(1)} + \Delta y$, $x_{k+4}^{(2)} = x_{k+3}^{(2)} + \Delta y$, $y_{k+4}^{(1)} = y_{k+3}^{(1)} + \Delta y$, $y_{k+4}^{(2)} = y_{k+3}^{(2)} + \Delta y$, and the gradient element $\frac{\partial S_l^{(j)}(k)}{\partial y_k^{(2)}}$ is calculated as

$$\frac{\partial S_l^{(j)}(k)}{\partial y_k^{(2)}} \approx \frac{\Delta S_l^{(j)}(k + 1)}{\Delta y_{k+3}^{(2)}} = \frac{S_l^{(j)}(k + 4) - S_l^{(j)}(k + 3)}{y_{k+4}^{(2)} - y_{k+3}^{(2)}} = \frac{S_l^{(j)}(k + 4) - S_l^{(j)}(k + 3)}{\Delta y}$$ (5.5)

### 5.4 Various Gradient Scenarios

As can be seen in Figure 5.2, when the two robots hold the line of sight between each other, their receiving signal strength is strong enough for communication, which
Figure 5.2: Two robots move in the experiment field, with one trapped in the cage.

is indicated by yellow boxes, and their gradient directions point towards each to the
direction of a strong RF signal, which is indicated by arrows. However, when one of
the robots is trapped inside the cage, the signal strength magnitude become small and
the gradient is less effective, which is indicated by green boxes and arrows. The small
movement of the robot which is the outside of the cage do not result in a noticeable
increase of the signal strength. However, small movement of the trapped robot results
in a significant increase of the signal strength once it leaves the cage as can be noticed
in Figure 5.2. In Figure 5.3, the robot moves extremely close to the cage in a step
wise trajectory while the other robot stands still on the left side of the cage. In the
presence of the line of sight between the two robots the gradient points in the direction
of the strongest signal strength of the other robot. However, the gradient is subject
to scatter when the RF obstacle blocks the two robots.

Figure 5.4 shows the signal strength gradient direction, and the signal strength
magnitude for the scenario when one robot is close to one corner of the cage while the
other one moves in a stepwise trajectory around the cage. Similarly, as the previous
Figure 5.3: The left robot stays still and the right robot moves in stepwise trajectory. The example the gradient points toward the other robot when there is a line of sight, and it is subject to scatter as the robots are separated by RF obstacle. The impression from Figure 5.3 and Figure 5.4 shows that gradient directions can lead the robots to the favorable positions to maintain their connectivity. Consequently, the total path cost of Meta-routing protocol will be effected positively as the communication cost function goes down and the likelihood of success to repair a link goes high.

Figure 5.5 shows a scenario where two robots move in parallel taking turns along different trajectories around the cage. The robot at the left side moves two segments in a step wise trajectory, one segment in $x$-direction and the other one in $y$-direction while the other robot stands still. Then, the robot who was standing still moves one segment in $y$-direction along a straight line trajectory and this process repeated along each trajectory in the experiment field. In this experiment, the gradient is calculated for the right robot according to Equations 5.2 and 5.4. The gradient directions and magnitudes of the signal strength are shown at each robot position. This confirms that the gradients are helpful in finding favorable locations to maintain RF links between...
robots. Consequently, this will help the Meta-Routing protocol to reduce the total overhead cost results from the node movement and increases the likelihood of success to repair a broken link while achieving assigned tasks.

5.5 Gradient Algorithm Experimental Results

The gradient algorithm works on an experimental field area as shown in Figure 5.6. The area or the configuration space of the robots is divided into grids as explained in section 6.2. As shown in Figure 5.6, two robots move in the area defined by the yellow grids, measure the signal strength, and compute the gradient for any two points in the field for both moving robots. A database was established, which contains the robots positions, RF signal strength measurements, and gradient computation results for each time $k$. The flowchart of the gradient algorithm is shown in Figure 5.7. The algorithm starts by picking the $x_0^{(1)}, y_0^{(1)}$ position of robot 1 and the $x_0^{(2)}, y_0^{(2)}$ position of robot 2. The algorithm seeks its database for the robots position coordinates. If the
robots positions are found in the database, then the algorithm checks the measured signal strength between the two positions of the robots. If signal strength power is above some threshold, then the two robots must move according to their normal velocity. Otherwise, each robot computes its gradient. The robot with higher gradient should proceed first in the direction of its gradient direction.
Figure 5.6: Configuration space of Two robots.

Figure 5.7: Gradient algorithm flowchart.
The gradient algorithm is used for various scenarios, to verify its performance and success in driving robots towards favorable positions in the experimental field. In the first scenario, Figure 5.8 shows two robots’ trajectories, where robot 1 starts at $x_0^{(1)} = 20, y_0^{(1)} = 11$, and robot 2 starts at $x_0^{(2)} = 38, y_0^{(2)} = 14$ both at time $k = 0$ in the experiment field. The gradient algorithm drives the robots through trajectories that avoid the RF obstacle shadow and maintain their connectivity. In the second scenario, Figure 5.9 shows at time $k = 0$ two trajectories, where robot 1 starts at $(x_0^{(1)} = 17, y_0^{(1)} = 15)$, at the entrance of the cage obstacle and robot 2 starts at $(x_0^{(2)} = 38, y_0^{(2)} = 15)$, on the right side of the obstacle. Both trajectories show that the gradient algorithm can assist the robots to approach each other to avoid the effect of the RF obstacle and maintain the robots’ connectivity. Consequently, this will help minimize the Meta-Routing overhead cost, $C_{Mov}$, and maximize the $L_{Mov}$ by controlling the direction of robots’ movement in the robots configuration space.

Figure 5.8: Robots start at $x_0^{(1)} = 20, y_0^{(1)} = 11$ and $x_0^{(2)} = 38, y_0^{(2)} = 14$ at time $k=0$. 

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Figure 5.9: Robots start at $x_0(1) = 17, y_0(1) = 15$ and $x_0(2) = 38, y_0(2) = 15$ at time $k=0$.

Figure 5.10: Robots start at $x_0^{(1)} = 22, y_0^{(1)} = 17$ and $x_0^{(2)} = 40, y_0^{(2)} = 23$ at time $k=0$.

The scenario in Figure 5.10 shows two robots’ trajectories where robot 1 starts at $x_0^{(1)} = 22, y_0^{(1)} = 17$ and robot 2 starts at $x_0^{(2)} = 40, y_0^{(2)} = 23$ at time $k = 0$. This experiment illustrates how the algorithm performs when robot 1 faces the RF obstacle and robot 2 moves at far right most of RF obstacle. The trajectories in Figure 5.10
and Figure 5.11 show that the gradient algorithm has the ability to drive the robots properly and maintain their connectivity.

Figure 5.11: Robots start at $x_0^{(1)} = 19, y_0^{(1)} = 16$ and $x_0^{(2)} = 40, y_0^{(2)} = 20$ at time $k=0$.

5.6 Gradient Algorithm Scenarios Using Network Simulator

In this simulation scenario, an area of the $2 \times 2 \ m^2$ was chosen. The freeway motion model of the nodes was defined as a movement model for our experiments. The simulation uses 2 nodes. The maximum speed was set to $2.2 \ cm/s$ and minimum speed is set to $1.5 \ cm/s$. The traffic generated was the FTP (File Transfer Protocol) on the TCP (Transmission Control protocol) agent. The MAC layer was set to MAC/802.11. The AODV protocol was simulated with a source-destination pair. Nodes generate packets at different times. After running the simulation, the network animator (NAM) was used to show the data transfer between nodes. The trace files were analyzed for moving nodes. Using the trace file, the node movement time was calculated.
Table 5.1: Simulation Environment.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel</td>
<td>WirelessChannel</td>
</tr>
<tr>
<td>Topology</td>
<td>$2 \times 2$</td>
</tr>
<tr>
<td>Nodes</td>
<td>2</td>
</tr>
<tr>
<td>Mac layer</td>
<td>Mac/802 - 11</td>
</tr>
<tr>
<td>Routing protocol</td>
<td>AODV</td>
</tr>
<tr>
<td>Traffic Type</td>
<td>FTP</td>
</tr>
</tbody>
</table>

The scenario in Figure 5.12 (a) shows two mobile nodes. One node moves at a speed of 2.2 $cm/s$ and the other node moves at a speed of 1.5 $cm/s$. The nodes are moving and transmitting data packets. The nodes and simulation environment parameters are shown in table 5.1. As the two nodes move, they approach an RF obstacle. The RF obstacle affects the communication signal between the mobile nodes. Therefore, the $S/N$ goes down below the communication threshold. As a result, the nodes can not communicate anymore as shown in Figure 5.12 (b).

![Figure 5.12: Two robots in (a) are transmitting data packets and in (b) are losing communication.](image)

Figure 5.12: Two robots in (a) are transmitting data packets and in (b) are losing communication.
In Figure 5.13 (a), the mobile trapped node has started to move back through a free locomotion into a position where it can gain a strong signal strength to regain communication with the other node. According to the gradient algorithm both nodes start to calculate the gradient to decide the strong signal direction when the signal strength goes below some threshold. The node with the higher gradient would move first in the direction of its gradient as shown in Figure 5.13(a). If the signal strength is above the threshold, the nodes would regain the communication signal and would start transmitting information packet again; consequently, both nodes would move in the direction of their normal velocity as shown in Figure 5.13 (b).

![Figure 5.13](image)

(a) (b)

Figure 5.13: The robots in (a) are moving back and in (b) are regaining communication.

We run multiple scenarios where the trapped node moves at lower speed than the rightmost node and when the two nodes move at the same speed. The conclusion is that the node movement velocity is scaled as the nodes calculate the gradient to determine the direction of motion to maintain the network connectivity.
5.7 Gradient and Node Movement based on RF Mapping and Classification

As discussed earlier in this chapter and the previous chapters, the robot controlled movement can drive the robots to favorable positions in the field. Once the robots reach strong signal strength positions, they can regain the communication with the robotic network. The robot control mechanism performs this in order to accomplish tasks assigned to the robots and maintain their network connectivity. An appropriate robot controlled motion algorithm can manage the network faster than discovering a new node when there is a network failure in some cases. In relation to robot controlled motion, the gradient descent method is required for connectivity maintenance of the robotic network. The gradient descent algorithm will determine the trends of the strong signal strength for robots; eventually, the robots will move in the direction that support their connectivity. The proposed Meta-Routing relies on the node controlled movement and the gradient algorithm by reducing the total path cost function and increasing the likelihood of success to repair links in order to increase the communication links quality and maximize the broken communication links.

The robots can map the RF obstacles in a harsh RF environment a priori by knowing the gradient magnitude and direction. Therefore, if a robot starts to move into the RF obstacle shadow, can the robot realize that it is moving into a temporary shadow? In other words, can the robot move into the RF shadow easily or will the RF shadow go deeper? As a result, the robot will totally lose the connection with the other robots. Knowing the depth of the RF shadow, it is possible for estimating and reducing the overhead cost; consequently, increasing the likelihood of success of
moving robots a way from that shadow and then this will lead to reduce the total path cost of Meta-Routing protocol.

The RF shadow recognition and classification concerns mapping of RF obstacles in RF environment for estimating the depth of an individual RF shadow to reduce the total path cost of Meta-Routing protocol. The estimation process will lead to minimizing the routing overhead cost results from moving deeply into the RF shadow. Why do we need RF mapping? Another vital question arises. In fact, we can achieve Meta-Routing using node movement and applying gradient descent, but still we need to find the best cost estimate either for repairing a broken link or discovering a new link or node. When two robots are moving in an unknown environment and they start losing the communication signal, could we know what are the effects of the environment (RF obstacle) on the communication signal between robots? Also, could we estimate the depth of the RF shadow affecting the communication? In addition, could we recognize and classify the RF environment so that we can put a best cost estimate of repair specifically on this link, but not the likelihood of average links like hybrid protocols did? The answer to the aforementioned questions and other questions will be presented in the next chapters, where we are going to detail the RF environment recognition method. The RF environment recognition method, the robot controlled motion algorithm and the gradient method will help reduce the overall path cost estimate, compared to the route discovery phase for achieving Meta-Routing.

5.8 Summary

In this chapter, various gradient estimation experiments are presented. The multi-dimensional gradient of the RF signal strength measurements is estimated to deter-
mine the direction of the signal strength, which is used to control robots’ movements to maintain the network connectivity. The gradient process has a significant impact on the performance of the Meta-Routing protocol. The gradient method allows the robot to move in the direction of the strong RF signal strength; eventually, it affects the cost function of computing the total lowest path. Simultaneously, the likelihood of success, $L_{Mov}$, to move robots in the direction of communication coverage, becomes high. Therefore, the gradient descent method affects the overhead cost, $C_{Mov}$, which is a dominant part of the total path cost of the Meta-Routing protocol in our specific scenarios. In summary, the gradient method has a significant impact on $C_{Mov}$ and $L_{Mov}$, which affects the overhead cost and would eventually affect the total path cost of the Meta-routing protocol. Different RF signal strength gradient scenarios were tested and examined. The overall results for all experiments showed that the gradient method has the potential to support robots moving toward the direction of the strong signal strength for their connectivity maintenance. The gradient results can help the robots map the RF obstacles and determine the direction of robots’ movements.
Chapter 6

RF Mapping for Controlled Motion and Estimate Refinement

In this chapter, RF mapping or RF electromagnetic field (EMF) environment recognition, is discussed in detail. RF Mapping endeavors to measure the effects of RF obstacles in the physical environment that may attenuate signals as a transmitter/receiver pair moves through the environment. By mapping these attenuation patterns, nodes can avoid known "RF shadows" and other anomalies due to certain transmitter/receiver configurations. More importantly, using RF obstacle "primitives" extracted from the RF attenuation maps, RF shadows can be inferred for other transmitter/receiver configurations. This information can be used both to control motion for link maintenance and to make better estimates of hypothesized nodes. A small initial set of primitives is explored here for proof-of-concept and the recognition of primitives from partial data is explained in chapter 7.
6.1 RF Environment Recognition

As discussed in chapter one, maintaining connectivity optimizes the performance metrics in networks. Therefore, RF mapping or RF environment recognition is a way to optimize the performance metrics in networks. RF mapping aims to improve the cost estimation of communication path between robots. Therefore, RF mapping attempts to reduce the overhead cost, $C_{Mov}$, which affects the total path cost, and increase the the likelihood of success, $L_{Mov}$, to move robots in the direction of strong communication path. RF mapping focuses on how to map RF environment regions using radios as a sensor to perform the gradient descent on the error to minimize the error signal. Consequently, RF environment recognition aims to recognize and classify the RF environment type where the robots are, and provide the knowledge to the node controlled motion algorithm, which controls the robot movement based on the RF recognition method and the gradient results. The RF environment recognition is based on RF signal strength measurements along the robots trajectories.

6.1.1 RF Mapping versus Physical Mapping

Currently it is possible for a team of robots to map the physical area. They can travel through the physical environment using sonar, laser range finders or other technologies. Each sensor works independently to produce a composite map of the area. Physical objects reflect radiation (active radiation in the case of light detection and range (LIDAR), sonar, Infrared (IR), passive radiation in the case of vision) to yield range. In physical mapping, the configuration space of the obstacle consists of the $(x, y)$ locations that the robot can not visit while exploring the environment.
RF Mapping is different from physical mapping. Physical mapping clearly shows where obstacles in the mapped environment are located, while RF mapping shows the effects those RF obstacles have on RF signals. In RF mapping, the sensor measurements require two agents (transmitter and receiver) to transfer and receive the RF signal. These sensor measurements are not uniquely or directly tied to physical objects, but they are affected by multi-path, fading or interference. The configuration space of the RF obstacle consists of \((x_1, y_1, x_2, y_2)\) coordinates of a 2 Degree of Freedom (DoF) transmitter and a 2-DoF receiver if an Omni-directional antenna is used. Thus, with this scenario a four dimensional configuration space is formed, which makes RF mapping more difficult compared to that of physical mapping. In our work, we simplified the 4-DoF configuration space to a 2-DoF configuration space for visualization. We assumed constant sized types of the RF obstacles, a fixed distance between the transmitter and receiver pair as well as fixed orientation, see Figure 6.1.

### 6.2 Formulation for RF Environment Recognition

The RF environment recognition method is based on RF signal strength measurements along the robot trajectory. The method aims to identify and classify the RF environment shadow type along the robots' paths. After that it provides the knowledge to the robot controlled motion algorithm. The HMM results based on the RF environment recognition method informs moving robots whether they are under the effects of RF obstacle shadow or not. Afterwards, the robot controlled motion algorithm based on the HMM results decides the required robot movement mechanism that helps to recover from the RF obstacle shadow and maintains the robots' connectivity. The robot controlled motion algorithm has to choose whether moving the
robots forward in the same trajectories under the RF environment effects or moving them back, through a free locomotion to favorable positions. The controlled motion algorithm decides this depending on the knowledge of the RF obstacle size and type gained from HMMs results. The RF environment recognition method based on HMM and the gradient results would reduce the overhead path cost results from robots’ movements, and increase the likelihood of success of maintaining connectivity of broken links. Consequently, the performance of the robot controlled motion algorithm is improved and the Meta-routing protocol would be achieved with higher efficiency.

Figure 6.1: (a) Experimental scenario with two robots moving on different sides of a wall, and (b) the 2-D space divided by grids in numerical experiments.
6.2.1 RF Environment Modeling

In the RF recognition application scenario, we use two mobile nodes to transmit and receive RF signals at 2.4 GHz, respectively. The "sensor measurement" is the RF signal strength at the current location of the receiver, which may be affected by multi-path, fading and interference [46]. The robots are positioned in the 2-D Cartesian coordinates \((x_k, y_k)\) at time \(k\). The 2-D space for the RF environment is divided into grids. The grid width is \(\Delta_x = L_x / M\) in \(x\)-direction and \(\Delta_y = L_y / N\) in \(y\)-direction. Here, \(L_x\) and \(L_y\) are the length and width of the space, and \(M\) and \(N\) are the number of segments in \(x\)-direction and \(y\)-direction as in Figure 6.1 (b). In our numerical experiments, we assume the robots move in this 2-D space along the following trajectories to collect RF signal strength measurements. The \(l\)th trajectory is given by

\[
x_{k,l}^{(i)} = x_{0,l}^{(i)}, \quad y_{k,l}^{(i)} = y_{0,l}^{(i)} + k\Delta_y, \quad k = 1, 2, \ldots, N, \tag{6.1}
\]

where \(l\) is the trajectory index, \(i \in \{1, 2\}\) is the robot index, \((x_{0,l}^{(i)}, y_{0,l}^{(i)})\) denotes the initial location of the \(i\)th robot at time 0. Equation 6.1 describes the \(i\)th robot’s movement which begins at \((x_{0,l}^{(i)}, y_{0,l}^{(i)})\) and then moves along \(y\)-direction with a step size of \(\Delta_y\) for each time step. Furthermore, for the 1st robot, we assume \(x_{0,l}^{(1)} = l\Delta_x\), \(y_{0,l}^{(1)} = 0\) for the \(l\)th trajectory and for the 2nd robot, we assume \(x_{0}^{(2)} = x_{0}^{(1)} + d\) and \(y_{0}^{(2)} = y_{0}^{(1)}\), which means these two robots are separated by a fixed distance \(d\) in \(x\)-direction but they are with the same coordinate in \(y\)-direction. This experiment scenario with two robots is demonstrated in Figure 6.1(a). The sensor measurements at time \(k\) for the \(l\)th trajectory in the presence of RF obstacle type \(j\), which is the received RF signal strength at the receiver location, is denoted as

\[
S_l^{(j)}(k) = f(x_{0,l}^{(1)}, y_{0,l}^{(1)}, x_{k}^{(1)}, y_{k}^{(1)}, x_{0,l}^{(2)}, y_{0,l}^{(2)}, x_{k,l}^{(2)}, y_{k,l}^{(2)}, \phi_j), \tag{6.2}
\]
which is a function of the initial robot positions \((x_{0,i}, y_{0,i})\), robots positions \((x_k, y_k)\) at time \(k\) and the RF obstacle characteristics \(\phi_j\). Here the index of the trajectory \(l = 1, ..., L^{(j)}\) for each \(j\), where \(L^{(j)}\) is the total number of the trajectories with the presence of type \(j\) RF obstacle. In equation 6.2, \(j \in \{1, 2, 3\}\) denotes the obstacle type and \(\phi_j = \{(x_c^{(j)}, y_c^{(j)}), \theta^{(j)}\}\) denotes the RF obstacle characteristic set, which contains the central position of the RF obstacle \((x_c^{(j)}, y_c^{(j)})\) and the shape parameters of the RF obstacle \(\theta^{(j)}\). For example, the wall obstacle has the parameters of central coordination \((L_x/2, L_y/2)\), and the shape parameters \(\theta^{(j)}\) contains its width, length and height information. The signal strength measurements in the experiment field with the presence of three RF obstacle types are demonstrated in the following sections.

### 6.2.2 RF Signal Strength Measurements

The signal strength measurements in the experiment field with the presence of three RF obstacle types are demonstrated. In addition, we presented the measurement sequence obtained from different trajectories. By investigating how the signal strength changes at different locations, it is possible to recognize and classify the RF signatures of certain RF obstacle types. For the simulation experiments, we used Computer Simulation Technology (CST), which is a professional tool for the 3-D Electro Magnetic simulation of high frequency components [57]. CST microwave studio enables quick and accurate analysis of high frequency devices such as antennas, filters, planar and multi-layer structures [57]. In our simulation, we used a 60 mm \(\times\) 60 mm patch antenna to send and receive the communication signal and made the interference source out of pure electric conducting material as shown in Figure 6.1(a).
6.2.2.1 Wall Obstacle

In wall experiments, we use three different wall sizes, which are $7 \text{ cm} \times 30 \text{ cm} \times 30 \text{ cm}$, $10 \text{ cm} \times 30 \text{ cm} \times 30 \text{ cm}$, and $15 \text{ cm} \times 30 \text{ cm} \times 30 \text{ cm}$. The RF signal strength measurements of the experiment field with a wall obstacle of the size $10 \text{ cm} \times 30 \text{ cm} \times 30 \text{ cm}$ are shown in Figure 6.2. The signal strength becomes extremely low when the transmitter is extremely close to the edge of the RF obstacle at one side, and the receiver is located one meter away from the other side, or vice versa. As the transmitter or receiver moves away from the RF obstacle, the signal strength becomes significantly stronger as shown in Figure 6.2. Figure 6.3 shows the top-down view of Figure 6.2 where the dark red spots represent the four negative spikes of Figure 6.2.

Figure 6.2: RF signal strength measurements in the experiment field with a wall obstacle.
Figure 6.4 shows different signal shapes at different distances from the RF obstacle at the receiver position. The signal shapes reflect the RF obstacle effects on the RF communication signal between the robots when they move around the RF obstacle.

Figure 6.3: Top down view of Figure 6.2.

Figure 6.4: RF signal strength measurement sequences corresponding to different trajectories for the wall obstacle.
In summary, Figure 6.2, Figure 6.3 and Figure 6.4 demonstrate the impact of the RF wall obstacle on RF signals. As the transmitter and receiver move along a known trajectory at each side of the RF obstacle, the signal strength measurement sequences are shown to hold sufficient information to allow the recognition and classification of the RF obstacle shadow. Furthermore, the RF obstacle shadow on the RF signal strength measurements produces different signal features. Consequently, the signal shapes and features would help in estimating the type and the size of the RF obstacle. As a result, a reduced overhead cost and an increased likelihood of success are achieved to maintain and repair broken links for the overall goal of the Meta-Routing protocol achievement.

Figure 6.5: RF signal strength measurements in the experiment field with a cage obstacle.
6.2.2.2 Cage Obstacle

The cage obstacle shown in Figure 6.5 is a Faraday cage, which is made of pure electric conducting material. The cage size is $30 \text{ cm} \times 30 \text{ cm} \times 30 \text{ cm}$. The signal strength decreases and becomes extremely weak when one of the antennas is located inside the cage as shown in Figure 6.5. The signal strength oscillates when the transmitter or the receiver approaches the entrance of the cage due to conducting material effects. Figure 6.5 shows that the signal strength becomes weak because the cage prevents the line of sight between the transmitter and receiver. The signal strength intensity image of Figure 6.5 is shown in Figure 6.6, which shows that the signal strength becomes stronger as the antennas move away from the cage and there is a line of sight.

![Figure 6.6: Top down view of Figure 6.5.](image_url)
Figure 6.5, Figure 6.6 and Figure 6.7, demonstrate the effect of the cage obstacle on RF signal strength measurements. Figure 6.7 shows the measurement sequence obtained from different trajectories at different distances from the RF obstacle.

![Graphs showing signal strength measurements](image)

Figure 6.7: RF signal strength measurement sequences corresponding to different trajectories for the cage obstacle.

6.2.2.3 Cylinder Obstacle

In cylinder experiments, we use three different cylinder radiuses, which are $r = 10$ cm, $r = 15$ cm and $r = 20$ cm; the height of the cylinders is 30 cm. Figure 6.8 shows the simulation results of signal strength measurements in the experimental field with a cylinder obstacle. The cylinder obstacle is located at the center of the experiment field, with a diameter of 15 cm. As we can see in Figure 6.8, the signal strength becomes weak as the receiver moves closer to the cylinder. The signal strength intensity image of Figure 6.8 is shown in Figure 6.9.
Figure 6.8: RF signal strength measurements in the experiment field with a cylinder obstacle.

Figure 6.9: Top down view of Figure 6.8.

Figure 6.8, Figure 6.9 and Figure 6.10 show the effect of the cylinder obstacle on the RF signal strength measurements. As the antennas move along a straight line at each side of the RF obstacle, the signal strength measurement sequence shows that
it holds sufficient information to allow recognition of the RF obstacle type. The RF obstacle shadow on the RF signal strength measurements produces different signal shapes at different distances as the receiver antenna moves closer to the RF obstacle.

![Graph of RF signal strength](image)

**Figure 6.10**: RF signal strength measurement sequences corresponding to different trajectories for the cylinder obstacle.

### 6.3 Physical Obstacles Experiments

To conduct regular physical experiments, we started with modeling simple conducting RF obstacles such as walls, cylinders, and cages. We created an nearly clean physical environment to minimize unknown sources of interference. Two Texas Instruments CC2510 development kits were used (one transmitter, one receiver), and the antennas were moved manually around a copper obstacle that laid on top a cardboard box in a laboratory environment. A 2.4 GHz transmitter and receiver antennas were moved around the physical RF obstacles in the experiment field. We recorded
signal strength at different antenna positions as they moved around a single source of interference. The source of interference itself had been centered in the middle of the experiment field, and measurements were taken at up to 100 cm on either side, as well as above and below the source of the interference. We constructed different RF obstacle shapes that were similar to the RF obstacles used for the simulation. The physical results were based on the environment, especially the ground floor where we put the antennas and then moved them. The carpet material has different effects than wood or concrete. After many trials, we found that a cardboard box of 15 cm height is more convenient and provide satisfactory results compared to the simulation results.
6.3.1 Copper Wall Obstacle

We created a wooden box frame (10 cm × 30 cm × 30 cm) and covered it with a copper screen as shown in Figure 6.11. The physical results of moving the transmitter and the receiver around the wall are shown in Figure 6.12. The signal strength oscillates between high and low and becomes extremely low (the spikes in Figure 6.12) when either the transmitter or the receiver is extremely close to the RF obstacle from one side, and the other Transmitting antenna is 1 meter away on the other side. As the transmitter moves around the wall between the edges, the signal strength is still low but better than that when the transmitter or the receiver are at the edges, which matches the simulation results shown in Figure 6.2. Figure 6.13 shows the index image of Figure 6.12 where the spikes show the lowest signal strength. The spikes on the figure can help to estimate the thickness and the width of the wall. Physical and simulation results show that it is possible to estimate the size and the shape of RF obstacle. The signal strength becomes stable when the transmitter and the receiver move far from the RF obstacle, and there is a line of sight.

Figure 6.12, Figure 6.13 and Figure 6.14 determine the effectiveness of the copper wall obstacle on RF signals. As the transmitter and receiver move along a straight line at each side of the RF obstacle, the signal strength measurement sequences are shown to contain sufficient information to enable the recognition and classification of the RF obstacle type. Furthermore, the RF obstacle shadow on the RF signal strength measurements produces different signal shapes as the antenna moves toward the copper wall obstacle as a result of RF obstacle effects as shown in Figure 6.14.
Figure 6.12: Copper wall obstacle physical results.

Figure 6.13: Top down index of copper wall obstacle.
6.3.2 Copper Cage Obstacle

In this experiment, we created a four sided wood frame cage (30 cm × 30 cm × 30 cm) and then covered it with a copper screen. The cage was centered on a large cardboard box. The transmitter and receiver moved around the cage at a regular 1 meter distance apart. The signal strength was measured for different positions outside and inside the cage. The signal strength decayed and becomes extremely low when the transmitter or the receiver was located inside the cage as shown in Figure 6.15. The signal strength oscillated when the transmitter or the receiver approached the entrance of the copper cage as a result of the conducting material effects. We got closer results from the simulation when an antenna was at the entrance of the cage as shown in Figure 6.15. The left side of Figure 6.15 shows how the signal strength goes down as the copper cage prevents line of sight between the transmitter and
receiver. The index image of Figure 6.15 is shown in Figure 6.16. The signal strength significantly increased as the transmitter and the receiver moved away from the cage and preserved a line of sight, which is consistent with the simulation results as shown in Figure 6.5. The signal strength became much better at the rear side (see Figure 6.16) as the antennas move away from the cage, which is right for the simulation result of Figure 6.5, but with a difference of \(-5\) dB better than the physical result, as a result of electromagnetic effects that came from the surrounding physical environments.

The RF obstacle shadow on the RF signal strength measurements produces different signal shapes as the receiver antenna moves closer to the RF obstacle as shown in Figure 6.17. In summary, Figure 6.15, Figure 6.16, and Figure 6.17 show the effect of the copper cage obstacle on the RF signal strength measurements. As the anten-
nas move along a straight line trajectory at each side of the RF obstacle, the signal strength measurement sequence shows that it holds sufficient information to enable recognition of the RF obstacle type.

Figure 6.16: Top down index of copper cage obstacle.

6.4 Simulation and Physical Results Validation

In this section, we aim to present physical results and CST simulation results validation for cage and wall obstacles. We performed the physical experiment in different places and buildings. The results of physical experiments depends on how clean the experiment is. The physical and simulation results are plotted together to compare their accuracy. The physical results are effected by the sources of interference in the experiment environment.
Figure 6.17: Different signal shapes of copper cage obstacle.

6.4.1 Wall Results Validation

We carried out different copper wall physical experiments to verify the CST simulation. We moved antennas about the copper wall in an area $2 \, m^2$, in two different places, as shown in Figure 6.11. We chose two places in different buildings to perform the experiments. We sought environments with fewer sources of interference to guarantee reliable communication signal between the transmitter and the receiver. Figure 6.18 shows different wall signal shapes for CST simulation and physical experiments.
Signals that are black represent simulation results, whereas signals that are red and blue are physical results. Blue physical signals are close to the CST signals (black) and signal strength difference is between $-2$ dBm up to $-8$ dBm, whereas the blue signals cause a difference of $-15$ dBm and above. The decrease in signal strength results from different interference sources.

![Graphs showing signal strength comparison between CST and physical results.](image)

Figure 6.18: Wall obstacle physical and simulation results comparison.
6.4.2 Cage Results Validation

Different copper cage physical experiments to verify the CST simulation are carried out. We moved antennas around the copper wall in an area $2 \, m^2$ in two different places. We choose two places in different buildings to perform the experiments. We sought environments with fewer sources of interference to guarantee proper communication signal between the transmitter and the receiver. Figure 6.19 shows different cage signal shapes for CST simulation and physical experiments. Signals that are black represent simulation results, whereas signals that are red and blue are physical results. Blue physical signals are close to the CST signal (black), and the signal strength difference is between $-3 \, \text{dBm}$ up to $-20 \, \text{dBm}$, whereas the red signals produce a difference of $-20 \, \text{dBm}$ and above. The decrease in signal strength results from different interference sources.

6.5 Summary

In this chapter, we have presented the concepts of RF Mapping or RF environment recognition. We have showed that RF Mapping is different from physical mapping of RF obstacles in many ways. We have explained the RF environment recognition method for RF obstacle shadow recognition and classification. We showed that the RF recognition method based on RF signal strength measurements, are effective along the robot trajectory in the experimental field to identify obstacle shadow. The RF environment recognition aims to identify and classify the RF environment shadow type along the robots’ paths. It classifies the RF environment shadow based on HMMs classifier results. The RF environment recognition method reduces the overhead cost, $C_{Mov}$, which affects the total path cost between the communicating robots,
and increase the likelihood of success, $\mathcal{L}_{Mov}$, to move robots in the direction of strong communication signal to repair links. We carried out several simulation experiments for different RF obstacle types and sizes and showed the effects of the RF obstacle on the RF signal measurements, which produces various signal shapes. Signal shapes for three types of RF obstacle are shown and explained in details. In addition, we have presented different physical RF obstacles experiments and verified the simulation and the physical results.

Figure 6.19: Cage obstacle physical results comparison.
Chapter 7

Link Maintenance Based on RF Mapping

In this chapter, Hidden Markov Models are applied to the problem of recognizing RF obstacle primitives from partial signal strength data.

7.1 Categorization of RF Shadow Primitives with HMMs

The block diagram in Figure 7.1 summarizes the major steps of our algorithm for achieving RF environment recognition method from partial data. First, each measurement vector obtained from different robot trajectories is segmented into small segments as in Figure 7.2. Each segment is then transformed into the frequency domain for extracting features using fast Fourier transform (FFT). We use a subset of all feature vectors for training and the remainder is used for testing. The extracted feature vectors for training are clustered using the K-means clustering algorithm to
generate observation sequences $C_t^{(j)}$. The generated observation sequences are used to train three HMMs, one for each RF obstacle type. Each HMM model consists of five states, corresponding to five concatenated segments of the robots movement through a specific trajectory. As described above, each model was trained using a set of observation sequences. The HMMs classification models were tested using the testing set of feature vectors. Using the trained HMMs results, the RF environment recognition is achieved and then utilized by the robot controlled motion algorithm aiming at robot connectivity maintenance.

Figure 7.1: Block diagram of RF environment recognition processing steps.

Generally, the robot motion is a sequential event, and we were interested in classifying based on its temporal ordering. There exists a strong similarity of RF environment classification using signal strength measurements to word recognition using speech patterns (see [58]). The use of HMMs provides an intuitive approach to classification. It naturally breaks up the robot trajectory into constituent parts, similar to
the way they are synthesized. The HMMs approach also provides a simple mechanism for classifying a subset of segments in the robot trajectory through an RF obstacle shadow during its movement, as opposed to classification at the completion of a trajectory. The following paragraphs review HMMs and our application of them to RF environment recognition method.

HMMs [59] is a method to model stochastic events. A model $\lambda$ consists of states $Q$ and their corresponding probabilities of observations $B$, as well as probabilities of transitions between states $A$. Given a sequence of observations, $O$, and a model $\lambda$, one can drive what is $P(O|\lambda)$, the probability of observations $O$ given $\lambda$. Essentially, this is a measure of how sensitive the model represents the event. In the case that the model is unknown (i.e. hidden), the model can be learned. To train a model, training data, a set of observations $O_i$ for $(i = 1, \ldots, n)$, is used to modify an initial estimate of model parameters with the goal of maximizing $P(O|\lambda)$ using Baum-Welch, EM, or gradient methods. For classification, a model is created for each class $\lambda_{(j)}$ for
(j = 1, ..., m_o), where m_o is the number of RF obstacle types. To assign RF obstacle type membership to a novel observation O, \( P(O|\lambda_{(j)}) \) is calculated for each type j, and the class whose model has the highest probability is assigned to O.

In speech recognition (see [58]), a model is created and trained for each spoken word. In the initial research, an observation sequence corresponded to a sequence of recognized phonemes, but now it more commonly corresponds to the coded segments of the speech signal (i.e. a segment of the signal is mapped to a frequency space then coded using a look-up table). States of the model correspond either to these segments, or more typically, to the phonemes in the word (although phonemes are not explicitly recognized). The detailed algorithm description and HMMs results are presented as follows.

7.2 Measurement Segmentation and Feature Extraction

We denote the measurement vector collected in the robot movement along the lth trajectory as \( \beta_l^{(j)} = [S_l^{(j)}(1) S_l^{(j)}(2) \cdots S_l^{(j)}(N_{m_o})]^T \), where \( N_{m_o} \) represents the number of signal strength measurements along the lth trajectory for the jth RF obstacle type. Each \( \beta_l^{(j)} \) is segmented into five segments denoted as \( \alpha_{l,u}^{(j)} = [S_l^{(j)}(5(u - 1) + 1) \cdots S_l^{(j)}(5u)]^T \), \( u = 1, 2, \cdots, 5 \) as in Figure 7.2. Afterwards, each measurement segment \( \alpha_{l,u}^{(j)} \) is converted using FFT into the frequency domain, and the results of FFT are denoted as \( \Gamma_{l,u}^{(j)} = \text{FFT}(\alpha_{l,u}^{(j)}, N_{FFT}) \), where FFT(\cdot) denotes the FFT operation, \( N_{FFT} \) denotes the number of points in the FFT results. The first 10 elements in the FFT result \( \Gamma_{l,u}^{(j)} \) are defined as the feature vector \( \gamma_{l,u}^{(j)} = [\Gamma_{l,u}^{(j)}(1) \Gamma_{l,u}^{(j)}(2) \cdots \Gamma_{l,u}^{(j)}(10)]^T \) of the measurement corresponding to the lth trajectory and jth RF obstacle type.
Once each segment is transferred into frequency space, the feature vector $\Gamma_{i,u}^{(j)}$ is clustered using the $K$-means clustering algorithm. Then, the HMMs use these binned segments to classify the RF obstacle shadow based on the probabilistic sequence of segments. In our numerical experiments, we tried different training sets to assess their impact on the recognition rate. We found that the recognition rate is affected positively by the size increase of the training sets. Data was randomly split into training and testing sets for the verification of the HMMs classifier. We randomly select 60% of the measurement vectors into the training set $S_{\text{train}}^c$, which is used for clustering and training, and the excess constitutes the testing set $S_{\text{test}}^c$.

### 7.3 Unsupervised Clustering for Observation Generation

The measurement vectors $\gamma_{l,u}^{(j)}$ in the training set $S_{\text{train}}^c$, are clustered into $G$ clusters using the $k$-means clustering algorithm. We denote the $G$ clusters as $D_1, D_2, \cdots, D_G$ so that the within-cluster sum of squares (WCSS) is minimized. The $k$-means algorithm is summarized in (7.1) as

$$\arg \min_{D_1, \cdots, D_G} \sum_{g=1}^G \sum_{\beta^{(j)} \in S_{\text{train}}, \gamma_{l,u}^{(j)} \in D_g} \| \gamma_{l,u}^{(j)} - \mu_g \|^2$$

(7.1)

where $\mu_g$ is the centroid of $D_g$, i.e. the mean of points in $D_g$, $\| \gamma_{l,u}^{(j)} - \mu_g \|^2$ is the squared Euclidean distance between the vector $\gamma_{l,u}^{(j)}$ and $\mu_g$.

After $D_g$ and $\mu_g$ are generated by the $k$-means clustering algorithm, they are used to assign observation symbols to the feature vectors to generate observation sequences for HMMs training and testing. First, we denote the symbol set used for representing
HMMs observations as $\mathcal{C} = \{C_1, \cdots, C_G\}$ with $C_g$ as the $g$th symbol. The symbol $C_{l,u}^{(j)}$ corresponding to the data segment $\gamma_{l,u}^{(j)}$ is assigned with the value $C_g$ if $\|\gamma_{l,u}^{(j)} - \mu_g\|^2$ has the minimum value among all $g \in \{1, 2, \cdots, G\}$. In other words, $C_{l,u}^{(j)}$ is assigned with symbol $C_g$, if the closest cluster centroid to the feature vector $\gamma_{l,u}^{(j)}$ is $\mu_g$. We concatenate the $C_{l,u}^{(j)}$ corresponding to the segments from the $l$th trajectory to form the vector $C_l^{(j)} = \left[ C_{l,1}^{(j)} \cdots C_{l,5}^{(j)} \right]^T$. The resulting vector $C_l^{(j)}$ is the observation sequence corresponding to measurement vector $\beta_l^{(j)}$. Observation sequence $C_l^{(j)}$ is in the HMMs training set $\mathcal{S}_{\text{train}}^{\text{HMM}}$ if its corresponding measurement vector $\beta_l^{(j)}$ is in the clustering training set $\mathcal{S}_{\text{train}}^c$, otherwise, it is in the HMMs testing set $\mathcal{S}_{\text{test}}^{\text{HMM}}$.

In summary, following the above procedure, a measurement vector $\beta_l^{(j)}$ for the $l$th trajectory in the presence of type $j$ RF obstacles is segmented into segments $\alpha_{l,u}^{(j)}$, $u = 1, 2, 3, 4, 5$. Consequently, each $\alpha_{l,u}^{(j)}$ is transformed into the frequency domain by FFT, and the FFT result is denoted by $\Gamma_{l,u}^{(j)}$. The first 10 elements in $\Gamma_{l,u}^{(j)}$ are selected to form feature vector $\gamma_{l,u}^{(j)}$. The feature vectors are clustered using the $k$-means algorithm to generate $G$ clusters, $\mathcal{D}_1, \cdots, \mathcal{D}_G$, and the corresponding cluster centroids $\mu_1, \cdots, \mu_G$. Using the cluster parameters, each segment feature vector $\gamma_{l,u}^{(j)}$ is assigned with a symbol $C_{l,u}^{(j)} \in \mathcal{C}$. We concatenate $C_{l,u}^{(j)}$ to form the observation sequence $C_l^{(j)}$. At this point, the measurement vector for each trajectory $\beta_l^{(j)}$ is transformed into observation sequence $C_l^{(j)}$ and ready for training or testing HMMs.

7.4 Numerical Results on HMMs Based Recognition

The HMMs training set $\mathcal{S}_{\text{train}}^{\text{HMM}}$ is used to train three HMMs, and each HMM corresponds to one of the three RF obstacle types. We denote the trained HMMs as
\( \lambda_{(j)} \), with \( j = 1, 2, 3 \) corresponding to RF obstacle type of wall, cage and cylinder, respectively. Given an observation sequence \( C_t^{(j)} \), which are composed of several observation symbols, the conditional probability of \( C_t^{(j)} \) given HMM \( \lambda_{(p)} \), \( P(C_t^{(j)} \mid \lambda_{(p)}) \), is calculated for \( p = 1, 2, 3 \) for classification. If the maximum \( P(C_t^{(j)} \mid \lambda_{(p)}) \) is obtained with \( p = \hat{p} \), we predict that the RF environment is with RF obstacle type \( \hat{p} \). We note that \( C_t^{(j)} \) is an observation sequence with arbitrary length, and thus may only contain the first few available observations. This corresponds to the scenarios where the robots are approaching an RF obstacle without all the observations being available.

### 7.4.1 Different Cylinder Sizes

In this experiment, a total of 535 measurement vectors are used. A subset of 321 measurement vectors are used for training, and the remainder are used for testing. These measurement vectors contain three different cylinder radiiues, which are \( r = 10 \) cm, \( r = 15 \) cm and \( r = 20 \) cm; and the height of the cylinders is 30 cm. The confusion matrix of the RF environment recognition results are shown in Tables 7.1, 7.2 and 7.3; each row of the confusion matrix represents the predicted class, and each column represents the actual class. Table 7.1 demonstrates the confusion matrix of RF environment recognition using the first 2 elements in observation sequences, and the classification rate achieved is 83\%. Table 7.2 demonstrates the confusion matrix using the first 3 elements in observation sequences, and the success rate is 92\%. Table 7.3 demonstrates the confusion matrix of RF environment recognition using 4 elements with the classification rate as 100\%.
Table 7.1: Confusion matrix of RF environment recognition by 2 observations.

<table>
<thead>
<tr>
<th>Cylinders</th>
<th>$r = 10$ cm</th>
<th>$r = 15$ cm</th>
<th>$r = 20$ cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r = 10$ cm</td>
<td>0.86</td>
<td>0.0</td>
<td>0.14</td>
</tr>
<tr>
<td>$r = 15$ cm</td>
<td>0.14</td>
<td>1</td>
<td>0.22</td>
</tr>
<tr>
<td>$r = 20$ cm</td>
<td>0.0</td>
<td>0.0</td>
<td>0.64</td>
</tr>
</tbody>
</table>

Table 7.2: Confusion matrix of RF environment recognition by 3 observations.

<table>
<thead>
<tr>
<th>Cylinders</th>
<th>$r = 10$ cm</th>
<th>$r = 15$ cm</th>
<th>$r = 20$ cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r = 10$ cm</td>
<td>1</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>$r = 15$ cm</td>
<td>0.0</td>
<td>1</td>
<td>0.24</td>
</tr>
<tr>
<td>$r = 20$ cm</td>
<td>0.0</td>
<td>0.0</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Table 7.3: Confusion matrix of RF recognition by 4 observations.

<table>
<thead>
<tr>
<th>Cylinders</th>
<th>$r = 10$ cm</th>
<th>$r = 15$ cm</th>
<th>$r = 20$ cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r = 10$ cm</td>
<td>1</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>$r = 15$ cm</td>
<td>0.0</td>
<td>1</td>
<td>0.0</td>
</tr>
<tr>
<td>$r = 20$ cm</td>
<td>0.0</td>
<td>0.0</td>
<td>1</td>
</tr>
</tbody>
</table>

The results show that the HMMs classifier can achieve satisfied classification performance when 2 observations are available, and the classification performance improves; and rates become excellent as more observations become available.
7.4.2 Different Wall Sizes

In wall experiments, a total of 455 measurement vectors are used. A subset of 273 measurement vectors are used for training, and the remainder is used for testing. The measurement vectors contain three different wall sizes, which are $7 \text{ cm} \times 30 \text{ cm} \times 30 \text{ cm}$, $10 \text{ cm} \times 30 \text{ cm} \times 30 \text{ cm}$ and $15 \text{ cm} \times 30 \text{ cm} \times 30 \text{ cm}$. The confusion matrices of the RF environment recognition results are shown in Tables 7.4, 7.5 and 7.6. Table 7.4 demonstrates the confusion matrix of RF environment recognition of wall measurement vectors using the first 2 elements in observation sequences, and the classification rate is 70%; while Table 7.5 demonstrates the confusion matrix using the first 3 elements in observation sequences, and the classification rate is 76%. Finally, Table 7.6 demonstrates the confusion matrix of RF environment recognition using the first 4 elements of the observation sequence the success rate is 92%. The results show that the HMMs classifier can achieve satisfied classification performance when 2 observations are available, and the classification performance improves as more observations become available.

Table 7.4: Confusion matrix of RF recognition by 2 observations.

<table>
<thead>
<tr>
<th>Walls</th>
<th>$w = 7 \text{ cm}$</th>
<th>$w = 10 \text{ cm}$</th>
<th>$w = 15 \text{ cm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w = 7 \text{ cm}$</td>
<td>0.85</td>
<td>0.46</td>
<td>0.0</td>
</tr>
<tr>
<td>$w = 10 \text{ cm}$</td>
<td>0.15</td>
<td>0.54</td>
<td>0.31</td>
</tr>
<tr>
<td>$w = 15 \text{ cm}$</td>
<td>0.0</td>
<td>0.0</td>
<td>0.69</td>
</tr>
</tbody>
</table>
Table 7.5: Confusion matrix of RF environment recognition by 3 observations.

<table>
<thead>
<tr>
<th>Walls</th>
<th>( w = 7 \text{ cm} )</th>
<th>( w = 10 \text{ cm} )</th>
<th>( w = 15 \text{ cm} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w = 7 \text{ cm} )</td>
<td>0.87</td>
<td>0.44</td>
<td>0.0</td>
</tr>
<tr>
<td>( w = 10 \text{ cm} )</td>
<td>0.13</td>
<td>0.56</td>
<td>0.16</td>
</tr>
<tr>
<td>( w = 15 \text{ cm} )</td>
<td>0.0</td>
<td>0.0</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Table 7.6: Confusion matrix of RF environment recognition by 4 observations.

<table>
<thead>
<tr>
<th>Walls</th>
<th>( w = 7 \text{ cm} )</th>
<th>( w = 10 \text{ cm} )</th>
<th>( w = 15 \text{ cm} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w = 7 \text{ cm} )</td>
<td>0.95</td>
<td>0.08</td>
<td>0.0</td>
</tr>
<tr>
<td>( w = 10 \text{ cm} )</td>
<td>0.05</td>
<td>0.92</td>
<td>0.12</td>
</tr>
<tr>
<td>( w = 15 \text{ cm} )</td>
<td>0.0</td>
<td>0.0</td>
<td>0.88</td>
</tr>
</tbody>
</table>

7.4.3 Different Walls, Cylinders and Cages Sizes

In this experiment, a total of a 825 measurement vectors containing the three aforementioned RF obstacles with different sizes. A subset of 495 measurement vectors are used for training, and a subset of 330 measurement vectors are used for testing. The confusion matrix of the RF environment recognition results are shown in Tables 7.7, 7.8 and 7.9, each row of the confusion matrix represents the predicted class, and each column represents the actual class. Table 7.7 demonstrates the confusion matrix of RF environment recognition using the first 2 elements in observation sequences, and the classification rate is 74%. Table 7.8 demonstrates the confusion matrix using the first 3 elements in observation sequences, and the success rate for this experiment is 84% and Table 7.9 demonstrates the confusion matrix of RF environment recognition using 4 elements of the observation sequences, and the classification rate is 92%.
The results show that the HMMs classifier can achieve satisfied classification performance when 2 observations are available, and the classification performance improves as more observations become available. Thus, these results demonstrate that the proposed method has sufficient capacity in RF environment recognition for robot controlled motion.

Table 7.7: Confusion matrix of RF environment recognition by 2 observations.

<table>
<thead>
<tr>
<th>Different obstacles</th>
<th>Cage 30 cm$^3$</th>
<th>Wall 10 cm</th>
<th>Wall 15 cm</th>
<th>Cylinder 10 cm</th>
<th>Cylinder 15 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cage 30 cm$^3$</td>
<td>1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Wall $w = 10$ cm</td>
<td>0.0</td>
<td>0.34</td>
<td>0.44</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Wall $w = 15$ cm</td>
<td>0.0</td>
<td>0.66</td>
<td>0.56</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Cylinder $r = 10$ cm</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.80</td>
<td>0.0</td>
</tr>
<tr>
<td>Cylinder $r = 15$ cm</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.20</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 7.8: Confusion matrix of RF environment recognition by 3 observations.

<table>
<thead>
<tr>
<th>Different obstacles</th>
<th>Cage 30 cm$^3$</th>
<th>Wall 10 cm</th>
<th>Wall 15 cm</th>
<th>Cylinder 10 cm</th>
<th>Cylinder 15 cm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cage 30 cm$^3$</td>
<td>1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Wall $w = 10$ cm</td>
<td>0.0</td>
<td>0.40</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Wall $w = 15$ cm</td>
<td>0.0</td>
<td>0.60</td>
<td>1</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Wall $r = 10$ cm</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.80</td>
<td>0.0</td>
</tr>
<tr>
<td>Cylinder $r = 15$ cm</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.20</td>
<td>1</td>
</tr>
</tbody>
</table>

7.5 Summary

In this chapter, we have presented the RF environment recognition based on HMMs results. Firstly, we obtained different measurement vectors from different trajectories as the robots explore different RF obstacle environments. Each measurement vector obtained from different trajectories is segmented into small segments containing a
number of signal strength measurements. Subsequently, each segment is transformed into the frequency domain for extracting features using FFT. A subset of all feature vectors are used for the training process, and the excess is used for the testing process. We used $K$-means clustering algorithm to cluster the extracted feature vectors used for the training set to generate observation sequences. The generated observation sequences are used to train three HMMs models, one for each RF obstacle type. Finally, each model was trained using a set of observation sequences. The HMMs classification models were tested using the testing set of feature vectors. Using the trained HMMs results, the RF environment recognition is achieved and then utilized for the robot controlled motion algorithm aiming at robots connectivity maintenance. The results show that the HMMs classifier can achieve satisfied classification performance for different numbers of observations. The main advantages of the RF environment recognition method based on the HMM classifier results are to reduce the overhead cost, $C_{Mov}$, results from the movement of the robot into the RF shadow and affects the total path cost between the communicating robots. In addition, the RF environment recognition method increase the likelihood of success, $L_{Mov}$, to move robots in the direction of strong communication signal to repair links.

Table 7.9: Confusion matrix of RF environment recognition by 4 observations.

<table>
<thead>
<tr>
<th>Different obstacles</th>
<th>Cage $30,\text{cm}^3$</th>
<th>Wall $10,\text{cm}$</th>
<th>Wall $15,\text{cm}$</th>
<th>Cylinder $10,\text{cm}$</th>
<th>Cylinder $15,\text{cm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cage $30,\text{cm}^3$</td>
<td>1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Wall $w=10,\text{cm}$</td>
<td>0.0</td>
<td>1.0</td>
<td>0.40</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Wall $w=15,\text{cm}$</td>
<td>0.0</td>
<td>0.0</td>
<td>0.60</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Cylinder $w=10,\text{cm}$</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>1.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Cylinder $w=15,\text{cm}$</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>
Chapter 8

Meta-Routing based on Robot Controlled Motion

In this chapter, the node controlled motion algorithm achievement and mechanism are discussed in more detail.

8.1 Robot Controlled Motion Achievement

The emerging importance of moving *ad hoc* networks in robotics has given rise to the concept of movement control for wireless network nodes, which is tied to the capability of the nodes to move to favorable positions to maintain network connectivity while performing tasks [60]. While opportunistic use of independent mobility has been extensively investigated, the use of movement control of mobile agents is largely unexplored [7]. In the application scenario, when a moving robot starts to lose communication connectivity with the team, its node movement control mechanism will guide the robot toward favorable positions in the field for maintaining connectivity or fixing a failing link. The controlled motion algorithm utilizes the
knowledge learned from RF environment recognition through HMMs results. Once the robot recognizes the RF obstacle shadow and estimates the RF obstacle size, the control motion algorithm would determine whether robots continue their trajectories or move back through a free locomotion to positions in the field where the robots can gain a strong signal strength and maintain the network connectivity. In addition, the controlled motion algorithm based on RF environment recognition method and the gradient descent method is incorporated into a routing protocol for link repair to achieve the Meta-Routing protocol. The robot controlled motion algorithm based on the gradient method detailed in chapter 5 and the RF environment recognition method discussed in chapter 6, would help in reducing the overall path cost estimate, compared to the route discovery phase for achieving Meta-Routing. The controlled motion algorithm main goal is to reduce the overhead cost, $C_{Mov}$, results from node movement in the field to repair links, and increase the likelihood of success, $L_{Mov}$, to ensure that the robot movement would repair the communication link and do not loss the communication with the robotic network.

8.2 Robot Controlled Motion Mechanism

The controlled motion algorithm has two decisions to perform for maintaining the robots connectivity. The controlled motion algorithm takes the first decision; therefore, it drives the robots to move across the RF obstacle shadow toward a favorable position to maintain their connectivity based on the RF recognition through the HMMs results. If the controlled motion algorithm chooses the second decision, the robots move back through a free locomotion and start computing the signal strength gradient to find the direction of the strong signal strength and then maintain their
Algorithm 1 Controlled Motion Algorithm.

1: **Input**: RF environment recognition results.
2: **Output**: Maintaining connectivity of mobile robots.
3: Get RFRecognitionResults()
4: 
5: if (Obstacle type and size are estimated) then
6:   if Segments length ≥ (estimated width/2) then
7:     MoveCurrentPath()
8:     GradientDecsentAlgorithm()
9:   else
10:     MoveBack()
11:     GetStrongSignalPos()
12:     GradientDecsentAlgorithm()
13: end if
14: else
15:     MoveBack()
16:     GetStrongSignalPos()
17:     GradientDecsentAlgorithm()
18: end if
19: MaintainConnectivity()

connectivity. We use the gradient-based controlled motion algorithm, by which the multi-dimension gradient of the RF signal measurements is extracted for controlling robot direction around the RF obstacle. In other words, depending on the HMMs results that estimate the type and the approximate size of the RF obstacle, the controlled motion algorithm decides whether to extend the movement through the RF obstacle shadow or to move back through a free locomotion to a position in the field that has a strong enough signal strength, and then it computes the gradient to determine the direction of robots’ movements to maintain their connectivity. The flowchart in Figure 8.1 and the Algorithm 1 summarize the main steps of the controlled motion algorithm. The whole picture of Meta-Routing flowchart that includes message routing protocol, link maintenance through node controlled motion (link repair) and route discovery process is summarized in Figure 8.2
Figure 8.1: The controlled motion algorithm flowchart.
Figure 8.2: Meta-Routing overall picture.
8.3 The Controlled Motion Algorithm Results

The HMMs results based on RF environment recognition method demonstrate detection and recognition of RF obstacle on the robot trajectory. In addition, it confirms the RF obstacle type and approximate size within a limited distance along the robot path. The controlled motion algorithm utilizes the HMMs results to drive robots to continue moving forward through the current trajectories if the segments length traveled by the robots are greater than or equal one half of the estimated RF obstacle size as shown in the scenario of Figure 8.4. Otherwise, the robots stop movement and move back through a free locomotion to a position where it can gain strong signal strength. Then, the robots run the gradient algorithm to define the direction of the strongest signal strength. Afterwards, the robots move in the direction of the gradient and attempt to regain communication as shown in the scenario of Figure 8.3.

8.3.1 Two Observation Sequence Scenario

In this subsection, we will present a scenario for two robots that are moving in the experimental field and exchanging information packets. The robots started at \( x_0^{(1)} = 14, y_0^{(1)} = 6 \) and \( x_0^{(2)} = 38, y_0^{(2)} = 6 \) at time \( k=0 \). The signal strength threshold between the robots was -60 dBm. When the signal strength went below this value, the controlled motion algorithm started to detect the RF obstacle interfering with the robots’ trajectories. In the meanwhile, the controlled motion algorithm started to identify the RF obstacle type and estimate the RF obstacle size.

In this scenario, two observation sequences were used. If the segments traveled by the robot was less than one half of the estimated RF obstacle width then the robots were moved back through a free locomotion to a strong signal strength position (in
in this scenario the number of traveled segments were two). Consequently, the robots run
the gradient algorithm to define the direction of the movement as well as maintaining
their connectivity. The zig zag trajectory in Figure 8.3 shows when the robots were
changing their direction according to the magnitude and the direction of the gradient.
Finally, the robots approached each other, moved away from where the RF obstacle
was located and maintained their connectivity.

8.3.2 Three Observation Sequence Scenario

In this subsection, we will present a scenario for two robots that are moving in
the experimental field and exchanging information packets. The robots started at

Figure 8.3: Control robots movement using two observations.
$x_0^{(1)} = 14, y_0^{(1)} = 6$ and $x_0^{(2)} = 38, y_0^{(2)} = 6$ at time $k=0$. The signal strength threshold between the robots was -60 $dBm$. When the signal strength went below this value, the controlled motion algorithm started to detect the RF obstacle interfering with the robots’ trajectories. In the meanwhile, the controlled algorithm started to identify RF obstacle type and estimate the RF obstacle size. In this scenario, three observation sequences were used. If the segments traveled by the robot was greater than or equal one half of the estimated RF obstacle width then the robots continued moving forward on the same direction in Figure 8.4 (three segments are used in this scenario). Consequently, the robots run the gradient algorithm to define the direction of the movement as well as maintaining their connectivity. Finally, the robots approached each other and maintained their connectivity.

Figure 8.4: Control robots movement using three observations.
8.4 Link Maintenance based on RF Recognition

Cost Estimation

The proposed link maintenance method for robot connectivity maintenance is based on the RF environment recognition method. The RF environment recognition method passes through several processes. The method starts with collecting signal strength measurement at a different point in the robots’ trajectories. The signal strength measurement vector obtained from different robots’ trajectories is segmented into five segments. Each segment is then transformed into the frequency domain for extracting features using FFT. We used a subset of all feature vectors as a training set, and the rest is used for testing. The extracted feature vectors for the training set are clustered using the $K$-means clustering algorithm to generate observation sequences. The generated observation sequences are used to train three or more HMMs models, one for each RF obstacle type. Each HMM model consists of five states, corresponding to five bound segments of robot movement through each trajectory. The HMMs classification models were tested using the testing set of feature vectors. The HMMs results were utilized by the robot controlled motion algorithm, to achieve robot connectivity maintenance. The time cost estimates for the link maintenance based on the RF environment recognition method is calculated in the next subsections.

8.4.1 Link Maintenance Cost Estimation

The total estimated time for our link maintenance method $T_{TOT}$ is the sum of the segmentation time $T_{SIG}$ (the time to segment signal strength measurement vector), the FFT transform time $T_{FFT}$ (the time to perform FFT transform), the time for $K$-means algorithm $T_{k}$ (the time to cluster the extracted feature vectors), the time
for HMMs classification $T_{(HMM)}$ (the time for HMMs training and recognition), and
the time for robot movement $T_{(MOV)}$, the time to move the robot back through a free
locomotion. The total estimated time summarized as

$$T_{(TOT)} = T_{(SIG)} + T_{(FFT)} + T_{(K)} + T_{(HMM)} + T_{(MOV)}$$  \hspace{1cm} (8.1)

To estimate the time cost for our link maintenance method, we created differ-
ent MATLAB programs and functions. We ran these programs on a DELL desktop
computer, model Optiplex980. The computer runs Windows 7 Professional, 64-bit
Operating System. The computer uses Intel(r) Core(TM) i7 CPU that run on 2.93
GHZ. The installed memory (RAM) capacity for the computer is 8 GB.

In the experiments, the segmentation and FFT transform times were $T_{(SIG)} +
T_{(FFT)}=0.3$ seconds, and the $K$-means and HMMs times were $T_{(K)} + T_{(HMM)}= 6$
seconds. Therefore, for a crawler robot that moves back a distance of 0.5 meters
at speed of 0.022 meters/second, the total estimated time $T_{(TOT)} = 0.3 + 6 +
0.5 / 0.022 = 29.027$ seconds, as shown in Figure 8.9. If the robots speed are increased
to 0.15 meters/second, the total estimated time is $T_{TOT} = 0.3 + 6 + 0.5 / 0.15 = 10$
seconds. The results show that the time cost estimate is effected directly by the robots
speed in the field. Thus, as the robots moves fast, the time cost decreases.

## 8.5 Node Movement Cost Estimation

In this section, we will show a scenario on how node movement time can be es-
timated by explaining simulation environment specification and node configuration.
The simulation was completed to estimate the time required to move two discon-
nected nodes back through a free locomotion to regain communication while running
the AODV routing protocol. The simulation was performed on the NS2 simulator.

8.5.1 Two Nodes Simulation Model

In the simulation, an area of the $2 \times 2 \ m^2$ were chosen. The freeway motion model
of the nodes was defined as a movement model for our experiments. The simulation
uses 2 nodes. The maximum speed was set to $2.2 \ cm/s$. The traffic generated was
FTP (File Transfer Protocol) on TCP (Transmission Control protocol) agent. The
MAC layer was set to MAC/802.11. The AODV protocol was simulated with a
source-destination pair. They generated packets at different times. After running the
simulation the network animator (NAM) was used to show the data transfer between
nodes. The trace files were analyzed for moving nodes. Using the trace file the node
movement time was calculated.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
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<tbody>
<tr>
<td>Channel</td>
<td>WirelessChannel</td>
</tr>
<tr>
<td>Topology</td>
<td>$2 \times 2$</td>
</tr>
<tr>
<td>Nodes</td>
<td>2</td>
</tr>
<tr>
<td>Mac layer</td>
<td>MAC/802 - 11</td>
</tr>
<tr>
<td>Routing protocol</td>
<td>AODV</td>
</tr>
<tr>
<td>Traffic Type</td>
<td>FTP</td>
</tr>
</tbody>
</table>

The scenario in Figure 8.5 (a) shows two mobile nodes. The nodes are moving
and transmitting data packets. The nodes and simulation environment parameters
are shown in table 8.1. As the two nodes move, they approach an RF obstacle. The
RF obstacle affects the communication signal between the mobile nodes. Therefore,
the $S/N$ goes down below the communication threshold. As a result, the nodes cannot communicate anymore as shown in Figure 8.5 (b).

Figure 8.5: Two robots in (a) are transmitting data packets and in (b) are losing communication.

In Figure 8.6 (a), the mobile nodes are moving back through a free locomotion into a position where they can regained the signal strength to communicate. The node movement time spent to regain the communication between the nodes was 29 seconds, as shown in Figure 8.9. The nodes regained the communication signal and started transmitting information packet again as shown in Figure 8.6 (b).

### 8.6 Route Discovery Cost Estimation

The route discovery time is a function of the distance to the destination, the size of the network, and the number of nodes in the network. The size of the transmitted data packet does not affect the route discovery time. A good route discovery process should have a short response time, which is how long the discovery mechanism takes to reach the destination, and should do so with minimal time cost. In communication
networks, the total delay for the application data packet as it is transmitted from source to destination plus the route discovery time, which is the round trip time from sending a route request until receiving the route reply, is called the end-to-end delay.

The total route discovery latency ($T_{RDL}$) is the sum of the request time ($T_{req}$), which is the time it takes for the first request message to traverse from the source to the destination, the reply time ($T_{rep}$), the time it takes for the first reply message to traverse from the destination back to the source, and the soft latency ($T_{soft}$), an extra waiting time happens at the source side after receiving the reply message. The total route discovery latency ($T_{RDL}$) is summarized as in the equation below:

$$T_{RDL} = T_{req} + T_{rep} + T_{soft}$$  \hspace{1cm} (8.2)

In the next sections, we will show a scenario on how route recovery time can be estimated. The simulation environment specification and node configuration will be detailed. The simulation is done to estimate the route discovery time of the AODV routing protocol. The simulation was performed on the NS2 simulator.
8.6.1 Three Nodes Simulation Model

In this simulation, the areas of the $2 \times 2 \ m^2$ were chosen. The freeway motion model of the nodes was defined as a movement model for our experiments. The maximum speed was set to $2.2 \ cm/s$. The traffic generated was FTP (File Transfer Protocol) on TCP (Transmission Control protocol) agent. The MAC layer was set to 802.11. The protocol have been simulated with 3 nodes. They generated packets at different simulation times. After running the simulation the NAM is used to show the data transfer between nodes. The trace files are analyzed for moving nodes. Using the trace file the node route discovery time is calculated.

<table>
<thead>
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</tr>
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<tbody>
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<tr>
<td>Mac layer</td>
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<td>AODV</td>
</tr>
<tr>
<td>Traffic Type</td>
<td>FTP</td>
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</tbody>
</table>

The scenario in Figure 8.7 (a) shows two mobile nodes. The nodes are moving and transmitting data packets. The nodes and the simulation environment parameters are shown in table 8.2. At the beginning, two nodes are moving in the experimental field, they approach RF obstacle. The RF obstacle affects the communication signal between the mobile nodes. Therefore, the $S/N$ goes down below the communication threshold. As a result, the nodes can not communicate anymore as shown in Figure 8.7 (b).
Figure 8.7: Two robots are (a) transmitting data packets (b) losing communication.

Figure 8.8: A new node (a) moved to the network (b) Regained communication with other nodes.

In Figure 8.8 (a), when the nodes lost communication, they started executing the route discovery phase. A third, new node from the base station was moved to join the network. The trapped node detected the new node. The new node acted as a bridge between the disconnected nodes. Therefore, the disconnected nodes regained
the communication signal and started to transmit information packets as shown in
Figure 8.8 (b). The route recovery time spent to regain the communication between
the nodes was 39 seconds, which is higher than the time cost of moving nodes back
through a free locomotion, as shown in Figure 8.9. In summary, the time spent to
move nodes back through a free locomotion is shorter than the time spent to recover
a new node. Thus, the node controlled algorithm is more effective than the route
recovery phase in some cases.

Figure 8.9: Node movement and route discovery time comparison.

8.7 Summary

In this chapter, the robot controlled motion algorithm is presented. The robot
controlled motion is a form of mobility where mobile nodes are moving to favorable
places in the experimental field. A mobile robot controlled motion algorithm can
effectively improve network performance by driving robots to favorable locations with
strong links in the robot configuration space. The robots run the gradient algorithm
to determine the direction of the strongest signal strength. Then, the robots will move in the direction of the gradient, and they will attempt to regain communication. The numerical simulations were conducted to evaluate the feasibility and performance of the controlled motion algorithm. The algorithm results have presented promising solutions to join message routing and physical link maintenance in robots network. In addition, simulation scenarios to estimate time costs of the node controlled movement algorithm and the route discovery algorithm show that the robot controlled motion is more effective than the route discovery phase in some scenarios. We expect that the presented methods can be a competitive alternative for broken link replacement and maintaining robot connectivity in robotic networks to achieve Meta-Routing.
Chapter 9

Conclusions and Future Work

9.1 Summary

In this dissertation, we have presented a new concept for a mobile robot routing protocol called the Meta-Routing protocol. Meta-Routing merges a message routing protocol and a link maintenance protocol in mobile robot ad hoc networks. The Meta-Routing protocol achieves message routing by applying routing protocols such as proactive, reactive and hybrid protocols, and it achieves link maintenance using various wireless mechanisms available, including controlled motion of nodes, transmit power adjustment, antenna pointing, and other forms of antenna tuning that varies the operating characteristics of nodes. Despite the array of maintenance options available, if the communication costs and the likelihood of success can be quantified, the mechanism can be incorporated into the Meta-Routing paradigm. In this work, the controlled motion of nodes based on the RF environment recognition and gradient results are used to repair broken and failed links to maintain the network connectivity. Most mobile ad hoc routing protocols were developed to handle static
networks. Therefore, they treat the message routing problem and link maintenance problem independently. These protocols only consider the message routing problem without control over the node movement to maintain or repair network links. These protocols run the route discovery phase immediately when a link failure occurs in the network. The route discovery phase in these protocol schemes incurs communication latency in the network. Traditional routing protocols deal with discovering existing links in the network, attaching these links together to create communication paths, and then choosing the best path among the created communication paths. The routing protocols attempt to minimize the path cost between two communicating nodes, which is the cost of each link in a path, using different optimization algorithms without attempting to repair broken links or create new links in the network. In general, traditional routing protocols find paths in a connection graph and they trigger an automatic route discovery when there is a link failure and no path to the destination. Whereas, Meta-Routing protocol augments the routing graph with hypothesized nodes, and this will be the Meta-Routing protocol triggers to find new paths in the augmented graph. Then, Meta-Routing computes the cost function and likelihood of success for each path. Meta-routing chooses the lowest path cost according to the computed cost function and likelihood of success of the communication path. Therefore, Meta-Routing total path cost is the sum of minimum communication cost of links and the minimum overhead cost. The innovation of the Meta-Routing protocol is in creating hypothesized graphs. Therefore, Meta-Routing is about hypothesizing new graphs and then applying the traditional protocols to these graphs to choose the lowest path cost.

We incorporate route repair directly into the routing protocol cost function as an alternative to the route discovery process, in order to create a new routing mechanism,
and improve network connectivity. Meta-Routing is the name of this routing mechanism. Meta-Routing attempts to figure out the cost of the lowest communication path between nodes. Meta-Routing is not only going to include the cost of each link in a path, but it is also going to reduce the cost of overhead to find that path.

As one way to achieve the Meta-Routing protocol, the robot controlled motion algorithm based on the RF environment recognition and the multi-dimensional gradient descent methods are used to provide a suitable solution to maintain robot connectivity and repair broken links. The RF environment recognition method uses signal strength measurements to learn and recognize adverse environments containing RF obstacles. The RF environment recognition helps to investigate the relationship between known RF obstacle types and their impact on the RF signal strength in different scenarios. The RF environment recognition reduces the overhead cost to repair a link by classifying the RF obstacle environment. The multi-dimensional gradient of the RF signal strength is calculated to estimate the direction of the strongest signal strength, which is used to control robot movement to maintain connectivity and increase the likelihood of success of the desired link.

In the application scenario, when a moving robots start to lose communication connectivity with the team, the controlled motion algorithm will guide them toward favorable positions in the experimental field for maintaining the connectivity or fixing the failing link. The controlled motion algorithm utilizes the knowledge learned from the RF environment recognition through HMMs results. Once the robot recognizes the RF obstacle shadow or RF obstacle type and size, the controlled motion algorithm will determine whether the robots continue their trajectories or move them back to a position in the field where they can gain a strong signal strength. The controlled motion algorithm makes the first decision: it drives the robots to move forward through
the RF obstacle shadow towards a favorable position to maintain their connectivity based on the RF environment recognition through HMMs results. If the controlled motion algorithm chooses the second decision, the robots start computing the signal strength gradient to find the trend of strong signal strength and then maintain their connectivity. We use the gradient based on the controlled motion algorithm, by which the multi-dimension RF environmental gradient of the RF signal measurements is extracted to control robot movement around the RF obstacle. In other words, the controlled motion algorithm has the decision to continue the movement through the RF obstacle shadow, or to move back to a position in the field that has a strong enough signal strength. Afterwards, the gradient algorithm computes the gradient to define the direction of robots’ movements to maintain their connectivity. The controlled motion algorithm performs the correct decision depending on the RF environment recognition through HMMs results that estimate the type and the approximate size of the RF obstacle. The controlled motion algorithm controls the robot movement to reduce the overhead cost and to increase the likelihood of success of the repaired link.

9.2 Contributions

In this dissertation, the Meta-Routing protocol is presented as a new concept of mobile robot and ad hoc network infrastructure management, which is not only introduced as a packet routing scheme, but also as a new strategy for maintaining communication links. The main contributions of this dissertation are:

1. Meta-Routing, which incorporates link maintenance directly into the routing protocols cost function as an alternative to route discovery for robust network connectivity. Meta-Routing expands current routing protocols to include not
only the traditional routing of packets, but also the maintenance of links in mobile agent scenarios. Thus, Meta-Routing minimizes the communication path cost and the overhead cost resulting from the discovery phase of new nodes. It achieves that by maximizing or repairing existing broken communication links.

2. Employment of the RF environment recognition and the gradient method into node controlled motion algorithm helps in the achievement of link maintenance in the presented Meta-Routing Protocol. The RF environment recognition intends to identify and classify the RF environment type where the robots are, and provide the knowledge to the node controlled motion algorithm. The gradient algorithm is used to determine the direction of the strong signal strength to maintain network connectivity.

3. Protocol unification, which merges the syntax of message routing protocol and the link maintenance mechanism through the physical reconfiguration of network nodes by controlling the movement of the nodes. The controlled motion algorithm enables the robot to fix failing and broken links and maintain robotic network connectivity. The controlled motion algorithm moves robots to favorable positions in the field to retrieve communication signal strength. It achieves the movement of nodes depending on the RF environment recognition based on HMMs results. The node controlled motion algorithm is incorporated into a routing protocol for link repair to achieve Meta-Routing.

9.3 Conclusions

To achieve the Meta-Routing protocol in an interconnected network of communication nodes in an adverse environment, it is necessary to perform link creation or
link repair techniques to manage broken links and reduce the overhead cost resulting from the node discovery process. The drawn conclusion has come after running extensive experimental simulations and comprehensive examinations on the effect of RF obstacles on RF environment recognition. The RF environment recognition method has been employed to develop and design an effective controlled motion algorithm that can achieve the desired performance in some scenarios. The numerical simulations have been conducted to evaluate the feasibility and performance of the RF environment recognition method, gradient algorithm and the node controlled motion algorithm. This dissertation has presented the Meta-Routing protocol and promising solutions to join message routing and link maintenance in mobile robot networks. Meta-Routing intends to reduce routing overhead cost resulting from route discovery protocol. We derive the following conclusions from the numerical simulation results:

1. The Meta-Routing protocol, which combines message routing and link maintenance as one unified problem, is expected to provide more robust ad hoc network infrastructure and reduce communication overhead and delays. Meta-Routing protocol should provide the capability of self-healing in the mobile robot network. It reduces network latency caused by the route discovery process and increases the network throughput.

2. The RF environment recognition method can successfully recognize and classify the surrounding RF environment featured by certain types of obstacles, which lays a proper foundation for successive node controlled motion and the link maintenance process. The RF environment recognition based on HMMs results demonstrates the recognition of RF obstacles on the robots’ trajectories. It confirms the RF obstacle type and size estimation within a limited distance along the robots’ trajectories.
3. The application of the robot controlled algorithm and the gradient method is effective in driving the robots to the desired positions for link maintenance for achieving Meta-Routing. The robot controlled motion algorithm and gradient method findings demonstrate promising research for mobile ad hoc networks of robot teams.

9.4 Future Work

The Meta-Routing protocol is achieved through merging the message problem and the link maintenance problem, which uses the RF environment recognition, the gradient descent method, and the robot controlled motion algorithm. The methods and algorithms presented in this dissertation form a good foundation for investigation of RF environments to discover RF obstacles that affect the RF signal measurements. These methods and algorithms lead to link repair for maintaining connectivity and reducing the overhead cost of communication paths; consequently, reducing latency and increasing network throughput. However, there is much work to be done to address weaknesses, expand functionality, and implement techniques in a real-world environment. The future work can be summarized in the following.

1. The RF environment recognition method based on HMMs results is used to classify the RF obstacle shadow on the RF signal measurements using known RF obstacle shapes, types and sizes. However, different RF obstacle shapes and sizes should be used to confirm the method effectiveness and efficiency in different environments.

2. Extensive physical experiments for different RF obstacle shapes, types and sizes, should be conducted to confirm the RF environment recognition method ability.
3. Segmentation and feature extraction of RF signal strength measurements, which is part of the RF environment recognition method implementation, may be an essential key to improve the recognition and classification process. However, using an extremely small number of segments may not help in the recognition process or have an impact on the recognition rate.

4. Unsupervised clustering is used to reduce the number of classifiers by finding similar patterns across multiple segments. However, supervised classification may be used to improve the recognition rate such as in speech recognition applications.

5. More refinement of the RF environment recognition and the classification method can be used to improve the recognition rate. Therefore, more work on the recognition of the RF environment based on partial RF signal strength measurements is essential to identify the RF environment at an early time and consequently prevent the robots from going deeply into the RF shadow.

6. Create different hypotheses for different types of link maintenance to improve the Meta-Routing overhead cost estimation.
Bibliography


