Target localization in unknown environments using static wireless sensors and mobile robots

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***Abstract*—This paper proposes a novel scheme for target localization in unknown environments using a prior-deployed static wireless sensor network (WSN). The goal is to have multiple mobile autonomous robots navigate from any point in a region to the closest identified target location just by interacting with the sensors. This is achieved in two ways: (i) by producing a pseudo-gradient in the region having its peak closest to the target, and (ii) by having the sensors assist the robots, guiding them to the target efficiently. Such a scheme makes use of the topology of the network to create a navigation path as the robot follows this pseudo-gradient in the network to reach the global maxima. It is assumed that there is no global coordinate frame for the region i.e. the WSN and robots are not aware of their position globally, and only make use of the relative localization based on neighborhood information. The performance of the scheme is analyzed in simulation with different node-densities and obstacle-filled regions.**

***Index Terms*—RSSI, Target Localization, Virtual Topological Gradient, WSN assisted navigation**

I. Introduction

Wireless Sensor Networks (WSNs) have proved themselves to be an effective media for environment monitoring. Some of the important characteristics of WSNs are: (i) low cost, (ii) low power requirements, (iii) multifunction capabilities, (iv) robustness, and (v) scalability. The multifunction capability allows them to provide a wealth of information regarding the state of the environment they are deployed in with a variety of sensors like seismic, magnetic, thermal, visual, etc. [1]. These characteristics allow the random deployment of WSNs in large numbers even in human-inaccessible terrains, where the sensors can be used to localize the source of the occurring event, such as fire, chemical leakage as well as people in case of search-and-rescue. In certain environments, like land-mine areas, disaster relief operations, etc., it is suitable to use automated agents to provide assistance. The use of multiple mobile autonomous robot (MAR) platforms with inherent intelligence and autonomous behavior is seen to afford several advantages, especially as it provides distributed, cooperative interaction with the static WSN [2], [3], [4], [5]. The robots interact with the WSN and utilize the information from the WSN to coordinate their response behaviors. As research in the field evolves, the applications have become varied and include area coverage, search-and-rescue, target detection and tracking, cooperative transport, etc. [6], [7], [8], [9]

Such interactive coordination in an unknown environment poses interesting challenges:

1) Efficient WSN-Robot interaction and navigation schemes are required.
2) Time-critical response ability is needed.
3) Distributed control algorithms with localized interactions are required to avoid dependence on global position information.

It is thus, of particular interest to develop an algorithm which can use low cost, low power and low complexity techniques in aiding the coordination between existing static WSNs and robots. In this paper, we introduce a novel technique for target localization and network-guided navigation for mobile robots in unknown surroundings. In a region uniformly covered by a WSN, each sensor node gets a magnitude assigned to itself depending on its communication distance from the target. The sensor node closest to the target (*target-node*) would consequently, have the highest assigned magnitude. In this way, decreasing magnitudes get assigned to sensors away from the target. The robot is then called upon to follow the magnitude in the increasing direction to reach the target from any location within the region. We call this the "pseudo-gradient" algorithm similar to the terminology used in [10] and [4]. Fig. 1 on the following page illustrates the concept. The targets could be anything from sources of fire, chemical leaks, etc. showing an inherent gradient in their distribution in the region, to actual people in a search-and-rescue application. In the latter case, a pseudo-gradient for a robot to follow and reach the target, can mimic the distribution of a physical phenomena like *temperature*. Since, we assume the non-availability of global positioning information, Received signal strength (RSS) and the number of communication hops (i.e. hop-count) in the WSN away from the target are critical artifacts in estimating the degradation in the magnitude away from the *target-node*. We propose that the inclusion of RSS and hop-count in distributing the magnitude is advantageous in unknown environments to overcome the problems posed by obstacles, noise, and link failures.

The remainder of the paper is organized as follows: Section II discusses related work in this area. Section III introduces our algorithm while Section IV discusses the implementation of the algorithm with experimental results. We present a comparative analysis of our algorithm with algorithms from [4] and [5]. Section V concludes the paper with a reference to future work.

II. Previous Work

Our work is inspired from previous work done by [2], [4], [5], [10], [11]. There are, essentially, two approaches in this research theme: (i) position-aware, and (ii) position-unaware algorithms. Position-aware schemes require some form of global positioning capability for WSN nodes like GPS or a prior implemented localization scheme. Position-unaware schemes require no such capabilities and involve algorithms independent of the locations of the nodes. They utilize the present topology of the WSN, while basing their control on the immediate neighborhood of the nodes. The algorithm in this paper falls in the (ii)nd category.

A. *Position-Aware Approaches*

Chen and Henderson [11] can be seen as early proponents of the smart sensor network philosophy which uses distributed computation in the sensor network and coordination with multiple robots. The authors state that the sensor network is an "information field" for mobile robots that can guide them to different targets. Using a model for temperature dissipation in a region, the authors analyze the cost and efficiency utility of the sensor network in improving the performance of mobile robots while detecting targets. Along with global position awareness requirement, the algorithm here also requires an inherent gradient to be present in the source-phenomenon being localized. Li et al. [2] show the ability of WSNs in acting as guides to navigate robots using novel networking protocols and robot navigation algorithms. The authors have developed an artificial potential field based method to navigate robots to a goal location keeping as far away from "dangerous" (obstacle) sites as possible.

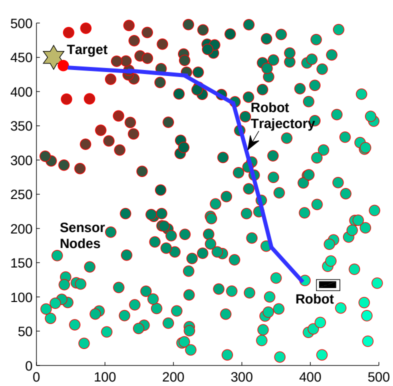

Figure 1. Robot moving toward target following the pseudo-gradient

In [12], the authors present three algorithms which present a gradient following technique for any mobile robot to reach a detected target. The target in this case is the source of a chemical leak, fire, etc. Although, one of the algorithms presented does not require global position awareness, the algorithm utilizes the inherent gradient present in the phenomenon being sensed. Hence, the algorithms will not work in cases of targets without inherent gradient such as search-and-rescue applications. Kotay et al. [3] explore the use of the synergy between GPS-enabled robots and networked sensors to provide localization, path planning and improved robot navigation. In [13], Verma et al. propose a scheme to guide the mobile sensor nodes (MSNs) to move to a goal assisted by a network of sensor nodes. The scheme assumes every node in the network is equipped with a positioning device. The MSN moves to the position which is calculated based on the virtual attractive force generated from the selected nodes' positions. Sukhatme and colleagues discuss how sensor networks can be used to mediate robot task allocations [14], and algorithms for optimizing sensor placement [15]. As is seen, all these methods require some technological ability to ascertain their position in a global frame (e.g., GPS, magnetic compass).

B. *Position-Unaware Approaches*

In [10], the authors present a novel scheme to discover the positions of individual sensing elements in a random-distributed sensor network. Assuming one sensor node knows its global position (i.e. a *seed* node), all other sensors use communication hops from this sensor to estimate their distance and then use iterative gradient descent to arrive at their (x, y) position estimates. The approach here is similar to what we propose, in that the *seed* serves as the *target-node* in our algorithm. Corke et al., 2005 [16] describe an elaborate scheme using a flying robot to localize sensor nodes, and then use these localized nodes to navigate robots and humans through the space. The scheme involves the use of a diverse set of hardware capabilities which require a high cost and complexity investment. In [17], Sheu et al. propose another position-unaware mobile robot navigation scheme for the purpose of replacing low-energy sensors. They propose the determination of direction of movement for the robot, based on to-&-fro movement of the robot itself. According to the authors, this allows the RSS value to change enough to ascertain the direction from which it is coming. This implementation is vulnerable to the environmental variation in RSS values as well as not being quick and efficient with all the back-&-forth movements. Reich & Sklar [4] propose a position-unaware navigation scheme for search and rescue purposes. The mobile robots follow the path guided by the sensors, which have artificial gradient assigned to them based on hop-count. The nodes closest to the target have low gradient values. The node nearest to the target initiates the gradient assignment flooding the network with its gradient value set as zero. Subsequent nodes set their gradient value as one plus the largest gradient value in their neighborhood. The research describes a simple scheme to navigate robot with the aid of a static sensor network. The implementation is vulnerable to degradation due to obstacle presence since the gradient assignment does not account for proximity/distance of nodes to targets or to each other. Here again, the RSS factor is not considered. Jiang et al. [5] present a novel scheme which introduces: (i) a message broadcast mechanism utilizing RSS values and farthest-node-forwarding (FNF), (ii) a message exchange based mobile robot coordination, and (iii) a tree-assisted navigation scheme for efficient navigation of the robots to the target locations. With these three schemes, the authors show improved performance in time and energy efficiency of the WSN-robot coordination. Although similar, one of the key differences in our approach is the non-reliance on RSS having a 1:1 correspondence with physical distance.

The work discussed in this paper is envisioned to be an improvement on the implementations of [4] and [5].

III. A Distributed Algorithm For Target Localization

Fig. 1 also shows an example of the pseudo-gradient distribution as the dispersion of color in the region. The *target-node* is 'Dark Red' and the color fades to 'Blue' further away from the target. The goal of the algorithm is to guide a robot suitably and efficiently in an unknown environment with the help of uniformly distributed intelligent sensor nodes. As far as this can be seen as a motion planning problem for robots, the key difference is the discretization of the motion space by the locations of the nodes in the WSN where the node-density of the WSN dictates how closely the motion space can be approximated by this discretization. The advantage of this discretization is that since the robot is limited to only interact with the WSN, its movements are dictated by the pseudo-gradient magnitudes at only the locations of the nodes. The robot does not concern itself with the non-represented space between two neighbor-nodes as it moves in straight line paths from node-to-node. It is up to the algorithm then to present a uni-directional path from start-to-end to the robot. In effect, the complexity and burden of motion planning is now shared by the robot and the distributed intelligence in the WSN.

Before describing the algorithm, certain important assumptions that are made with respect to the WSN & robot capabilities are stated here:

- The distribution of the sensor nodes is assumed to be uniformly random over the region of interest.
- The sensor nodes implement a flooding protocol which helps in periodically updating the memory of the nodes with the latest gradient value.
- The robots have the ability to communicate through the wireless medium with the sensor nodes. The robots have directional antennae for wireless interaction with the WSN.

A. Algorithm

As stated earlier, the algorithm consists of each sensor calculating the value of a function. The magnitude at each sensor depends on its distance estimate from the target itself which in turn utilizes the communication hop-count and the wireless signal intensity (or RSS) in the node neighborhood.

- The RSS gives an indication of the intensity of the signal in a wireless communication link [18]. It provides a metric for assessing how stable a connection is given environmental changes, such as noise, obstacles, interference, etc. or changes in position. Signal strength distance estimates have been empirically analyzed in [19] and [20].
- Communication hop-count is an indication of the straight line distance of a particular node in a WSN from a source node that initiates a message. This essentially derives from the breadth-first search tree [21], where each node maintains a minimal hop-count to the source node.

In essence, every node senses its vicinity for a particular target. The node closest to the target marks itself as a *target-node* and initiates a packet exchange via the flooding mechanism, which allows subsequent nodes to set their hop-count as well as the magnitude. The *target-node* sets its own magnitude as the highest in the region (this value is available to all the nodes as a preset). The hop-count for this node is set as '0'. The function used to calculate the magnitude at each node is:

$$vg^i_{calc} = vg^i_{node} \bullet \left[\frac{(RSS_i)}{(Hop\text{-}Count_i)} \right] \tag{1}$$

for all *i* neighbors. Each node stores the highest value as its *vg*-value. The RSS value is scaled between '0 ~ 1'. Each sensor node implements the algorithm (Algorithm 1 on the next page) independently by interacting with its immediate neighborhood. As described in the algorithm, each sensor node in the WSN calculates two magnitudes vg_{sense} and vg_{calc}.

1) vg_{sense} is the sensed value of the phenomenon itself. For instance, *temperature* shows an inherent gradient in its distribution in a region, which can be utilized in the pseudo-gradient in the WSN.
2) vg_{calc} is the calculated magnitude using equation 1.

The higher of the two values is retained as vg_{node} and propagated in the network. Algorithm 1 on the next page describes the logic more clearly.

As shown in equation 1, the calculated value of vg_{calc} at the node scales the received vg_{node} value from the neighbors by their respective RSS and hop-count values. Equation 1 signifies the following points:

- vg_{calc} at a particular node is dependent on the vg_{node} value it receives from its neighbors.
- Higher the RSS value, higher is the vg_{calc}. This factor incorporates how close the sensor node is to the highest vg_{node}-value node in its neighborhood.
- Higher the hop-count, lower is the vg_{calc}. This factor incorporates how far the sensor node is from the *target-node*.

Since the dBm value of RSS is always negative [18], it is scaled to the '0 ~ 1' range. A higher dBm will have a value closer to '1' and a lower dBm will show an RSS value closer to '0'. A key aspect of the algorithm is the sensor node retains the highest magnitude after getting updates from its neighbors. Implicit in this methodology is the fact that any

Algorithm 1 Magnitude assignment algorithm

Set MAX_VG = 100;
if target_pos==nearby **then** {node=*target-node*}
  Hop-Count = 0;
  vg_{sense} = sensed_entity
  vg_{calc} = MAX_VG
  if $vg_{sense} > vg_{calc}$ **then** {$vg_{node} = vg_{sense}$}
    do nothing
  else {$vg_{node} = vg_{calc}$}
    do nothing
  end if
else {node is not *target-node*}
  $vg_{sense} = \begin{cases} sensed\_entity & (if\_exists) \\ 0 & otherwise \end{cases}$
  for all nodes *'i'* in neighborhood **do** {get RSS, Hop-Count, vg_{node}}
    $Hop\text{-}Count_i = Hop\text{-}Count_{neighbor_i} + 1$
    Get vg^i_{calc} from equation 1 on the preceding page
  end for
  $Hop\text{-}Count = \min_{\forall i} (Hop\text{-}Count_i)$
  $vg_{calc} = \max_{\forall i} \left(vg^i_{calc}\right)$
  $vg_{node} = \begin{cases} vg_{sense}, & vg_{sense} > vg_{calc} \\ vg_{calc}, & vg_{sense} < vg_{calc} \\ vg_{calc}, & otherwise \end{cases}$
end if
broadcast [vg_{node}; Hop-Count]

Algorithm 2 Pseudo-Gradient-following navigation algorithm

loop
  Locate close to a node *'n'* in the WSN
  for all neighbors *'i'* in the neighborhood of *'n'* **do** {get vg_{node}}
    determine directions of all neighbors
    $\delta_{n_i} = vg^i_{node} - vg^n_{node}$
  end for
  $\delta_n = \max_{\forall i} (\delta_{n_i})$ {if all *'vg_i'* are negative, then *'n'* is *target-node*}
  nextNode = *'i^{th}'* neighbor corresponding to δ_n
  Move to nextNode as node *'n'* in a straight-line path
end loop {loop until *'n'* is *target-node*, i.e. target is reached}

node only broadcasts its highest value to its neighbors. If, from a received magnitude from a neighbor, the calculated value is less than the previous retained value, then the node discards this message and does not propagate it further. In effect, any sensor node only broadcasts a message when it sees a positive change in its magnitude assignment from the received message. This property not only limits the number of messages being exchanged by the network, but is also critical in terms of the convergence of the magnitude at any sensor node. The performance of the algorithm with respect to this property is shown later in the paper.

B. Robot-WSN interaction (pseudo-gradient following)

Once the magnitudes have been assigned to each sensor, the next step is the interaction between the robot and the WSN as it moves towards a target. As stated earlier, the robot utilizes directional antennae to determine the directions of wireless signals. Algorithm (2) shows the process followed by the robot in navigating to the *target-node*.

The robot thus estimates the gradient at each sensor node as the difference in magnitudes of the neighbors. It then follows the steepest positive gradient to the subsequent nodes and likewise, towards the target. As discussed in section III-C, the path thus followed by the robot is a uni-directional path without local maxima. The robot stops only when it reaches the *target-node*.

C. Correctness Analysis

Proposition 1: There is no local maxima in the magnitude distribution in the WSN.

Proof: A local maxima in this scheme implies two nodes having each other as the highest magnitude nodes in their respective neighborhoods. As shown in Algorithm (1), following the *target-node*, all subsequent nodes scale the vg_{node} value depending on RSS and hop-count. For a particular node, no two nodes in its neighborhood can have the same RSS value, the same hop-count as well as the same vg_{node} value. Therefore, the calculated vg_{node}-value for each neighbor using equation 1 on the preceding page, is different. Since all values are different, there can only be one vg_{node} value which is the greatest in a neighborhood. In other words, if two nodes in a neighborhood of a node have the same RSS value, hop-count and vg_{node} values, then they are located at the same position with respect to the node under consideration. In this case, the choice between these two nodes is irrelevant since they will guide the robot in the same overall direction. ■

Theorem 1: If a node has a vg_{node} value, then there exists a path from that node to any target located in the region covered by the WSN.

Proof: The prerequisite for this property is that the network be connected [22], i.e. there needs to exist a path (of any length) from every node to every other node in the WSN. If a node has a vg_{node} value, then it indicates that the node has a neighborhood with at least one other node. Following Proposition 1, there exists a node in its neighborhood with the highest vg_{node} value. Thus, the node has a path leading towards the *target-node*. Consequently, a connected graph implies that this node would have a path to all targets within the coverage area of the WSN. ■

IV. Experiments

Two critical requirements that need to be mentioned here pertain to the distribution of the WSN in a region and the characteristics of the region itself.

1) There needs to exist a geographic path from a particular starting point for the robot to traverse to reach the target.

The environment considered in our experiments is a 2-dimensional planar field with or without obstacles. The physical region and obstacle placement needs to be such that the target is not completely occluded from the robot in terms of path traversal.

2) If such a path exists then the WSN distribution should be such that there exist nodes physically located close to that path. Since the robot is to be guided by the WSN, the existence of the geographic path is not a sufficient condition for the success of the algorithm. The absence of nodes in close proximity to this path is a necessary condition for the algorithm to be useful.

Fig. 2 shows target-detection in a 50-node WSN uniformly distributed over a region. Fig. 3 shows a spline-interpolated image of the same network. The "Black dots" represent the node locations with their elevation representing the magnitudes. As seen, the global maxima exists close to the actual target location (the highest node is the *target-node*). The magnitude then decreases away from the target. The robot simply follows the steepest gradient to reach the target.

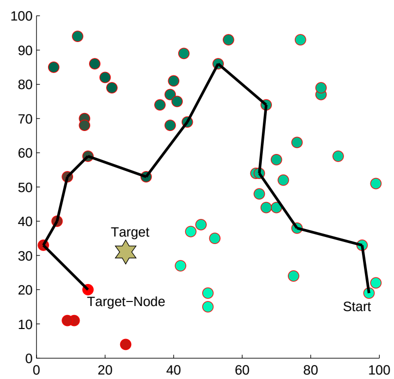

Figure 2. Navigation Path to a target

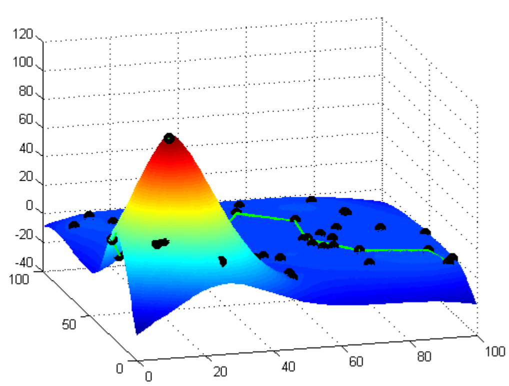

Figure 3. Spline-Interpolated magnitude distribution showing the target location as the peak of a hill

A. Convergence

Flooding as a routing protocol, implies the simple transmission of every incoming message that a node receives on every outgoing link, except the one it arrived on [21]. Without any damming mechanism like time-to-live or maximum number of re-transmissions, a single message can live forever in the network. The convergence of a network to a global equilibrium state after a start-up depends on the speed of information propagation in the network. In our case, convergence implies all the sensor nodes settling on their final magnitudes after a message has been initiated by the *target-node* and no further messages are exchanged by any node in the WSN. In order to reduce the wasteful exchange of messages, and thereby improve the convergence rate of the network, the algorithm allows the sensor nodes to re-broadcast a *vg*-value message only if the newly calculated value is greater than the stored value i.e., one transmitted by the node earlier. In effect, every sensor node transmits the *vg*-value message only as many times as it sees an incremental change in its stored value. Fig. 4 shows the average number of retransmissions and the average number of nodes involved in those, before no more packets are exchanged by the nodes and all the nodes have converged to their highest magnitudes. In all cases, only about 10% nodes are involved in retransmissions.

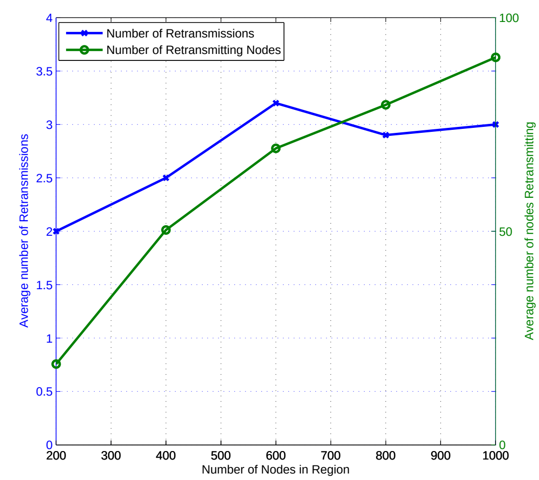

Figure 4. Convergence statistics of the WSN with the modified Flooding mechanism

B. Navigation Effectiveness

To analyze the effectiveness of the algorithm, two key parameters are: (i) travel-distance for the robot in reaching a target, and (ii) the number of nodes required in the navigation path from the start location to the target. The travel-distance parameter is measured as the ratio of the actual distance traveled by the robot to the shortest straight line distance from the start location to the target. For a good effectiveness measure, we have compared our algorithm with the Reich scheme [4] and the FNF scheme [5]. Fig. 5 shows the difference in trajectories for the three methods from the same starting point to a target. Figures 6 and 7 show the travel-distance and number of nodes taken by our algorithm as compared to FNF and Reich schemes. As seen, our algorithm performs similar to the Reich scheme and better than the FNF scheme in terms of the number of nodes taken to reach the target from the same starting location. It performs better than both the schemes on the travel-distance parameter. Since we use Received Signal Strength to scale the magnitude in a neighborhood along with hop-count, the effect is to create a steeper gradient in the neighborhood (see Fig. 3), which leads to a shorter path for the robot to follow. The main advantage in using RSS while calculating the magnitude distribution is in target-localization in an obstacle-filled region, as explained in the next section.

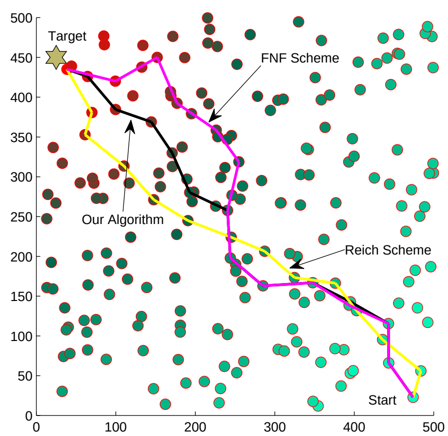

Figure 5. Trajectories of the mobile robot for three schemes

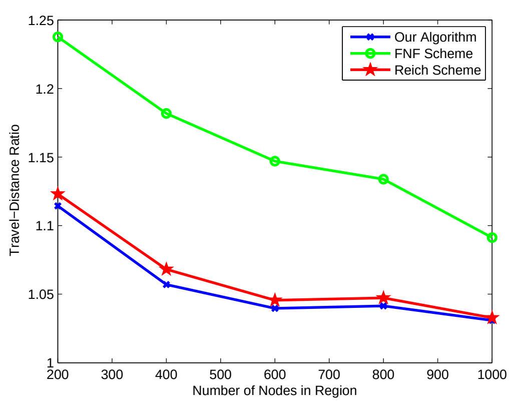

Figure 6. Travel-Distance comparison graph

C. Effect of Obstacles

Received signal strength in WSNs is an important characteristic that can be exploited in order to utilize more qualitative information regarding the topology of the network as well as the environment it is deployed in. Consider Fig. 8. Even though node C is closer to node A than node B, the presence of the obstacle between nodes A and C will cause the gradient

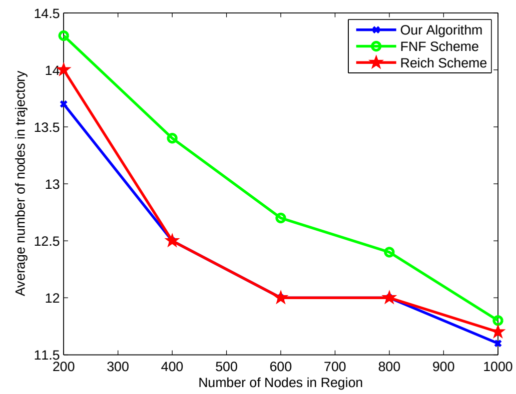

Figure 7. Number of nodes comparison graph

to be steeper between nodes A and C than nodes B and C[1]. This is due to the weaker link (i.e. lower RSS) between nodes A and C. Here, the robot would be ill-advised to follow the steepest gradient towards the target, since clearly, $[vg_A - vg_C > vg_B - vg_C]$. Algorithm (2) would lead the robot to node A from node C, traveling straight into the obstacle.

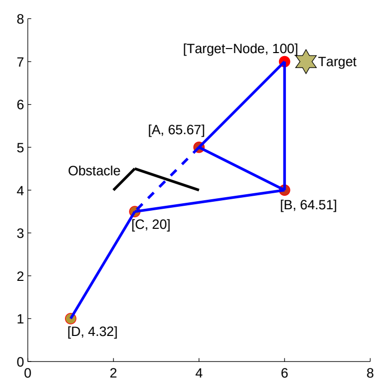

Figure 8. Qualitative Analysis of Obstacle Avoidance (shows IDs and *vg*-values at each node)

The robot, therefore, would rather consider the pseudo-gradient in all the directions at node C and follow the lower positive gradient which would lead it to the target by going to node B instead of node C, thus moving around the obstacle. This is an improvement over Algorithm (2). The robot now chooses the direction it wants to go in, rather than blindly following the steepest gradient. Depending on the concentration of obstacles in a region, the robot can be pre-programmed to choose a particular direction from the steepest positive gradient to the flattest positive gradient while moving towards the target. This is a key difference from algorithms like [4] and

[1]We assume that the obstacles are not large enough to completely preclude any wireless link between the nodes. This allows us to consider the performance of our algorithm in real environments such as office buildings, forest areas, etc. where the obstacles are easily penetrated by RF-signals at the cost of weaker connectivity.

[10]. With simply communication hop propagation, the robot would be directed to move from node C to node A, since node A is one hop closer to the *target-node*. Fig. 9, shows the obstacle avoidance by the robot following a flatter positive gradient. As expected, the trajectory is longer than that with the steepest gradient.

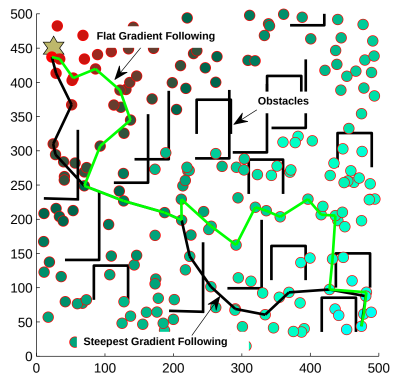

Figure 9. Obstacle Avoidance following a flat positive gradient

V. Conclusions and Future Work

In this paper, we have demonstrated a new mechanism for localizing targets in unknown environments using static wireless sensors. The important feature of the introduced technique is the non-dependence on global position information, which allows the algorithm to be used without sophisticated hardware while using it inside buildings and inaccessible areas. By creating a pseudo-gradient in the region, the mobile robot is guided to the detected target by having it follow the steepest gradient. Another artifact of the mechanism is the ability to avoid obstacles in the region by choosing a suitable gradient direction i.e. "differentially tuning" the gradient following mechanism.

For further research, we plan to analyze its performance with different levels of obstacle presence, as well as with the introduction of noise and link failures. Another dimension to further research would be multiple target detection and multiple mobile robot navigation. Fig. 3 gives an understanding of the pseudo-gradient distribution in the region. We plan to characterize the relationship of this distribution with that of the actual physical phenomenon occurring in the region, like chemical leak distribution, temperature distribution, etc. The algorithm shall also be tested on hardware using TMote Sky [23] wireless sensors and a generic mobile robot platform.

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