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Autonomous navigation using received signal strength and bearing-only pseudogradient interpolation*



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HIGHLIGHTS

- Efficient WSN-assisted AMR navigation by only 1 modality, received signal strength.
- Novel use of standard artificial potential field for way-point estimation.
- Introducing implicit surfaces for inter-node pseudogradient interpolation in WSN.
- Novel use of standard particle filtering for RSS-based WSN-node bearing estimation.
- Extensive simulation and hardware experimental validation.

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ABSTRACT

Autonomous mobile robots (AMRs) interacting with an *a priori* distributed wireless sensor network (WSN) in a region can address the three-tier challenge of navigating in unknown environments: (i) identifying target locations, (ii) planning paths to the targets, and (iii) efficiently executing the navigation paths to the targets. This paper presents low-complexity algorithms to address the second-tier and third-tier challenges, i.e., efficiently planning and executing paths to target locations. These novel approaches use only the information inherent in WSNs, i.e., received signal strength (RSS). The objective is to have the AMR navigate to a target location by: (i) producing an RSS-based artificial magnitude distribution in the navigation region, (ii) using particle filtering based bearing estimation for orientation information, and (iii) using interpolated pseudogradient for efficient path planning and navigation. Here, the AMR does not require: (i) the global location information for itself or the WSN, (ii) *a priori* information of the direction of a target location, or (iii) sophisticated ranging equipment for prior mapping. The AMR relies only on local, neighborhood information and low-cost wireless directional antennas for navigation. Real-world and simulation experiments, using a variety of node-densities, demonstrate the effectiveness of the proposed schemes. The low-cost, low-complexity advantages of the WSN–AMR interactive navigation provide for efficient map-less and ranging-less navigation methods.

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1. Introduction

In applications such as land-mine search, disaster relief, searchand-rescue, etc., it is considered appropriate to use autonomous mobile robots (AMRs), with their inherent intelligence and autonomous behavior providing mobile computation and processing capabilities. Yet, being physically constrained in their size and range of perception, AMRs lack the global information to determine optimal navigation paths to target locations, especially in unknown environments. Wireless sensor networks (WSNs), with their lowcost, small-size, low-complexity, and multi-functionality advantages, can be deployed over larger terrains, where their sensors can be used to localize target locations, e.g., fires, chemical leakages,







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Fig. 1. Three-tier hierarchical navigation strategy. The concept of the color diffusion in the WSN is borrowed from Fig. 2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

etc. [1]. Through cooperative interaction with distributed WSNs, AMRs can potentially extend their perception range [2,3], utilizing the information from the WSN in applications including area coverage, search-and-rescue, target detection and tracking, cooperative transport, etc. [4,5].

In WSN-assisted AMR navigation, three-tier hierarchical challenges exist: (i) identifying target locations, (ii) planning paths to the targets, and (iii) executing the paths efficiently, as shown in Fig. 1. This research article presents novel approaches to utilizing the WSN-AMR interaction in addressing these challenges and builds on prior research from the authors on this topic [6].

1.1. Problem definition

Considering that a network of uniform randomly deployed wireless nodes is covering an *a priori* unknown geographical area and an AMR is placed into such an environment, the goal is for "the AMR to reach an identified target location autonomously using its interaction with the static WSN only". The WSN assists the AMR by first identifying the target location (through its on-board sensors) and then generating an artificial vector field in the area. This field is based on the received signal strength (RSS), which is an indication of wireless signal intensity in WSN communication. This research proposes that having only this one modality for the AMR, i.e., RSS from the WSN, is a sufficient condition to provide efficient navigation in an online manner without relying on location, ranging, or mapping information of any kind.

1.2. Related research

The state-of-the-art in WSN-assisted AMR navigation can be classified into three categories:

- 1. Prior mapping and localization: The topology and connectivity of the deployed WSN is used to localize the WSN nodes or map the entire region. For instance, Batalin et al. [7] describe a Valuelteration based method where transition probabilities are preassigned at each node by an AMR traversing the network several times before others can navigate the region. Corke et al. [8] describe a scheme using a flying robot to localize sensor nodes, facilitating navigation of robots and humans. Similarly, Twigg et al. [9] determine local received signal strength (RSS) gradients in a WSN for target paths using a combination of exploration and navigation. Bachrach et al. [10], Liu et al. [11], and Menegatti et al. [12] are other examples in this domain.
- 2. Global position aware navigation: The *a priori* knowledge of a localized WSN in the region (from category 1 above or with Global Positioning Systems (GPS)) informs the AMR to intelligently navigate the region. Li et al. [5] utilize GPS coordinates to assign artificial potentials to nodes—repulsion from "dangerous" (obstacle) sites and attraction to "goal" sites. Verma et al. [13] propose a hop-count gradient scheme for guidance to a goal with known WSN-node locations. Other examples include Arora et al. [14], Henderson and Grant [15], Severino and Alves [16].
- 3. Position unaware navigation: Here, only the WSN–AMR interaction is responsible in providing the path, allowing map-less, position unaware navigation. Chen and Henderson [17] explored distributed computation in a "smart" sensor network for coordination with multiple robots, providing gradients for the AMR to follow. Jiang et al. [18] present a farthest-node-forwarding (FNF) scheme utilizing RSS values while building a hop-count based navigation tree. Other research in this domain includes Reich and Sklar [19] and Sheu et al. [20], which follow hopcount based gradient generation in the WSN.

The important limitation in these previous research approaches is their reliance either on: (i) sophisticated hardware [8], (ii) complex algorithms [10], or (iii) naive exploitation of the inherent WSN information [19]. Having the capability to navigate without global position awareness removes the requirement of sophisticated, expensive hardware. Yet, it needs to be supported in both cost and performance by the advantages offered in low-cost sensor networks: (i) density, (ii) redundancy, and (iii) communication information like RSS and topology. Based in this philosophy, the research in this article is part of category 3 above.

2. Materials and methods

Earlier research by the authors in Deshpande et al. [6] presented novel schemes addressing the first and second-tier challenges of identifying target locations and planning paths to them. The schemes used only RSS and topology information. In brief, that research executed the following WSN–AMR interactive procedure:

- 1. The node closest to a sensed target location marked itself as a *target-node* and initiated a packet exchange in the WSN via a flooding mechanism.
- 2. Each subsequent sensor node used its communication hopcount, RSS, and the PG-algorithm [6], to have a magnitude (termed *pseu_g*) assigned to itself. Thus, the *target-node* got the highest *pseu_g*-value assigned, and the subsequent values reduced gradually away from it. A pseudogradient (PG) was thus produced in the WSN-covered region.
- 3. The Basic PG-following navigation algorithm [6] had the AMR communicate with the WSN nodes to follow the direction of increasing *pseu_g* magnitude to reach the target.



Fig. 2. Pseudogradient magnitude distribution in the WSN as described in [6]. The pseudogradient is seen as a color diffusion in the WSN-covered region, from the target-node (RED) to the edges of the WSN. (a) AMR Trajectories in the WSN. (b) Corresponding pseudogradient. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 2 explains the schemes from [6]. The presented schemes were shown to perform better than contemporary schemes in the literature. This was attributed to the utilization of RSS combined with the network topology for AMR navigation. The techniques that were presented in [6] were basic and not designed to optimally utilize the information inherent in the WSN.

- 1. For path planning (Tier-II), the algorithm assumed that the PG is discretized by the locations of the WSN nodes. This implied that the AMR had to follow basic node-to-node straight line paths for navigation, as seen in Fig. 2(a). Without global information for the region and the target, the inter-node region was not represented in the motion space of the AMR, and was unutilized.
- 2. For the navigation execution (Tier-III), a simple, bearing-based triangulation algorithm was presented. It assumed ideal conditions for RSS and directional antenna radiation patterns. As demonstrated later in this paper, the practical implementation of the technique was suboptimal and inefficient.

The research in this article builds on this prior research. It addresses the highlighted shortcomings and proposes novel solutions by utilizing: (i) the RSS in the inter-node region, and (ii) probabilistic filtering to account for the inherent noise in RSS. An example of this is seen in Fig. 2(a) where a visibly shorter trajectory is evident through utilization of the inter-node space.

2.1. Research contribution

Once a WSN is uniform randomly deployed in an *a priori* unknown region of interest, it uses its on-board sensors to identify

a target, e.g., fire, etc. It then executes the PG-algorithm from [6], through a flooding mechanism, which assigns *pseu_g*-values to each WSN node, creating a pseudogradient in the region. An AMR is then introduced into this region.

The objective of this article is to provide novel algorithms to allow the AMR to plan efficient navigation trajectories and optimally execute them as it seeks to reach the target location.

- 1. *Efficient path-planning to target locations* (Tier-II): For efficient path planning, interpolation of the pseudogradient in the region allows the AMR to compute way-points in the inter-node space, allowing it to traverse from one neighborhood to the next, as it moves successively to the target location. The article addresses Tier-II in the hierarchy of Fig. 1, through:
 - a. An artificial potential field based scheme; and
 - b. An *implicit surface interpolation* scheme.
- 2. Improved orientation information for navigation execution: The AMR utilizes filtered orientation information to execute the navigation trajectories optimally. This part addresses Tier-III of Fig. 1, allowing online, map-less, and ranging-less navigation using a particle filtering based neighbor-node bearing estimation for pseudogradient orientation information.

The research explores the combination of low-complexity, probabilistic methods using low-cost hardware for improved navigation efficiency. Experimental results, in simulation and hardware, demonstrate the efficacy of the presented schemes. The utility of the novel techniques is also demonstrated in an obstacle avoidance scenario.

2.2. System architecture

- 1. WSN and Sensor node model:
 - a. The density of the WSN node deployment is sufficient for a connected WSN [21]. The communication range is such that the entire network cannot be traversed in a single communication hop. There exists a physical, geographical path from any starting point for the AMR to traverse to a defined target.
 - b. Each node in the WSN has a unique identification (ID) and consists of a processing unit, memory, radio, power source, and sensors of different types, including thermal, chemical, accelerometer, pressure, humidity, etc.
 - c. Target locations can be of two types: (i) targets having an inherent gradient in their distribution, e.g., fire, chemical leaks, etc., or (ii) targets without such a gradient, e.g., human search-and-rescue. The capability of the WSN to identify target locations and to define the closest node as the *target-node* is assumed for the purposes of this article.²
 - d. The TMote Sky motes ([22, Fig. 3]), having on-board omnidirectional antennas, are used as WSN nodes. The communication parameters are noted in Table 4.
- 2. Location information for the WSN, the AMR, or the target locations is not available. No prior mapping of the WSN or the region has been done. The hardware devices to acquire such information are also not available, i.e., no GPS. The main reasons to add this last constraint are:
 - a. The target applications such as search-and-rescue operations, unknown area exploration, navigation inside buildings, etc., are generally in GPS-denied environments.
 - b. GPS can pose a security threat, especially in military operations, due to its vulnerability to infiltration.

- c. It is advantageous to prove algorithms in GPS-denied regimes to establish a baseline for system performance with less information.
- 3. The AMR platform is based on the iRobot Create robot base [23], which has a two-wheeled differential drive (Fig. 4(a)). The AMR uses three TMote Sky motes, suitably modified to use directional antennas (instead of the on-board antennas) for bearing estimation.³ It also uses one TMote Sky mote with its on-board omnidirectional antenna for raw RSS measurement for the PG-algorithm [6].
- 4. The particular directional antennas used on the AMR are in Fig. 3 [24].⁴ Their wireless radiation patterns indicate a gain of 7 dBi in the Line-of-Sight direction (0°). Based on this, a 120°-offset mounting is used for the antennas. The AMR is not equipped with any ranging sensor for distance estimation to WSN nodes. The Log-normal shadowing model [26] is used to model the relationship between Euclidean distance and RSS.

2.3. Efficient path-planning to target locations (Tier-II)

As stated earlier, in the second-tier the AMR has to plan efficient trajectories to the *target-node*. Instead of only relying on node-tonode navigation [6], the AMR can minimize the overall trajectory by utilizing the inter-node space. The key insight here is that the AMR *itself* acts as a node when navigating through the WSN. This allows the AMR to estimate the gradient (magnitude and direction) at its current location and for its consequent motion. This process is repeated as the AMR incrementally moves towards the target location.

Two mechanisms for the utilization of the information in the local neighborhood are explored.

- 1. Artificial Potential Field (APF) Scheme: This scheme utilizes the concept of assigning potentials to the neighborhood nodes which are a function of their *pseu_g*-values—higher the *pseu_g*-value, higher the attractive potential for that node. The local neighborhood way-point is then computed by combining the potentials over all the neighbor-nodes.
- 2. Implicit Surface Interpolation (ISI) Scheme: This technique utilizes a radial basis function based interpolation scheme that approximates the pseudogradient distribution by constructing a surface fit using the *pseu_g*-values at the neighbor-nodes.

2.3.1. Artificial potential field (APF) scheme

Artificial potential fields (APFs) have been used extensively in WSN–AMR interaction [5,17,27]. The APF approach uses a scalar function that has a minimum value at or near a target location [28]. The PG-algorithm from [6] is essentially an inverted artificial potential field, with its peak lying at the target location. Therefore the concepts of attractive and repulsive forces can be readily applied to the WSN-guided AMR motion. These forces will be a function of the respective *pseu_g*-values at the nodes and the AMR as well. The procedure adopted for APF-based WSN–AMR interaction is as follows:

1. The AMR communicates with the nodes in its neighborhood to collect the *pseu_g*-values and estimates their bearings⁵ in the process. The neighborhood is considered as a square $(2 \times 2 \text{ ft}^2 = 0.6 \times 0.6 \text{ m}^2)$ around the AMR. This "unit" square is chosen due to its simplicity for matrix multiplications and it also eliminates the need of RSS-based ranging which is noisy and uncertain [29]. Fig. 5 explains the concept.

² Indeed, multiple WSN-nodes can sense a target location in their vicinity. An algorithm based on the target sensing intensity and distance could be used to identify the closest node to the target, the *target-node* [14].

 $^{^3}$ Only the AMR has the directional antennas. The WSN nodes use their omnidirectional on-board antennas.

⁴ The cost of the antennas is \$50 each [24], considerably less than on-board GPS devices, costing upwards of \$500 [25].

⁵ This is the Tier-III challenge elaborated upon in Section 2.4.



Fig. 3. System hardware components.

N

a. The AMR determines the neighbor-node having the highest *pseu_g*-value. It then uses (1) to calculate the *pseu_g*-value at its location.

 $pseu_g_{AMR} = pseu_g_{node} \cdot RSS_{node}.$ (1)

- b. The AMR assigns a local coordinate frame to its neighborhood with its location being the origin (0, 0). Based on the bearing information, appropriate $\vec{x_i} ([x_i \ y_i]^T)$ are assigned to each neighbor.
- Point masses are assumed to be located at the node locations which can exert attractive and repulsive forces on the AMR. The potential function used for the forces is given by:

$$\omega_i = \delta \cdot \mathcal{F} (pseu_g_i, pseu_g_{AMR}) \quad \forall i \text{ neighbors}$$
(2)

 ω_i acts as a weighting factor and δ is a scaling factor. The function \mathcal{F} is so chosen as to present an attractive potential (positive) at the AMR for *pseu_g*-values higher than *pseu_g_AMR*, while presenting a repulsive potential for *pseu_g*-values lower than *pseu_g_AMR*. The function that satisfies this condition is:

$$\mathcal{F}(a, b) = \log\left(\frac{a}{b}\right).$$
 (3)

For cases where the argument to function \mathcal{F} is less than 1, i.e., for *pseu_g*-values lower than *pseu_g_{AMR}*, the weight becomes negative.

3. The next way-point for the AMR is then calculated using the weighted-sum of the neighbor-node locations:

$$\vec{\mathbf{x}} = \sum \omega_i \cdot \vec{\mathbf{x}}_i. \tag{4}$$

4. The AMR moves from one neighborhood to the next through the estimated way-points towards the target location. As seen in Fig. 6, the intermediate locations $(1 \rightarrow 9)$ are way-points through which the AMR traverses. At each of these, it implements the APF procedure to calculate the next way-point.

2.3.2. Implicit surface interpolation (ISI) scheme

As stated in Turk et al. [30], interpolated implicit surfaces, created by summing a set of weighted radial basis functions (RBFs), are constrained to pass through a pre-defined set of constraint points. For this research, the constraints are the node locations in the AMR neighborhood, and the surface approximates the pseudogradient magnitude distribution in it.

2.3.2.1. Interpolation problem statement. The interpolation problem is to find a function $\mathcal{F} : \mathbb{R}^m \to \mathbb{R}^1$ which satisfies the constraints:

$$\mathcal{F}\left(\vec{x}_{i}\right) = g_{i} \mid i \in N. \tag{5}$$

Here, $x_i \in \mathbb{R}^m$ are the pre-defined *N* constraints, and $g_i \in \mathbb{R}^1$ are a corresponding set of real numbers. For this research, $x_i \in \mathbb{R}^{m=2}$ are the locations in each AMR neighborhood, while g_i are the *pseu_g*-values. As described in [30], an RBF at a point *p* is described as $\varphi(\|p - c\|)$, based on a *basis-center* point *c* and a function $\varphi(\|\cdot\|)$, where $\|\cdot\|$ denotes the Euclidean norm. The RBF is termed radial since it returns the same value for all points *p* that are the same distance from *c*. Therefore, for a weighted sum of RBFs, the function *F* can be given as [30]:

$$\mathcal{F}\left(\vec{x}_{i}\right) = \sum_{i=1}^{N} \varphi\left(\left\|\vec{x} - \vec{x}_{i}\right\|\right) \cdot w_{i}$$
(6)

$$\therefore \sum_{i=1}^{N} \varphi\left(\left\|\vec{x} - \vec{x}_{i}\right\|\right) \cdot w_{i} = g_{i} \quad \dots \text{ from } (5) \dots$$
(7)

$$\therefore \Phi \cdot \vec{w} = \vec{g}. \tag{9}$$

Here, $\vec{w} \in \mathbb{R}^1$ are the weights assigned to the RBFs, called the *linear weight* vector. Φ is called the *interpolation* matrix and \vec{g} is called the *desired response* vector. In Φ , n is the number of points in the neighborhood, while there are N basis-centers. Each function $\varphi(m) \cdots (m \in \mathbb{R})$ is given by the Thin Plate Spline⁶ RBF $\varphi(m) = m^2 \cdot \log m$. Eq. (9) is a linear system of equations in the unknown \vec{w} . In order to solve this, Shewchuk [32] presents a straightforward, iterative algorithm for solving linear systems using the method of *conjugate-gradients*.

⁶ Spline interpolants are known for their stability, computing simplicity and convergence properties [31].



Fig. 4. AMR hardware and directional antenna characterization setup. (a) AMR hardware. (b) Trial setup for 5 ft.

2.3.2.2. Iterative ISI implementation. The process of producing the implicit surface fit is treated as a two-stage supervised learning problem:

- 1. The first stage trains the linear system, with known Φ and \vec{g} , to obtain \vec{w} :
 - a. This step executes the same procedure as in step 1 of the APF scheme. Using (1), the AMR obtains its $pseu_{gAMR}$ -value from the neighbor-node with the highest $pseu_g$ -value.
 - b. $\vec{g} \cdots (N \times 1)$ consists of the *N* pseu_g-values for the neighbor-nodes and pseu_g_{AMR}. The matrix $\Phi \cdots (N \times N)$ is constructed with a φ (*m*) at each of the *N* locations $\vec{x_i}$ of the neighbor-nodes and the AMR.
 - c. Then, $\vec{w} \cdots (N \times 1)$ is obtained using the method of *conjugate-gradients* [32].
- 2. The second stage interpolates the \vec{g} using the \vec{w} from stage 1, producing the surface fit in the AMR neighborhood:
 - a. The neighborhood of the AMR is represented as a $\sqrt{n} \times \sqrt{n}$ grid of *n* points. A new Φ matrix is constructed with a φ (*m*) at each of the *n* points, in relation to the *N* basis-centers. Therefore, the new Φ is ($n \times N$).
 - b. By solving (9), the new $\vec{g} \cdots (n \times 1)$ is obtained with a *pseu_g*-value at each of the *n* points.

The AMR then moves to the point which has the highest *pseu_g*-value in its *n*-point neighborhood. Fig. 7 is an example of the interpolated surface using the Thin Plate Spline (TPS) RBF. At each of the intermediate way-points ($1 \rightarrow 5$ in Fig. 7), the AMR executes the 2-stage process noted above in order to determine the next way-point in the trajectory. The interpolated magnitude distributions for each of the intermediate way-points are shown in Fig. 8.

2.4. Improved orientation for efficient navigation execution (Tier-III)

Once the AMR path to the target location has been planned in Tier-II, in the third-tier, the AMR looks to efficiently execute the planned trajectory. As noted in literature [9], bearing information



Fig. 5. Triangulation-based range and bearing estimation on the "unit" square.

from RSS can simplify the navigation task of an AMR. A simple triangulation scheme for bearing estimation using RSS, from the lowcost directional antennas on-board the AMR was introduced in [6]. It provided sufficient information to facilitate online localization of the AMR node-neighborhood, but was sub-optimal [6].

For a preliminary characterization of that scheme, RSS values were recorded at the three directional antennas for the AMR's communication with a single stationary node at three separate distances—5 ft., 15 ft., and 25 ft. (see Fig. 4(b)). At each location, the AMR was rotated "in-place" counter-clockwise for the full 360°, with RSS values being recorded every 30°. One hundred samples were recorded with an inter-packet interval of 100 ms for indoor and outdoor settings. Fig. 9 captures the errors in bearing measurements for the three distances. As is evident in the bar plot of Fig. 9, there is a lot of noise in the readings, with greater distortion observed outdoors as compared to indoors. Fig. 10



Fig. 6. AMR trajectory with and without APF-based way-point computation. The numbered way-points $(1 \rightarrow 9)$ are explained in Section 2.3.1.



Fig. 7. AMR trajectory with and without ISI-based way-point computation. The numbered way-points $(1 \rightarrow 5)$ are explained in Fig. 8. (a) AMR trajectories in the WSN. (b) Corresponding pseudogradient.

shows an example trial using this raw triangulation based bearing estimation. The AMR trajectory is tortuous and not optimal. Clearly, the bearing estimation scheme had to be improved, and some form of filtering of the antenna data was required.

2.4.1. Particle filtering algorithm

To overcome the inherent non-optimality of RSS, a probabilistic filtering mechanism would be appropriate. It would account for the uncertainties in RSS and antenna radiation patterns and determine the bearing which had the highest probability to advance the AMR in the optimal direction. The probabilistic *Bayes Filter* is a recursive algorithm which allows evaluation of multiple hypotheses for



Fig. 8. Interpolated pseudogradient at the intermediate locations in the ISI trajectory. From location 5, the AMR moves directly to the target-node. (a) Location 1. (b) Location 2. (c) Location 3. (d) Location 4.

bearings at each computational step. The advantage of such filtering is that it assumes that the state of the environment is Markovian, i.e., the probability of the current state of a bearing estimate is a combination of the probabilities of the previous state

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Variables in the particle	filtering algorithm.

Variable	Description
\mathfrak{X}_t	Set of N particles $x_t^{[n]}$ ($n = 1, 2,, N$), hypotheses of the bearing estimate at time t. Each $x_t^{[n]}$ is given as $[r, \theta]^T$. r is the range and θ is the bearing.
$w_t^{[n]}$	Importance weight assigned to each particle.
Z_t	Current state measurement, denoted as $[r, \theta]^T$.
<i>u</i> _t	Odometry update at time t, $[d, \phi]^T$. d is the commanded travel and ϕ is the commanded turn.
$\left[\dot{d}, \dot{\phi}\right]^{\mathrm{T}}$	Commanded linear and angular velocities.



Fig. 9. Errors in bearing estimation using the directional antennas and simple triangulation from [6].

of the bearing, the current measurement, and the previous applied controls to the AMR.

The *particle filter*, a non-parametric implementation of the Bayes filter can approximate a broad set of distributions, especially useful in the case of RSS to account for noise, interference, multi-path effects, shadow fading, etc. It represents the posterior probability as a set of random samples, *particles*, drawn from the probability distribution, recursively updated in an online manner. In this research, each particle represents a hypothesized bearing estimate for each WSN neighbor-node under consideration at the AMR. The variables are listed in Table 1.

 \mathfrak{X}_0 is initialized to a set of uniform randomly distributed values over the interval $[-180^\circ, 180^\circ)$ for θ , while r and u_0 are initialized to zero. The filtering involves the following steps:

1. **State update**: relating the current bearing state to the previous state.

$$\begin{aligned} x_t^{[n]} &= f\left(x_{t-1}^{[n]}, \ u_t, \ \omega_t\right) \\ &= x_{t-1}^{[n]} - u_t + \omega_t \end{aligned} \tag{10}$$

 ω_t implies that u_t is trusted with an associated uncertainty drawn from a normal distribution.

2. **Measure**: The new bearing state measurement $z_t = [r, \theta]^T$ using the triangulation scheme of [6]. The '*r*' is obtained on the "unit" square as noted in Fig. 5.

3. **Measurement update**: In this research, a Gaussian relationship between the state and the measurement sufficiently demonstrates the principle, expressed through the weights for each particle:

$$w_t^{[n]} = e^{-\frac{z_t - x_t^{[n]}}{\eta}} + \epsilon \tag{11}$$

 ϵ is a small value ('>0') to ensure $w_t^{[n]} > 0$ always. η is the uncertainty associated with z_t .

4. **Resampling**: The 'Select with Replacement Resampling' algorithm (pp. 33, Rekleitis [33]) is used in this research. The particles with a higher weight have a higher probability of being copied multiple times for the next iteration. The total count *N* of the particles is the same for every iteration.

To satisfy the constraint of ranging-less navigation, the AMR executes its motion in a constant-size neighborhood in every step (Fig. 5). This removes the requirement of using the range information 'r' in the measurement update step of the filter. As will be evident from the simulation and hardware experiments, such an arrangement yet proves superior to other schemes in literature. The advantage of the particle filter is that it makes no assumptions regarding the linearity or the likelihood distribution of the measurement process and variable. Its online implementation implies that the AMR can update its bearing estimates while moving towards its target location.



Fig. 10. Sample trial setup for AMR navigation characterization using raw bearing estimates based on the triangulation scheme from [6]. (a) Trial setup. (b) Corresponding AMR trajectory.



Fig. 11. Characterization of particle filtering algorithm-stationary trials. (a) Bearing particles distribution over time. (b) Bearing estimation convergence.

3. Results

The performance of the introduced schemes was analyzed through simulation and physical experimentation.

3.1. Characterization of the particle filtering algorithm

To characterize the particle filter method, two demonstrative experiments were conducted.

3.1.1. A stationary AMR, 0.5 m and 45° from a stationary node

As can be seen from Fig. 11, the bearing estimate particles start off in all possible directions. As the number of observations increases, the particles get pruned and the estimated bearing converges to the best estimate. Table 2 summarizes the statistics for the comparative analysis, i.e., with and without filtering. The lower root-mean-squared-error (RMSE) and standard deviation implies more accurate estimations over the duration of the trial.



Fig. 12. Characterization of particle filtering algorithm—motion trials. (a) AMR trajectories. (b) Bearing estimation convergence. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



Fig. 13. AMR trajectory comparison (simulation).

 Table 2

 Particle filtering based bearing estimation—statistics for stationary characterization.

Туре	RMSE value	Standard deviation
Bearing estimate—without particle filtering	21.90°	13.33°
Bearing estimate—with particle filtering	6.42°	3.38°



Fig. 14. Metrics comparison (simulation). (a) Travel-distance ratios. (b) Number of way-points.

It is noted, that the RMSE using the filter is non-zero, i.e., 6.42°. The Gaussian model used in the measurement update step does not ideally model the RSS behavior [29,34,35], and therefore, an average error of zero is not possible. Yet, as is seen in actual hardware trials, the model lends itself sufficiently in demonstrating a significant improvement in navigation efficiency.

3.1.2. A navigating AMR, 3 m and 180° from a stationary node

The AMR is considered to move incrementally towards a stationary node. The same experimental setup, as in Fig. 10(a), is used. The step-by-step navigation process involves:

- 1. AMR-Node communication: wherein 50 packets are exchanged at every bearing estimation step, with an inter-packet interval of 100 ms.
- 2. Bearing estimation: The particle filtering algorithm from Section 2.4 is executed. The new estimated bearing is then issued as the calculated bearing θ . 250 particles were used for the experimentation.
- 3. Way-point issuance: The way-point is then issued to the AMR in the form of control input $[d \phi]^T$, where $\phi = \theta$ from step 2. For

the characterization experiments, *d* is maintained as a constant at 0.3 m.

Fig. 12(a) compares the trajectories resulting from the two methods—with (BLUE) and without (BLACK) particle filtering. Fig. 12(b) captures the progression of the filtered bearing estimates. The particles indicate the posterior distribution of the bearing estimate, which over time, begin to cluster around the best filtered estimate, i.e., 0°. The raw bearings on the other hand, show low-to-no convergence properties resulting in a longer and more tortuous route for the AMR.

Table 3 captures the error statistics for the demonstrative experiment. It is evident that the particle filtering mechanism significantly improves the navigation efficiency of the WSN-assisted AMR navigation.

3.2. Experimental validation

Using Tier-II and Tier-III, the AMR adopts the following procedure during navigation:



Fig. 15. Hardware trials setup and AMR trajectory comparison.

1. The WSN is assumed to have *pseu_g* and hop-count values assigned to each node, using the algorithm in [6].

Table 3

- 2. The AMR begins by querying its neighborhood and obtains the *pseu_g* and hop-count values.
- 3. The AMR estimates the bearings of the neighbor nodes using its directional antennas and the Tier-III particle filtering scheme of Section 2.4.
- 4. The AMR then assigns a local coordinate frame to its neighborhood with its location being the origin (0, 0). Based on the bearing information, appropriate $\vec{x_i} ([x_i \ y_i]^T)$ are assigned to each neighbor node. As described earlier, this is done so as not to require the noisy, RSS-based ranging estimate to be included into the navigation process (Fig. 5).
- 5. The $\vec{x_i}$ and the *pseu_g*-values are then used in the respective Tier-II methods APF or ISI to calculate the next way-point $\vec{x_k} \left(\begin{bmatrix} x_k & y_k \end{bmatrix}^T \right)$ in the neighborhood of the AMR.
- 6. The control input $[d \phi]^T$, consisting of the distance and bearing to the estimated way-point, is issued to the AMR.
- 7. The AMR repeats steps 2–6 at each way-point as it moves from one to the next, until it reaches the *target-node*. The AMR thus needs neither the knowledge of the whole WSN nor all the way-points *a priori*. For experiment purposes, the AMR is said to have arrived when the RSS value between itself and the *target-node* is greater than -40 dBm.

Table 4 lists the various parameters used during experimentation, computed after extensive trials in experimental settings, while following suggestions in [25,26,36]. The effectiveness of the methods was established through the following performance metrics:

- 1. Travel-Distance Ratio: measured as the ratio of the actual distance traveled by the AMR to the Euclidean distance between the starting and target locations; it captures the energy expenditure and quick-response capabilities.
- 2. Number of Way-points: signifies the number of intermediate locations required by the AMR in its trajectory from the starting to target location; it captures the WSN–AMR communication overhead during navigation.

3.2.1. Simulation experiments

The simulation experiments provide a comparison of the APF and ISI schemes with the Basic PG-following navigation scheme from [6], as well as other similar schemes from literature. The simulations were conducted with 30 different random generations of node locations over a $500 \times 500 \text{ m}^2$ area, and a 95% confidence interval was computed for the data. Fig. 13 compares the trajectories for the different schemes. Clearly, the schemes utilizing the inter-node space are more efficient as evidenced in the results. Fig. 14(a) and (b) summarizes the performance. As seen, the introduced neighborhood way-point computation schemes

Table 4

Experiment parameters.

WSN parameters			
Transmit power	0.5 mW	Antenna sensitivity	—95 dBm
Number of packets per WSN-AMR interaction	50	Path loss exponent	1.6 (Indoors) 2.4 (Outdoors)
Inter-packet interval	100 ms		2.1(00000)
Particle filtering and navigation parameters			
Number of particles Uncertainty in bearing	$50 \\ \eta = (3/4) \cdot \pi$	Uncertainty in odometry Linear velocity Angular velocity	$egin{aligned} &\omega_t = 0.1^c \ \dot{d} = 0.25 \ \mathrm{m/s} \ \dot{\phi} = 0.61^c/\mathrm{s} \end{aligned}$



Fig. 16. Qualitative assessment of the obstacle presence scenario. (a) Trial layout (in feet). It depicts the locations, the noted RSS values and the calculated *pseu_g*-values at the nodes. The RSS values are calculated as the mean of 150 packets exchanged with the target-node, at -25 dBm transmit power. (b) ISI-surface using assigned *pseu_g*-values. It shows the interpolated surface using ISI. The flatter pseudo-gradient following trajectory is shown as well.

significantly improve the navigation efficiency. A few important points are noted from the figures:

- 1. In both figures, a lower value of the metric indicates better performance. It is evident that both APF and ISI schemes perform better than those existing in literature. Also, their confidence intervals are narrower, indicating superior consistency.
- 2. The density of the WSN impacts the performance of the interpolation schemes.
 - a. For low density, there are a lower number of neighborhood locations, both for the training stage of the ISI, and the total attractive potential of the APF. This causes the AMR to follow trajectories similar to the Basic PG-following from [6].

Table 5 Metrics comparison (ba

Metrics comparison (hardware).						
Setting	Indoors (2-hop)		Outdoors (3-hop)			
Method	Basic	APF	ISI	Basic	APF	ISI
(a) Travel-distance ratios						
Trial 1	1.654	1.380	1.279	1.749	1.313	1.407
Trial 2	1.604	1.452	1.227	1.709	1.293	1.415
Trial 3	1.609	1.317	1.254	1.714	1.355	1.323
Average	1.622	1.383	1.253	1.724	1.321	1.381
(b) Number of way-points						
Trial 1	43	16	15	50	20	20
Trial 2	40	18	14	48	18	20
Trial 3	41	15	15	48	21	19
Average	41.3	16.3	14.7	48.7	19.7	19.7

- b. As the density increases, the inter-node space is better approximated by the ISI and APF methods, resulting in better performance.
- c. Beyond 400 nodes, the improvement in performance reduces. This result is consistent with [37], which relates that with increased training samples, the problem becomes overdetermined. This reduces the advantages of the schemes.

3.2.2. Hardware experiments

For the hardware navigation experiments, three trial runs each were conducted indoors and outdoors. The chosen network layouts are shown in Fig. 15. The indoor experiments were conducted using a 2-hop network, i.e., the AMR was placed in the network field where it was two hop-counts away from the *target-node*. The outdoor experiments were conducted using a 3-hop network. The pre-assigned hop-count and *pseu_g*-values, calculated by executing the PG-algorithm independently, are listed alongside the node locations in Fig. 15.

For the indoor setup, the actual distance between the AMR start and target locations was 7.5 m, while for the outdoor setup, it was 9.15 m. Fig. 15 also shows representative sample trials for comparison of the trajectories for the Basic PG, the APF, and the ISI methods. A comparison of the metrics values is shown in Table 5.

4. Discussion

Two specific advantages form the basis of the contributions in this research: (i) utilizing probabilistic online orientation estimation, and (ii) utilizing the inter-node space in a WSN field. Practical WSN-AMR interactive navigation is improved by using particle filtering for bearing estimation. Experimental results demonstrate the consistent superiority in performance of the filtered bearings against using raw RSS values (Tables 2 and 3). In utilizing the internode space in a stationary WSN, the interpolated implicit surfaces (ISI) and artificial potential fields (APF) significantly improve the navigation efficiency of the AMR, as shown by the statistics in Table 5. The choice of the method therefore, is between APF and ISI, as further discussed below.



Fig. 17. AMR trajectory—with and without obstacle avoidance computation.

Table 6

Average trajectory execution times-hardware (seconds).

Setting	Indoors (2-hop)	Outdoors (3-hop)
Basic PG	338.08	429.76
APF	307.71	334.79
ISI	286.62	367.42

These improvements also impact the overall response time of the AMR. The *Trajectory Execution Time* is proportional to the number of way-points in the trajectory. The comparative average values for the response times with the hardware trials are noted in Table 6.

Pronounced reductions in metric values are observed in Tables 5 and 6, signifying the superiority in performance of the Tier-II schemes. The hardware trials corroborate the results from the simulation trials. The node-to-node (Basic PG) navigation is a naive implementation. Although it utilizes the knowledge of the pseudogradient in the WSN, it fails to take complete advantage of it in the WSN-covered region. This information is exploited in the neighborhood way-point computation algorithms.

4.1. Comparison of APF and ISI

It is observed that the ISI method outperforms the APF method in simulation. On the other hand, the methods show similar performance in hardware trials, with the APF method slightly better, although this was a limited set of trials. Both methods have their advantages and disadvantages:

- 1. APF is more computationally simple to implement as compared to ISI.
- APF uses weighted pseudogradient values discretized by node locations in the AMR neighborhood. ISI, on the other hand, approximates the distribution of the pseudogradient in the whole neighborhood, which is advantageous in planning alternative paths.

3. APF is more sensitive to noise in RSS and bearing estimates than ISI. ISI performs better indoors (more noise, interference, multipath effects), while APF is better outdoors.

The choice between the two methods would depend on: (i) parameters to be controlled, e.g., savings on time and energy vs. savings on computational resources, (ii) navigational setting, e.g., outdoors vs. indoors, and (iii) information utilization, e.g., optional paths for obstacle avoidance.

4.2. Obstacle avoidance using pseudogradient interpolation

RSS provides qualitative information about the environment that WSNs are deployed in. It experiences attenuation when it travels through objects such as metals, wood, walls, etc., due to absorption, reflection, diffraction, and scattering [26]. This artifact reflects in the *pseu_g*-values as well, as observed in the qualitative assessment of Fig. 16(a). Although node 4 is closer to node 0, the presence of the obstacle between them causes the pseudogradient to be steeper at node 4 than at node 6. If the Basic PG-following navigation algorithm [6] were used at node 6, the AMR would be directed to follow this steepest gradient, and run into the obstacle. In such situations, the AMR would rather consider alternative paths to avoid the obstacle.

Here, the interpolation of the pseudogradient in the neighborhood becomes advantageous. The presence of the obstacle can be reflected in the ISI scheme, generating a surface with a visible "trough" in the region around the obstacle (Fig. 16(b)). In order to avoid the obstacle, the AMR can choose way-points following the flatter gradient, instead of the steepest. This proposed procedure was also tested in an example simulation of a 150-node WSN with random locations of obstacles. As can be seen in Fig. 17, the path employing the flatter-gradient following goes around the obstacles, whereas the trajectories for the Basic PG-following and the ISI-based navigation, both travel through the obstacles. Such a method of obstacle avoidance has important limitations and is indeed incomplete, since it assumes that: (i) the obstacles are small enough to only attenuate the RSS, not block it completely; (ii) there is a lack of knowledge of the precise location of the obstacles; and (iii) the WSN is distributed in such a way that the obstacles do not completely obstruct all paths. Therefore, the proposed mechanism can only provide a higher-level estimation of the obstacle avoidance trajectory, and ideally, would work in conjunction with short-range sensors like proximity, LIDAR, etc., for completeness.

5. Conclusions

This paper successfully demonstrates optimization of WSNassisted AMR navigation. The main contribution of the paper is the description of a distributed, WSN-AMR interactive navigation technique, which is based on a single sensing modality-received signal strength (RSS). The Implicit surface interpolation (ISI) and Artificial potential field (APF) schemes significantly improve AMR navigation efficiency and the simulation and hardware experiments successfully demonstrated this in comparison to existing schemes in literature. The critical advantages of the mechanisms are the capability to operate without the need of global positioning, ranging, or prior mapping information. In scenarios where such information is not available, the WSN can efficiently guide the AMR using only RSS. A low-cost and lowcomplexity scheme for RSS-based, probabilistic bearing estimation was also presented. The article provides methods for implementing autonomous navigation with resource constrained systems.

In the extension of this research, the addition of information and sensing modalities to further optimize the navigation shall be explored. The addition of velocity information as well as WSN localization techniques would allow improved estimation of the AMR trajectory. This aspect can be further augmented by adopting a multi-AMR coordination strategy, where different AMRs can communicate and guide each other to optimize the navigation.

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