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Neuro-Dominating Set Scheme for a Fast and Efficient Robot Deployment in Internet of Robotic Things

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Abstract

Internet of Robotic Things (IoRT) is a new concept introduced for the first time by ABI Research. Unlike the Internet of Things (IoT), IoRT provides an active sensorization and is considered as the new evolution of IoT. In this context, we propose a Neuro-Dominating Set algorithm (NDS) to efficiently deploy a team of mobile wireless robots in an IoRT scenario, in order to reach a desired inter-robot distance, while maintaining global connectivity in the whole network. We use the term Neuro-Dominating Set to describe our approach, since it is inspired by both neural network and dominating set principles. With NDS algorithm, a robot adopts different behaviors according whether it is a dominating or a dominated robot. Our main goal is to show and demonstrate the beneficial effect of using different behaviors in the IoRT concept. The obtained results show that the proposed method outperforms an existing related technique (*i.e.*, the Virtual Angular Force approach) and the neural network based approach presented in our previous work. As an objective, we aim to decrease the overall traveled distance and keep a low energy consumption level, while maintaining network connectivity and an acceptable convergence time.

Keywords: Neural network, Dominating Set, Heterogeneity, Multi-robot systems

1. Introduction

Nowadays, Internet of Things (IoT) technology begins to take an important place in economic systems and in society daily life [1]. It has got a large success in several application areas [2, 3, 4], ranging from smart city [5, 6], Industry 4.0 [7], to smart grid applications [8]. However, most of actuated devices constituting IoT paradigm are only passive so far. Adding an active role for these actuated devices will be needed, in order to optimize the systems where they are present. Willow Garages PR2 robot [9] and Wifibot robot [10] are a good example of dynamic actuated devices.

Robotic systems match very well to this new need, since robots can sense and interact with the environment. Therefore, ABI Research introduced a new concept called Internet of Robotic Things

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1 (IoRT) [11], defined as an intelligent set of devices that can monitor events, fuse sensor data from
2 a variety of sources, use local and distributed intelligence to determine a best course of action, and
3 then act to control or manipulate objects in the physical world. This new concept is expected to
4 be the evolution of Internet of Things (IoT) and robotics [12].

5 In various IoRT applications (*e.g.*, smart agriculture, smart environment monitoring, smart
6 exploration, smart disaster rescue, etc.), the use of mobile robots' teams brings many advantages
7 over one powerful IoRT device. As a matter of fact, a team of robots can accomplish tasks more
8 efficiently, faster and more reliable than a single robot [13, 14, 15]. To carry out cooperative tasks,
9 IoRT team members need to communicate with each other, often via a wireless link *i.e.*, Wifi, and
10 Bluetooth. Maintaining communication and connectivity among multiple mobile IoRT robots is
11 therefore a crucial issue.

12 In our previous work [16], we proposed a distributed artificial neural network based approach
13 (namely, ANN-based), which allows the robots to reach the desired inter-robot distance and desired
14 communication quality, while ensuring global connectivity. Our ANN-based approach has been
15 trained from a set of data obtained by using virtual force based approach. We compared performance
16 of the ANN-based approach with a virtual force approach, and showed as the ANN-based is more
17 efficient in achieving final targets. However, robots were endowed with the same algorithm and
18 behavior to achieve these objectives.

19 In addition, one of the most recent approaches using VFA, that we can compare to, is in [17].
20 In [17], Casteigts *et al.* propose the Virtual Angular Force (VAF) technique to biconnect ² a fleet
21 of mobile robots. VAF is a mix of virtual force and angular force algorithms, so that the virtual
22 force is used to regulate the distance between two nodes, while the angular force is used to regulate
23 the angle between a node and its two consecutive neighbors in order to stabilize as an equilateral
24 triangle.

25 In this paper, we go a step further than our previous work [16] by studying the beneficial effect of
26 using different behaviors in the IoRT concept. We propose a Neuro-Dominating Set (NDS) approach
27 for global connectivity maintenance and robot motion control. We use the term Neuro-Dominating
28 Set to describe our approach, since it is inspired by both neural network and dominating set
29 strategies. Each IoRT robot ³ adopts a different strategy according whether it is a dominating robot
30 or a dominated robot. This heterogeneity of strategies may improve global efficiency (expressed
31 in terms of minimization of traveled distance by each robot), while keeping more or less similar
32 convergence time with respect to the ANN-based approach [16]. Finally, with the aim of providing
33 a more complete assessment analysis, we compare our technique with VAF algorithm, since it is
34 one of the most representative approaches of virtual and angular force based techniques.

35 The rest of this paper is organized as follows. Section 2 provides some backgrounds and explains
36 our motivations behind this paper. In Section 3 we detail the theoretical analysis and proof of our
37 proposed Neuro-Dominating Set algorithm. In Section 4 we provide the simulation results expressed
38 in terms of robot traveled distance, the average distance between any pair of robots, and the QoS
39 level achieved. A comparison with a related technique based on virtual forces [17] and with our
40 previous approach [16] is also carried out. Finally, conclusions are drawn at the end of the paper.

²A network is said to be biconnected if it is still connected after any of the nodes is removed or failed [17].

³In this paper, the terms *IoRT robot* and *robot* will be used interchangeably.

2. Background and Motivations

Biological societies show various examples of diversity allowing participants to self-organize and solve global problems in a more efficient way [15, 18, 19]. The use of this diversity –or heterogeneity– in IoRT context may therefore open possibilities to solve more complex tasks, since different skills and behaviors can be combined together. In the literature, the definition of the *heterogeneity* often varies according to used applications [20, 21, 22]. However, heterogeneity can be defined in terms of variety in robot capacity, hardware, size, cognition, behavior, etc.

In this paper, heterogeneity refers to difference in behavior since we adopt different roles among robots to enable them better achieve the global system performance. It follows that our main goal in this work is to reduce the overall traveled distance (and hence the energy consumption), while maintaining network connectivity and an acceptable convergence time. The robots deployment should be therefore efficient in terms of energy consumption since robots only work under battery.

Many approaches have been designed to maintain the connectivity in multi-robot systems [16, 17, 23, 24, 25, 26, 27, 28, 29, 30]. All these approaches can be classified into two groups according to the degree of *connectivity maintenance* *i.e.* (i) local, and (ii) global. With the local connectivity maintenance, the initial set of edges which define the connectivity graph must be always preserved over time. Unlike local connectivity maintenance, global connectivity maintenance allows suppression and creation of some edges, as long as the overall connectivity of the graph is conserved.

In Multi-Robot Systems (MRS), global connectivity maintenance is often used since the preservation of each local communication link in the network is a very restrictive requirement which significantly limits the capability of the MRS itself [24]. This is the main reason why we focused on global connectivity maintenance approach in our previous work [16].

Besides the connectivity maintenance, ensuring the *collective coverage* is also important to meet the application requirements. In the literature, coverage and connectivity issues are treated separately in general, mainly due to their antagonistic property. However, there are some approaches that could capture a trade-off between these two properties based on a certain relationship between the communication range (*i.e.*, R [m]) and sensing range (*i.e.*, r [m]) [31, 32, 33, 34]. Other approaches like ours do not need that kind of relationship to work.

To provide a full coverage, while maintaining the network connectivity (based on the relationship between R and r or not), many deployment algorithms can be used. These algorithms can be classified into three different categories *i.e.*, (i) virtual force approaches [16, 17, 35, 36, 37] (ii) geometrical approaches [38, 39, 40] and (iii) grid-based approaches [41, 42, 43].

Virtual force approaches use repulsive and attractive forces to move the nodes toward or away from each other in order to meet the full coverage. Nodes will continue to move until convergence (*i.e.* steady state) is reached. They are often used to enhance the coverage after a random deployment in a given area. Geometrical approaches provide a geometric computation in order to detect coverage holes in the region of interest (ROI). In these approaches, the geometric computation can only be done when the global location information of all the nodes in the network is known. Examples of geometry-based approaches include Voronoi diagram and Delaunay triangulation. Finally, grid-based approaches are focused on determining the location of nodes using a special grid pattern. The commonly used patterns are triangular lattice, square grid, hexagonal grid and Honeycomb grid. In these approaches, the ROI is divided into cells and according to the used strategy, the nodes are positioned either in the cell vertices or at the center of the cell. Grid-based approaches provide therefore also a way to compute the effectiveness of network coverage during deployment time.

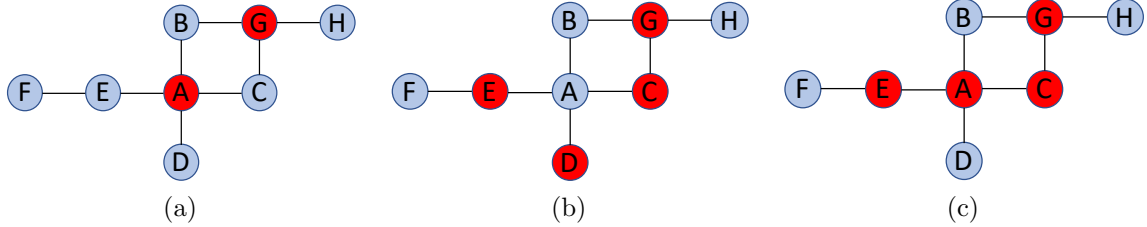


Figure 1: Dominating (*red vertices*) and dominated (*blue vertices*) nodes in different representations of dominating sets *i.e.*, (a) Undominating Set (US), (b) Dominating Set (DS), and (c) Connected Dominating Set (CDS).

1 In this work, we focus only on Virtual Force Approaches (VFA). Specifically, we consider a
 2 Multiple Mobile Robots (MMR) network composed of robots that are able to perform exploration
 3 of unknown environments. This type of activity is fundamental for several real-world applications
 4 such as search and rescue, map building, access to a toxic zone, etc. [44].

5 The deployment of MMRs for exploring purpose presents numerous benefits, like for instance
 6 the whole system is more robust, and the exploration of the unknown area is more efficient. In
 7 this paper we will consider a MMR network for *exploratory* and *coordination* activities in order to
 8 answer to a main question: “*who goes where?*”. In order to properly answer to this question, we
 9 will rely on two important tools, *i.e.*, (i) the concept of Dominating Sets in graph context with
 10 the aim of differentiating the robots and minimizing the traveled distance in order to enlarge as
 11 much as possible the coverage area, and (ii) Artificial Neural Network, in order to let the nodes
 12 learning information about the new position towards those nodes that have to move to keep global
 13 connectivity in the network.

14 Our MMR network can be modeled as a graph $G(V, E)$, where V is the set of vertices representing
 15 each robot and $E \subseteq V^2$ is the set of edges. E can be defined as:

$$E = \{(i, j) \in V^2 \mid i \neq j \wedge d(i, j) \leq R\}, \quad (1)$$

17 where $d(i, j)$ is the euclidean distance between the i -th and j -th robot, and R [m] is the communi-
 18 cation range. Following the above definition, let N_i be the one-hop neighborhood of the i -th robot.
 19 Thus, N_i is the set of robots that can exchange information with the i -th robot via a direct link,
 20 *i.e.*,

$$N_i = \{j \in V \mid d(i, j) \leq R\}. \quad (2)$$

22 The graph $G(V, E)$ may evolve over time due to the robots’ motion but has to be always
 23 connected.⁴

24 2.1. Dominating Sets in Graphs

25 By definition, a set $D \subseteq V$ of vertices in a graph $G(V, E)$ is called a Dominating Set (DS) if
 26 every vertex $v \in V$ is either an element of D or has a neighbor in it [45]. For instance, Figure 1
 27 (a) represents an undominating set, since not all the vertexes $v \in V$ have a neighbor in D (*e.g.*,
 28 the node F does not have a neighbor in D). The nodes in a DS are called *dominating* nodes (*i.e.*,

⁴An undirected graph G is connected if there exists a path between each pair of vertices.

1 the red nodes in Figure 1), the others are called *dominated* (*i.e.*, the blue nodes in Figure 1). This
 2 kind of set is not necessarily connected (see Figure 1 (b)). We refer to a Connected Dominating
 3 Set (CDS) when the subgraph induced by D is connected, as represented in Figure 1 (c). On every
 4 connected graph $G(V, E)$ it can be found at least one DS since the set of all vertices is dominating
 5 according to the definition.

6 In this work, we compute locally DS, while trying to minimize its size. The computation of DS
 7 is also periodically executed in order to take into account the variation of the graph $G(V, E)$ over
 8 time. Notice that the computation of minimum dominating set (MDS) is an NP-hard problem. In
 9 the literature several methods proposed an approximation version of MDS [46, 47]. In this work,
 10 we use the distributed greedy algorithm to approximate MDS; this is not the most efficient in terms
 11 of complexity but it represents the simplest approach to implement. The aim of this paper is to
 12 show that, with the help of the dominant set approach, we can reduce the distance traveled by a
 13 single robot, and then the energy consumption.

14 2.2. Artificial Neural Networks

15 Artificial neural network (ANN) was inspired by the human brain and was designed as a compu-
 16 tational model to solve specific problems. Its architecture is defined by (*i*) basic processing elements
 17 called artificial neurons, and (*ii*) the way in which they are interconnected. The output value of a
 18 single neuron is given by:

$$19 \quad \text{output} = f \left(\sum_i w_i x_i + b \right) = f(\mathbf{W}^T \mathbf{X} + \mathbf{b}), \quad (3)$$

20 where x_i are the inputs, w_i are the connections' weights between x_i and the neuron, \mathbf{W} the weights'
 21 vector, \mathbf{X} is the inputs' vector, \mathbf{b} is the vector of bias, and f is the activation function.

22 The basic architecture of ANN contains three neuron layers *i.e.*, input layer, hidden layer, and
 23 output layer. In this case, the outputs of one layer become the inputs of next layer [48]. A key
 24 element of an artificial neural network is its ability to learn. This means that ANN has to learn
 25 from a data set in order to match the inputs to the desired output. During the learning process,
 26 weights and biases are adjusted till the desired output will be reached. There are several learning
 27 algorithm but in this paper back-propagation algorithm [49] will be used.

28 In our previous work [16], we proposed a distributed trained neural network in order to (*i*)
 29 maintain the global connectivity, and (*ii*) control the robots' motion. ANN-based approach was
 30 trained from a set of data obtained through the centralized IoT-based approach proposed in [16].
 31 The trained ANN is constituted by 2 input units, and 1 output unit. The two input units are $d(i, j)$
 32 and θ_{ij} , while the output is \vec{P}_{ij} (see Table 1).

33 Algorithm 1 summarizes the ANN-based approach. First, the i -th robot needs to know its one-
 34 hop neighbor (*i.e.*, Phase I). Then, it computes the force \vec{P}_{ij} that it has to exert with its neighbor
 35 j by using the trained ANN (*i.e.*, Phase II). If the robot i has many neighbors (*i.e.*, > 2), its new
 36 position \vec{P}_i is calculated as the summation of the forces with respect to all the neighbors (*i.e.*, Phase
 37 III), *i.e.*,

$$38 \quad \vec{P}_i = \sum_{j \in N_i} \vec{P}_{ij}. \quad (4)$$

39 Finally, each robot i moves to its computed new position. Further details on this approach can be
 40 found in our previous work [16].

Inputs	θ_{ij} : the orientation of the line segment from the i -th and the j -th robots
	$d(i, j)$: the euclidean distance between the i -th and j -th robot
Output	\vec{P}_{ij} : vector position that dictates the force between the i -th and the j -th robot

Table 1: Inputs and output of the ANN-based approach.

Algorithm 1 ANN-Based approach (runs every t units of time)

Phase I: Neighbor Discovery

MyNeighbor = FindNeighbor(RobotId)

Phase II: Estimate the position \vec{P}_{ij} between two robots

$$\vec{P}_{ij} = \text{trained_ann}(d(i, j), \theta_{ij})$$

Phase III: Compute the new position \vec{P}_i

$$\vec{P}_i = \sum_{j \in N_i} \vec{P}_{ij}$$

Phase IV: Deployment

move to \vec{P}_i

1 3. Neuro-Dominating Set schemes

2 It is easy to observe that if a subset of robots in the network moves less than the other robots,
3 the global traveled distance will be decreased, and hence the energy consumption as well. In order
4 to benefit from this effect, we need to exploit the good properties of Dominating Set.

5 [Table 2 collects the main variables used in this section.](#) Let us consider a robot network that
6 can be decomposed into two subsets *i.e.*, (i) a dominating set and (ii) a dominated set. Let A be
7 the dominating set and $m = \|A\|$ its cardinality (respectively, B the dominated set and $l = \|B\|$
8 its cardinality). If we have n robots in the network and the computed dominating set has a minimum
9 size, then the following formulas are always true:

$$10 \quad n = m + l, \quad (5)$$

11 and

$$12 \quad m \leq l. \quad (6)$$

13 Now, let $Dist_{Tot}(t)$ be the total distance traveled by all robots in the network at time t .

Table 2: Main variables used in the Neuro-Dominating Set theory.

Variable	Definition
n	Number of robots
m	Number of nodes in the dominating set
l	Number of nodes in the dominated set
d_i	Distance traveled by the i -th node
d_a	Distance traveled by a dominating robot
d_b	Distance traveled by a dominated robot
α	Reduction factor
\vec{P}_i	Position vector of the i -th node w.r.t. its neighbors

1 $Dist_{Tot}(t)$ can be defined as:

$$\begin{aligned}
 Dist_{Tot}(t) &= d_1(t) + d_2(t) + \dots + d_n(t) \\
 &= \|\vec{P}_1(t)\| + \|\vec{P}_2(t)\| + \dots + \|\vec{P}_n(t)\| \\
 &= \sum_{i=1}^n \|\vec{P}_i(t)\| = \sum_{i=1}^n d_i(t),
 \end{aligned} \tag{7}$$

3 where $d_i(t)$ is the traveled distance of the i -th robot at time t , and $\vec{P}_i(t)$ is the position vector of
4 the i -th robot with respect to all its neighbors. It follows that $d_i(t) = \|\vec{P}_i(t)\|$.

5 Considering that some robots are dominating and some others are dominated, we have:

$$Dist_{Tot}(t) = \sum_{a \text{ in } A} d_a(t) + \sum_{b \text{ in } B} d_b(t), \tag{8}$$

7 where $d_a(t)$ is the traveled distance of a dominating robot a at time t , and $d_b(t)$ is the traveled
8 distance of a dominated robot b at time t . It follows that two possible approaches can be deduced
9 from Eq. (8) *i.e.*, (i) dominating robots move less distance than dominated robots so that

$$\sum_{a \text{ in } A} d_a(t) < \sum_{b \text{ in } B} d_b(t), \tag{9}$$

11 and (ii) the dominated robots move less distance than dominating robots *i.e.*,

$$\sum_{b \text{ in } B} d_b(t) < \sum_{a \text{ in } A} d_a(t). \tag{10}$$

13 Let us call NDS-A the first approach (*i.e.* dominating robots move less distance than dominated
14 robots) and NDS-B the second approach.

15 The total traveled distance using NDS-A approach can be defined as:

$$Dist_{Tot_A}^{NDS-A}(t) = \alpha \sum_{a \text{ in } A} d_a(t) + \sum_{b \text{ in } B} d_b(t), \tag{11}$$

1 while, the total traveled distance using NDS-B approach is defined as:

$$2 \quad Dist_{TotB}^{NDS-B}(t) = \sum_{a \text{ in } A} d_a(t) + \alpha \sum_{b \text{ in } B} d_b(t), \quad (12)$$

3 where $\alpha \in [0, 1]$ is a reduction factor. For $\alpha < 1$, the dominated robots (*i.e.*, the set of nodes in
4 NDS-A) travel less distance in respect of nodes belonging to the set NDS-B. On the other hand,
5 for $\alpha = 1$, the NDS algorithm is equivalent to the ANN approach.

6 To know which approach is the most efficient in term of minimization of traveled distance, let
7 us subtract Eq. (12) and (11), *i.e.*:

$$8 \quad \begin{aligned} Dist_{TotB}^{NDS-B}(t) - Dist_{TotA}^{NDS-A}(t) = \\ = (1 - \alpha) \cdot \left[\sum_{a \text{ in } A} d_a(t) - \sum_{b \text{ in } B} d_b(t) \right]. \end{aligned} \quad (13)$$

9 As $(1 - \alpha) \geq 0$, we will focus our study on $\sum_{a \text{ in } A} d_a(t) - \sum_{b \text{ in } B} d_b(t)$. We assume that all the
10 robots have the same velocity either they are dominating or dominated. If $a \in A$ is a dominating
11 robot, it is connected at least to one robot in B . Therefore, d_a is a magnitude of a resultant force
12 generated by one or more robot in B . This means that:

$$13 \quad \sum_{a \text{ in } A} d_a(t) \leq \sum_{b \text{ in } B} d_b(t). \quad (14)$$

14 Therefore, we get:

$$15 \quad Dist_{TotB}^{NDS-B}(t) \leq Dist_{TotA}^{NDS-A}(t). \quad (15)$$

16 The above formula proves that better efficiency, in term of minimization of traveled distance, is
17 obtained when NDS-B approach is used. In other word, the global traveled distance of our robot
18 network will improve if the dominated robots move less distance than the dominating robots.

19 3.1. NDS algorithm

20 In this work, we consider that each robot aims to reach the desired inter-robot distance and
21 the desired communication quality, while ensuring global connectivity in the whole system. As
22 mentioned before, our goal is to decrease the overall traveled distance while maintaining network
23 connectivity and an acceptable convergence time. In this paper, we state that an algorithm con-
24 verges if after some iterations the euclidean distance between any pair of robots is equal to a desired
25 distance D_{th} . NDS algorithm is a mix of ANN-based approach and dominating set strategy. In this
26 algorithm, NDS-B approach will be used since its effectiveness with respect to NDS-A has already
27 been proved in the previous section. In this case, the dominated robots have to travel less distance
28 than the dominating robots.

29 The major steps of the chosen NDS-B algorithm that run in each robot are enlisted as follows
30 *i.e.*, (i) neighbor discovery, (ii) computation of the dominating set, (iii) computation of the vector
31 position between two neighboring robots, (iv) computation of the robot new position, and (v)
32 movement towards the computed position.

33 Algorithm 2 summarizes our proposed NDS-B approach. First, the i -th robot needs to know its
34 one-hop neighbors (*i.e.*, Phase I). Then, in Phase II it computes the MDS through a distributed
35 greedy algorithm that approximates the MDS. The distributed greedy algorithm was chosen due

Algorithm 2 Neuro-Dominating Set approach (runs every t units of time)

Phase I: Neighbor Discovery

MyNeighbor = FindNeighbor(RobotId)

Phase II: Compute the Dominating Set

DS = GetDS()

Phase II: Compute the position \vec{P}_{ij} between two robots

if (RobotId \in DS) then

$\vec{P}_{ij} = \text{trained_ann}(d(i, j), \theta_{ij})$

else

$\vec{P}_{ij} = \alpha * [\text{trained_ann}(d(i, j), \theta_{ij})]$

end if

Phase III: Compute the new position \vec{P}_i

$\vec{P}_i = \sum_{j \in N_i} \vec{P}_{ij}$

Phase IV: Deployment

move to \vec{P}_i

1 to its simplicity. However, faster algorithms such as in [46, 47, 50] can be used for the MDS
2 approximation. The slowest of these algorithms runs in $O(\log n \log \Delta)$ rounds with high probability,
3 where n is the number of nodes and Δ is the maximal degree of the graph G .

4 The computation of the MDS is NP-hard, therefore a lot of works in the literature proposed
5 an approximation version of MDS. The aim here is to show that, with the help of the dominant
6 set approach, we can reduce the distance traveled by a robot. After identifying the MDS, the i -th
7 robot computes the force \vec{P}_{ij} that it has to exert with its j -th neighbor by using a trained ANN
8 (*i.e.*, Phase III). The computation of \vec{P}_{ij} is different according whether the i -th robot is dominating
9 or dominated. If the i -th robot has many neighbors, its new position \vec{P}_i is calculated according
10 to Eq. (4). Finally, the i -th robot moves to the computed position (*i.e.*, Phase IV). It is worth to
11 mention that each robot knows its own position by using GPS (in case of outdoor environments)
12 or other localisation systems (for indoor environments).

13 Finally, we point out that for what concerns the ANN algorithm, the complexity is $O(|n|)$,
14 where n is the number of neighbors. For the dominating set part, the distributing greedy algorithm
15 computes a $\ln \Delta$ -approximation for the minimum dominating set problem in $O(n)$ rounds, where
16 $\ln \Delta$ is the performance ratio of the approximation. We recall that a dominating set D is a f -
17 approximation (with $f \in \mathbb{R}^+$) to a minimum dominating set S if $|D|/|S| \leq f$.

18 **4. Performance Evaluation and Simulations**

19 In this section, the proposed approach will be assessed in outdoor environment, although a
20 validation in indoor scenarios can be also provided by means of collaborative localisation tech-

	Propagation	Two ray ground
	Error model	Real
Physical	Antennas gain	$G_{Tx} = G_{Rx} = 1$
	Antennas height	$h_{Tx} = h_{Rx} = 1$ m
	Communication range	250 m
	<hr/>	
Topology	Width \times height	3×3 km ²
	Number of robots	[5, 70]
<hr/>		
Statistics	Number of samples	100
	Simulation time	3000 s
	Confidence Interval	95%

Table 3: Simulation parameters, [51].

	Computation of the new position	see Algorithm 2
Mobility	Reduction factor, α	[0, 1]
	Desired distance, D_{th}	212 m
	<hr/>	
ANN	Layer number	4
	Input number	2
	Output number	1
	Neuron number in hidden layers	15
	Desired Error	0.00001
	Max epochs	10000
	Activation function	Sigmoid symmetric
	Learning rate	0.2
Training algorithm	Backpropagation	

Table 4: Algorithm parameters.

1 niques [52, 53, 54, 55]. Beacon messages are used to allow robots exchange their positions with
2 their one-hop neighbors.

3 We provide simulation results of our algorithm, and we are interested in studying how the
4 proposed technique converges to the desired distance D_{th} between any pair of robots. The influence
5 of the parameter α in our proposed approach will be also highlighted. A comparative analysis of
6 our technique w.r.t the ANN-based [16] and VAF [17] approaches will be described. Specifically, we
7 will assess our algorithm with respect to (i) the minimized robot traveled distance, (ii) the average
8 distance between any pair of robots, and (iii) the QoS level expressed in terms of RSSI (Received
9 Signal Strength Indicator). Simulations have been carried out in NS2 for a variable number of
10 robots (*i.e.*, ranging from 5 to 70 robots) in an outdoor area of 3×3 km². Notice that the presence
11 of obstacles along the traveled path of the robots is not an issue since our robots (*e.g.*, WiFibots
12 and turtlebots) are equipped with ultrasound sensors allowing them to overcome the obstacle and
13 turning around.

14 All the algorithms in this paper have been implemented in version 2.29 of Network Simulator
15 with patch from [51] that reflects a realistic channel propagation and error model. This patch
16 is used in order to provide the effect of interference and different thermal noises to compute the
17 signal-to-noise plus interference ratio (SINR) and accounting for different bit error rate (BER) to

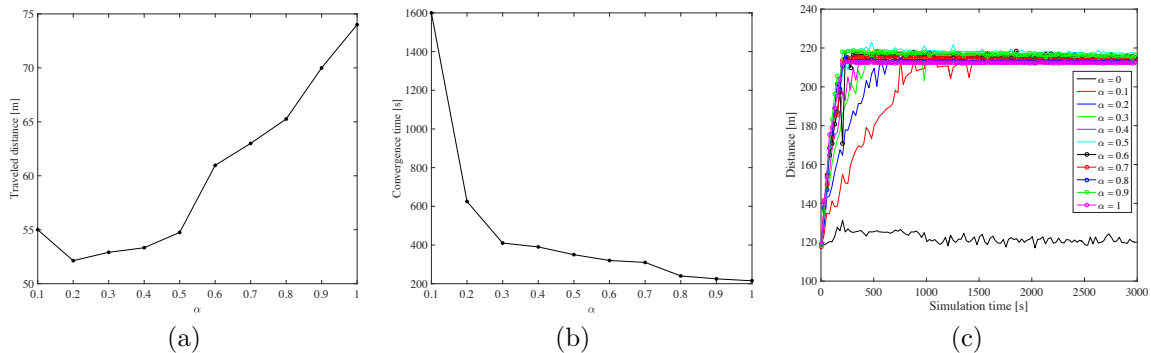


Figure 2: Performance assessment in terms of (a) traveled distance, (b) convergence time, and (c) variation of robot position, versus α , in a network scenario comprised of 15 robots.

1 SINR curves for the various codings employed [56]. Table 3 summarizes the parameters used in the
 2 simulations. All of the obtained results are the average of 100 times simulations and we assume
 3 that the topology is totally connected at the beginning of each simulation. According to [17], in
 4 order to meet the full coverage deployment, the only constraint is that $D_{th} \leq \sim 0.851 \cdot C_R$. In this
 5 paper, we set D_{th} to the upper bound *i.e.*, $D_{th} = 0.851 \cdot C_R$, where C_R [m] is the communication
 6 range of a single robot.

7 The main simulation parameters are reported in Table 3, while, the main configuration param-
 8 eters of the algorithm are summarized in the table 4.

9 The initial position of each robot is known through GPS or other localisation systems, and it is
 10 set randomly. A synchronous model for communications is used, that is, in every communication
 11 round, each robot is allowed to send a probe packet to each of its direct neighbors in the network.
 12 In this work, we assume also that each robot decides to move independently of the other robots.
 13 Each robot moves only on the basis of its local neighborhood knowledge.

14 The discount factor α is one of the most important parameters of our proposed algorithm,
 15 since its value affects the efficiency improvement. If α is small, the traveled distance decreases but
 16 the convergence time increases accordingly since the system needs more time to converge in this
 17 case. According to Figure 2, we can say that for $\alpha \rightarrow 1$, the traveled distance increases, while the
 18 convergence time reduces to minimum value (*i.e.*, 200 s). Furthermore, in Figure 2 (c), for α equal
 19 to zero, the algorithm does not even allow the robots to converge to the desired distance D_{th} (*i.e.*,
 20 212 m). Notice that the choice of evaluating α on a network of 15 robots was arbitrary. We can
 21 actually evaluate it on different number of robots but the conclusion will remain the same, *i.e.*, a
 22 small value of α decreases the traveled distance but increases the convergence time. As a result, the
 23 value of α has to capture the trade-off between the traveled distance and the convergence time.
 24 Thus, for the purposes of our evaluation, α is set to 0.7 since after the sensitivity analysis we found
 25 that this value captures well the trade-off between the traveled distance and the convergence time.

26 Figure 3 depicts the performance comparison –expressed in terms of traveled distance– of the
 27 proposed approaches with respect to ANN [16] and VAF [17]. We observe that whatever the used
 28 approach and when the number of robots is less than 60, the distance traveled by the robots is
 29 proportional to the number of robots in the networks. Therefore, the average traveled distance
 30 of a robot is sensitive to the number of robots in all these algorithms. This can be explained by

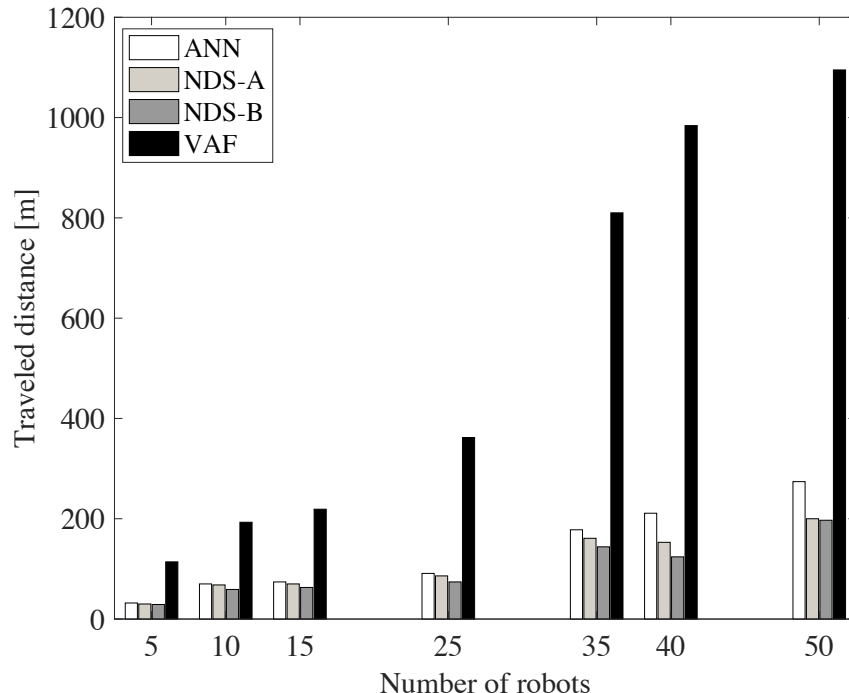


Figure 3: Traveled distance according to the number of the robots, for different approaches.

1 the fact that a robot is expected to have more neighbors when the number of robots increases.
 2 This property is no longer valid when the density of the robots is quite high (*i.e.*, specifically for a
 3 number of robots higher than 50). In this case, there will be a strong collision and the knowledge
 4 of the neighborhood will not be exact. From Figure 4 we can notice a false information about the
 5 neighborhood when the number of the robots is more than 50. The average number of neighbors
 6 for 60 and 70 robots is less than 2, which is completely false.

7 In the following, we present simulation results for different robot networks *i.e.*, ranging from
 8 10 (Figure 5) to 70 robots (Figure 8). We aim to assess the effectiveness of our proposed NDS
 9 approaches with respect to ANN and VAF. As stated before, results are expressed in terms of
 10 (*i*) average traveled distance by a single robot, (*ii*) inter-robot reciprocal distance for a desired
 11 threshold D_{Th} , and (*iii*) power level, meaning the maintained QoS level, versus the simulation
 12 time.

13

14 4.1. Average traveled distance

15 In Figure 5 (a) we notice that our algorithms decrease considerably the average distance traveled
 16 by a robot, reaching a maximum value of ≈ 60 m. On the other hand, high values of traveled
 17 distance are obtained by VAF approach, which shows an increasing slope, and then it is stable
 18 at ≈ 190 m. Similar performances are observed in Figure 6 (a) and Figure 7 (a), where NDS-A
 19 and NDS-B present lower values of traveled distance than ANN and VAF. Obviously, due to the

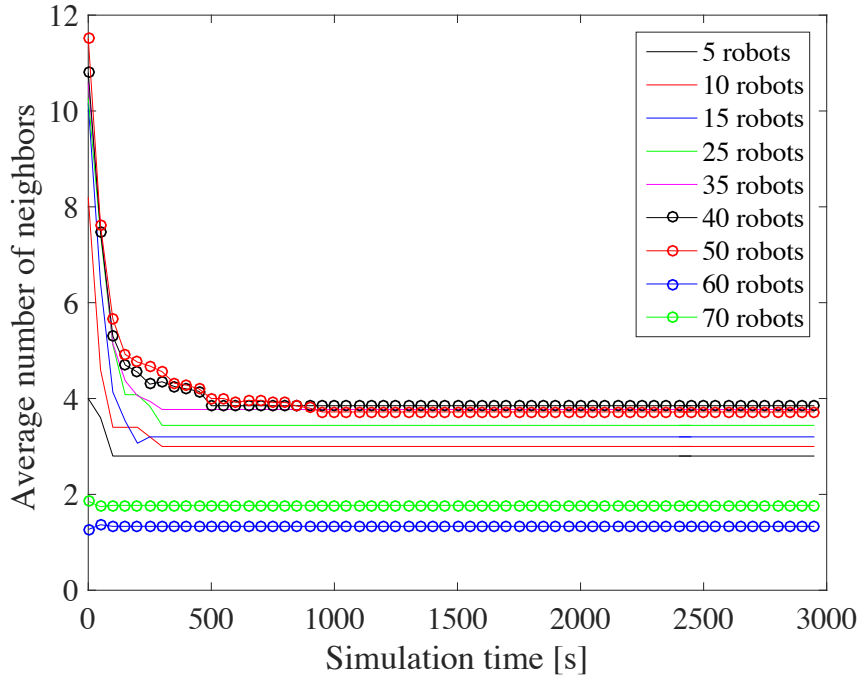


Figure 4: Average number of neighbors for different number of robots.

1 increasing robot density in these scenarios, the traveled distance is higher than the value obtained
 2 in case of 10 robots only (*i.e.*, ≈ 200 m).

3 In case of increasing network size (see Figure 7 (a)), we observe the loss of the linearity property
 4 noticed when the robot network is less than 50 (*i.e.*, the average traveled distance increases with
 5 the robot number). However, NDS-B algorithm remains the most effective in terms of traveled
 6 distance, which validates our theoretical model described in Section 3. In contrast, VAF shows a
 7 very low convergence time, as well as a slow decrease toward the desired RSSI level, as depicted in
 8 Figure 7 (b) and Figure 7 (c), respectively. Finally, by considering the relationship between energy
 9 and traveled distance, we can say that our NDS approaches are energy efficient since they decrease
 10 the average distance traveled by a robot (hence, the energy consumed by a robot decreases as well).

11 12 13 4.2. Convergence time

14 Figure 5 (b) illustrates the convergence of the algorithms to the desired distance set to 212 m.
 15 We can see that the convergence time of our NDS approaches is more or less equal to the convergence
 16 time of ANN, while VAF presents a slow slope towards the desired distance.

17 Neighbor discovery is a key component in our approaches since each robot uses the knowledge
 18 of the neighborhood to compute its new position. Therefore, a poor knowledge of the neighborhood
 19 can affect the effectiveness of our algorithms; this can happen in low density scenarios, due to lower
 20 number of robots in the network. In case of the scenario with 50 robots, we observe a slow increase
 21 of VAF (*i.e.*, it needs more time to converge to the desired distance D_{Th}). As stated before, this

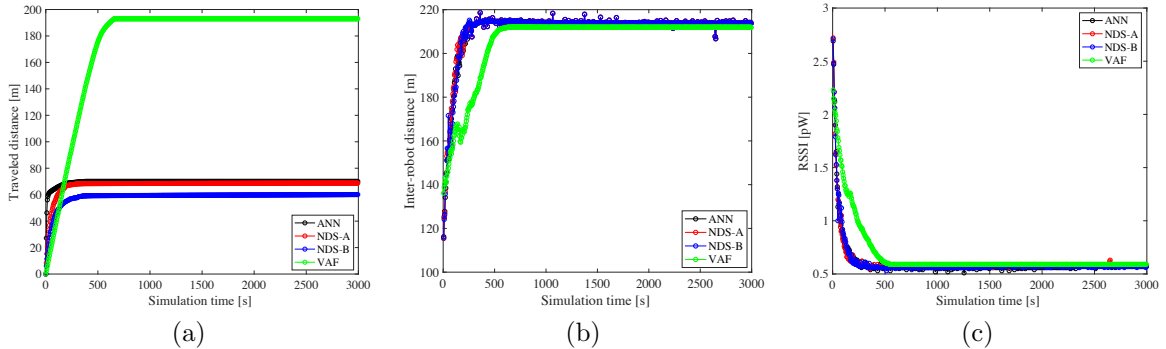


Figure 5: Simulation results in terms of (a) traveled distance, (b) inter-robot distance, and (c) RSSI, obtained with 10 robots.

1 is due to the fact that VAF does not have only to regulate the distance to the desired distance but
 2 it has to regulate the angle between a robot and its two consecutive neighbors. It should be noted
 3 that the convergence is acquired if and only if, for any pair of robots (u, v) in the network we have
 4 $d(u, v) = D_{th} \pm \epsilon$, where ϵ is the tolerance value.
 5

6 4.3. QoS assessment

8 Finally, Figure 5 (c) shows that our proposed approaches can maintain the desired QoS level
 9 (expressed as RSSI of ≈ 0.5 pW) among neighboring robots. In this paper, the choice of the desired
 10 QoS level was made on the basis of the desired distance D_{th} *i.e.*, the RSSI measured at a distance
 11 D_{th}) but can be used of course independently. For example, we can setup the desired QoS level
 12 based on the results in [57], which show that the packet received rate is at least 85% for links with
 13 RSSI above 3.16 pW (*i.e.*, -87 dBm), using CC2420 single-chip RF transceiver that is compliant
 14 with IEEE 802.15.4 standard. In Figure 5 (c) we observe that VAF reaches the desired RSSI
 15 slowly, while in other scenarios with higher robot densities VAF approaches higher RSSI values (see
 16 Figure 6 (c), Figure 7 (c), and Figure 8 (c)).

17 To summarize, we can conclude that our approaches outperform VAF for what concerns the
 18 traveled distance, the convergence time and the desired power level. This occurs both in low and
 19 high density scenarios. NDS-A and NDS-B present better performances also with respect to ANN.
 20 We observe that for increasing network size NDS-A and NDS-B have a faster convergence time, as
 21 well as a fast slope toward the desired RSSI level. Finally, the distance traveled by a single robot
 22 is reduced with the proposed techniques, as compared to both ANN and VAF.
 23

24 5. Conclusions

25 In this paper, we introduced the NDS algorithm with the aim of efficiently maintain the global
 26 connectivity among multiple mobile robots to a desired distance and quality-of- service level. The
 27 proposed approach is based on neural network and dominating set strategies. Our contribution was
 28 to demonstrate that heterogeneous behavior of robot in MMR networks and IoRT concept can lead
 29 to decrease the global traveled distance while achieving an minimum convergence time. Through

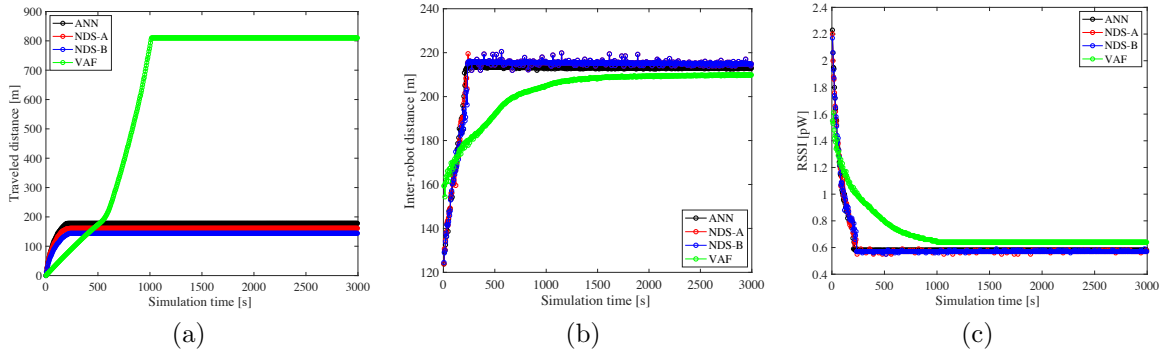


Figure 6: Simulation results in terms of (a) traveled distance, (b) inter-robot distance, and (c) RSSI, obtained with 35 robots.

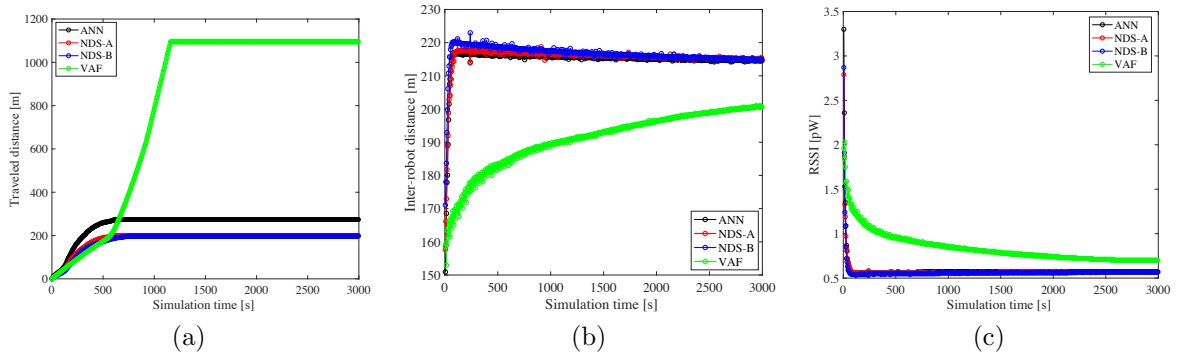


Figure 7: Simulation results in terms of (a) traveled distance, (b) inter-robot distance, and (c) RSSI, obtained with 50 robots.

1 a theoretical analysis and extensive simulations, we showed that our approach outperforms the
 2 ANN-Based and VAF approaches proposed in [16] and [17] in terms of traveled distance, while
 3 maintaining similar convergence time.

4 Due to the nature of the problem on the real world *i.e.*, environmental changes, presence of
 5 interference, etc., our algorithm must be further evaluated by real experiments. Our future work
 6 will focus on this direction; to create a real MMRS scenario by using real mobile robots.

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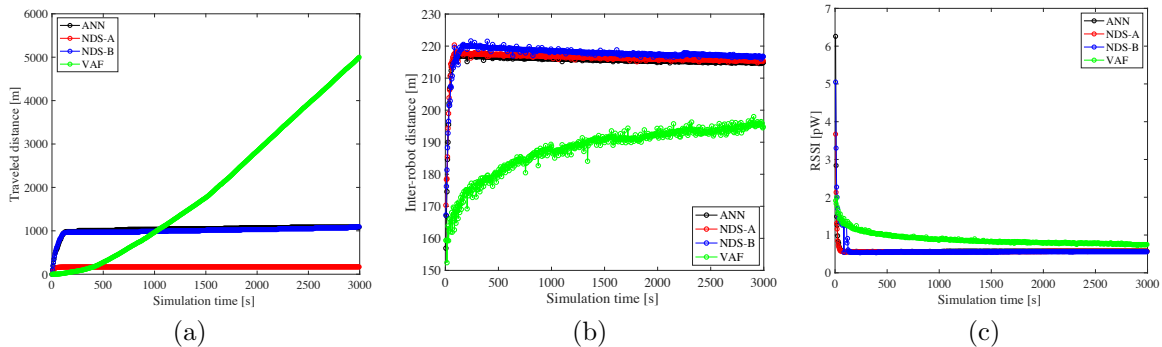


Figure 8: Simulation results in terms of (a) traveled distance, (b) inter-robot distance, and (c) RSSI, obtained with 70 robots.

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