

Artificial Neural Network and IoT Based Scheme in Internet of Robotic Things

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Abstract—Internet of Robotic Things (IoRT) is trending concept which is already in existence. By providing an active sensorization IoRT is considered as the new evolution of IoT. In this paper, we are focusing particularly on two issues: (i) connectivity maintenance among multiple IoRT robots, and (ii) collective coverage of IoRT robots. We are proposing IoRT scheme and artificial neural network control scheme to efficiently maintain the global connectivity among multiple mobile robots to attain a desired level of quality-of-service (QoS). The biconnectivity of the multiple robots can be achieved by the virtual force algorithm. The back propagation approach will find a trade-off between collective coverage and communication quality of multiple IoRT's. The IoT-based approach is completely based on the computation of the algebraic connectivity and the use of extended virtual force algorithm. The neural network controller, in turn is completely distributed and perfectly reflects the IoT-based approach.

Keywords— IoT-based, connectivity maintenance, coverage, IoRT, neural network.

I. INTRODUCTION

Internet of Things (IoT) [1] technology has an important place in economic systems and in society's daily life. Robotic system can sense and interact with their surrounding environment. Hence matches very well to the economic system. IoRT is defined as an intelligent set of devices that can monitor, manipulate, Control, determine and distribute the intelligence of objects in the physical world. Team of robots can accomplish the tasks more efficiently, faster and more reliable. They have been designed to maintain the connectivity through multi-agent systems [3][8].

Many approaches have been designed to maintain the connectivity of multi-robot and multi-agent systems. These Approaches can be classified into two group's i.e. (i) local and (ii) global connectivity maintenance. With the local Connectivity maintenance, the initial set of edges which define the graph connectivity must be always preserved over time. As local connectivity provides some restrictions for the connectivity of mobile robots, Mobile Robot System (MRS) [6] uses global connectivity. The major problematic in global connectivity maintenance is to

maximize the network connectivity. Excluding connectivity maintenance it creates some edges and suppression when overall connectivity is conserved. Graph connectivity metric is used to maintain the global connectivity of mobile IoRT robots. The coverage issue aims to monitor the sensing field and is formulated by Virtual Force Algorithm (VFA) [5]. To summarize and addressing two problems. 1) Connectivity maintenance. 2) Collective coverage. By proposing two motion control strategies to maintain global connectivity of IoRT robots to a desired Quality of Service (QoS) level.

- 1)IoT-based.
- 2)Distributed trained neural network controller.

II. LITERATURE SURVEY

A. Graph representation and Eigenvalues

Multi-Robot Systems (MRS) can be represented by a graph $G(V,E)$. Where V is the set of vertices representing each IoRT Robot.

$E \subseteq V^2$ is the set of edges.

$$E = \{(i,j) \mid |i-j| \leq d(i,j) \leq R\}. \quad (1)$$

Where $d(i,j)$ is the Euclidean distance between i -th and j -th IoRT robots and R is the communication range.

Let N_i be the one-hop neighborhood IoRT robot which can exchange information.

N_i can be defined as

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

The eigenvalues of $L(G)$ can be ordered such that

$$0 = \lambda_1 \leq \lambda_2 \leq \lambda_3 \leq \dots \leq \lambda_n. \quad (3)$$

Definition 1. An undirected graph G is connected if there exists a path between each pair of vertices. Here, the graph G may evolve over time due to the IoRT robots motion but it has to be always connected.

Definition 2. Let define a matrix $A \in R^{n \times n}$. The scalar is an eigenvalue of A . Also there exists a non-zero vector w such that

$$A.w = \lambda.w \quad (4)$$

The vector w is called eigenvector of A corresponding to λ .

B. Artificial Neural Networks

Artificial Neural Networks (ANN) [2] was designed to solve specific problems. Its architecture is defined by artificial neurons and interconnections.

The output value of a neuron is given by:

$$\text{Output} = f(\sum w_i x_i + b) = f(W^T X + b) \quad (5)$$

Where

x_i : the inputs.

w_i : connections weights between x_i and the neuron.

W : weights vector.

X : inputs vector.

b : Bias.

The basic architecture of ANN contains three neuron layers:

Input layer. 2. Hidden layer. 3. Output layer.

ANN has to match the outputs to the desired given inputs.

During the process, weights and biases are adjusted till the desired output will be reached with the help of back propagation algorithm [3]

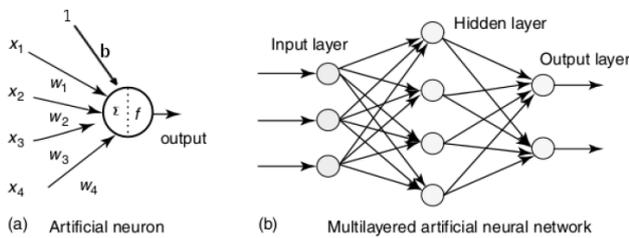


Fig 1. (a) Architecture of an artificial neuron and (b) a multilayered neural network.

III. IOT-BASED AND ANN-BASED APPROACH

The design of two approaches have the following properties:

IoRT robots works with central object which has high computation capability. Connectivity of IoRT robots is kept all along the deployment procedure and converges to the desired communication quality level. Distributed virtual force algorithm or trained neural network controller is used to access the central object. IoRT team members need to communicate often with each other via wireless link (i.e. Wi-Fi, Bluetooth).

There connectivity can be classified into two groups

(i) Local connectivity maintenance, the initial set of edges which define the graph connectivity must be always preserved over time.

(ii) Global connectivity maintenance allows suppression of the signal sent by the mobile robots to the Multi Robot systems which is controlled by central object. As long as the overall connectivity of the graph is conserved .

In Multi-Robot Systems (MRS), global connectivity maintenance is often used since the local connectivity maintenance provides some restrictions. Network connectivity is important to ensure reliable communication between any pair of IoRT robots. Any strategy which maintains λ_2 at positive values guarantees global connectivity among MRS. The central object allows each IoRT robot to move to their new positions if and only if $\lambda_2 > 0$. The proposed approach uses a Central Object (CO) with high computation capability and monitor the connectivity of the overall multi-robot system assuming that each IoRT robot knows its position by using GPS or other localization system. It is important to note that IoRT robots and CO can communicate to each other through an IoT platform. Beacon messages (These are the messages or the information which are transmitted through packets or through WLAN's and contains all the information about the network connectivity of the multiple mobile robots) [4] are used for IoRT robots to exchange their positions with their one-hop neighbors according to the information provided and is distributed by extended virtual force algorithm to control its movement. In order to keep the desired distance

i^{th} IoRT robot moves from $j \in N_i$

Algorithm 1

Stage I: Computing the distance between two robots.

If $d(i,j) < D^{th}$. Moves away.

Stage II: Computing the distance between two robots.

if $d(i,j) > D^{th}$. Moves close.

There exist a desired distance D^{th} between each IoRT robots. The control law generates a vector position P_{ij} such that to keep the line of sight between i^{th} and j^{th} IoRT robots.

$$P_{ij} \text{ is denned as: } P_{ij} = (0.1 \times k \times \text{error}, \theta_{ij}) \text{ if } d(i,j) > D^{th} \text{ and error} > \epsilon$$

$$(k \times \text{error}, \theta_{ji}) \text{ if } d(i,j) < D^{th} \text{ and error} > \epsilon$$

Where:

$$\text{error} = |d(i,j) - D^{th}| \quad (6)$$

θ_{ij} is the line segment from robots I to j .

k is the damping co-efficient.

ϵ is a lower bound of error.

In order to overcome the problem in the original VFA, we set the attractive coefficient W_a to one tenth of repulsive coefficient

$$k \text{ (} W_a = 0:1 \times k \text{).} \tag{7}$$

When the i^{th} IoRT robot has more than one neighbor, its new position is calculated as the summation of the position decisions with respect to all the neighbors:

$$\vec{P}_i = \sum \vec{P}_{ij} \quad (j \in N) \tag{8}$$

After calculating their new positions, each IoRT robot sends the computed position to the Central Object (CO). Providing an ANN-based technique can perfectly matches the behaviors of IoT-based approach.

Algorithm 2 IoT-based (runs every t units of time)

Stage I : Neighbor Discovery

MyNeighbor = FindNeighbor(RobotId)

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

Compute \vec{P}_{ij} using Formula (6).

Stage III : Compute the new position P_i .

Compute P_i using Formula

Stage IV : Compute algebraic connectivity

Compute λ_2 of the dynamic Laplacian matrix $L(G)$

Stage V : Deployment.

if $\lambda_2 > 0$ then

move to P_i .

Else

Do not move.

The trained ANN is constituted by 2 input units $[d(i, j)$ and $ij]$ and 1 output unit P_{ij} . The overall movement of all IoRT robots will allow trained Artificial Neural Network to converge at a desired distance D^{th} from one IoRT robot to other IoRT robot.

Algorithm 3 ANN approach (runs every t units of time)

Stage I: Neighbor Discovery

MyNeighbor = FindNeighbor(RobotId)

Stage II: Estimate the position P_{ij} between two robots

$P_{ij} = \text{trained ann}(d(i, j), \theta_{ij})$

Stage III: Compute the new position P_i

Compute P_i using Formula (8)

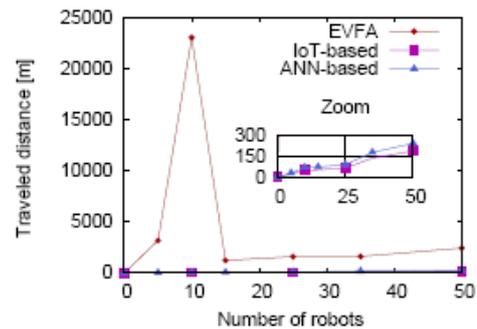
Stage IV: Deployment

move to P_i .

IV. SIMULATION & EVALUATION OF THE RESULTS

Our approaches is compared and described by EVFA (Extended Virtual Force-Based Approach). An Extended Virtual Force based approach is integrated [6][8]. In Extended

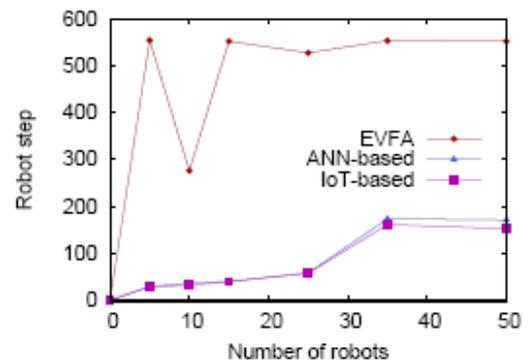
Virtual Force Algorithm, the orientation force proposed by Virtual Force Algorithm is efficiently and successfully overcome and guaranteed the continues connectivity[9] of multiple mobile robots. The continues connectivity and ideal deployment of the orientation force in sensor networks of different ratio of communication range to sensing range. EVFA was designed to overcome the connectivity maintenance and nodes stacking problems in which it could not be achieved by Virtual Force algorithm (VFA). The trained ANN is located or allocated for each IoRT robot to control its movement according to its neighbor's distance. EVFA is based only on the orientation force of the different robots which are in mobility. Basically EVFA holds good for the algebraic connectivity, the distance traveled by robot, the average distance. Simulation of our techniques by travel distance of the robot to gather several information and robot step. Considering the robot movement and distance travelled, the mobile robots with EVFA based approach is more appreciable than ANN based and IoT based approach. The convergence to the desired distance enlarges the collective coverage of the information. Network connectivity is important to ensure reliable communication between any pair of IoRT robots.



(a) Traveled distance

Fig 2(a). Travelled distance of a robot.

Though there is a drastic increase in the graph, the distance traveled and the information collected and sent as a bacon messages is more in EVFA approach.



(b) Robot step

Fig-2(b) Robot step of EVFA approach compared to other approaches.

Initially the robots are very close to each other, If the distance between two or more mobile IoRT robots is larger than the desired distance, the coverage of the information will be decreased but high communication quality is obtained. Simulations have been carried out for a variable number of robots in an area of 3x3 km by its RSSI (Received Signal Strength Indicator).

A. Simulation parameters

Network Simulator reflects a realistic channel propagation [10] and error model. The patch is used to provide the effect of interference and different thermal noises which is used to compute the signal to noise plus interference ratio (SINR) and bit error rate (BER) for the various coding's.

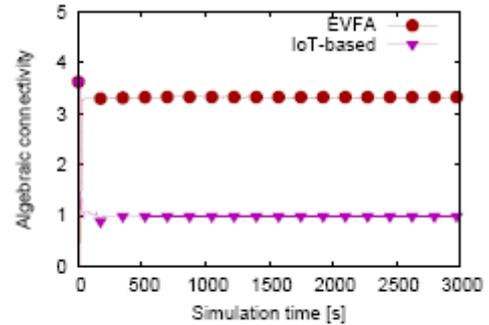
Table 1. Simulation parameters of EVFA.

Physical	Propagation model. Error model. Antennas gain. Antennas height. Communication range.	Two ray ground Real Gt = Gr = 1 ht = hr = 1 m 250 m
Statistics	Number of samples. Simulation time. Confidence Interval.	100 3000s 95%
Mobility	Damping coefficient k. Dth.	0.5 212 m
ANN	Layer number. Input number. Output number. Number of neurons in hidden layers. Desired Error. Max epochs. Activation function. Learning rate. Training algorithm.	4 2 1 15 0.00001 10000 sigmoid symmetric 0.2 back propagation
Topology	Topology width. Topology height.	3000 m 3000 m

B. Simulation results

The ambiguity of distance coverage and gathering of information is overcome and proven that it can be achieved to the desired level of communication and distance travelled by the robots by using EVFA and Back propagation algorithm. The following results are considering the average of 100 times simulation in small area assuming that topology is connected from beginning of simulation. IoT-based approach always kept the global connectivity as it always takes algebraic connectivity constraint. The connectivity in EVFA is appreciable when the robots density is higher than λ . Global connectivity must be greater than 0. It is achieved by this approach. Approaches are energy efficient as compared to EVFA.

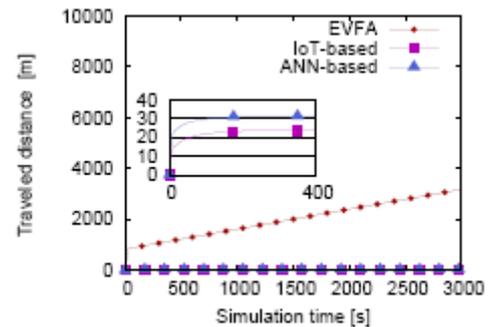
ANN perfectly reflects the behaviors of the IoT-based approach and has made a bit more step to converge. Approaches converge quickly to the above mentioned parameters as our neural network has been well trained. Observing the graphs.



(a) Algebraic connectivity

Fig-3 (a) Algebraic connectivity of multiple robots.

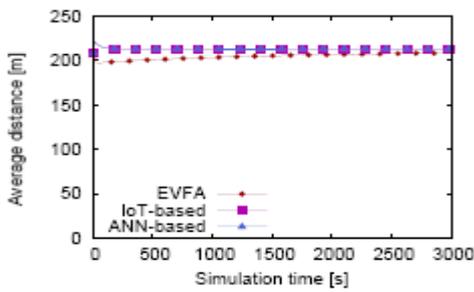
The IoT-based approach always kept the global connectivity since it takes the constraints of the mobile robots in to consideration. Observing Algebraic Force connectivity, we can see that IoRT using Extended Virtual Force Algorithm have a better outcome than IoT based algorithm approach.



(b) Traveled distance

Fig-3(b) The distance travelled by multiple robots.

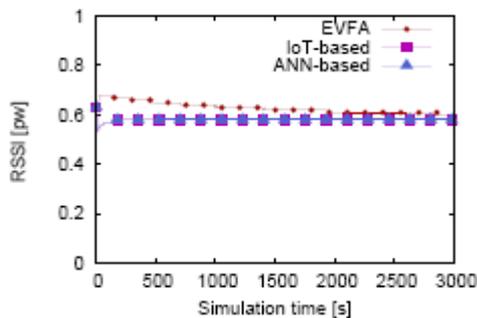
The distance traveled by a robot during the simulation time. The travelled distance of IoRT is greater using EVFA than Virtual Force Algorithm.



(c) Position

Fig-3 (c) Mobile robots position.

The position of the travelled robot is noted once the destination of the desired robot is approached. The comparison of the ANN and IoT based approach of the mobile robots is less compared to the EVFA approach.



(d) RSSI

Fig-3 (d) the received Signal Strength of the Information collected by mobile robots.

Position and RSSI illustrate the convergence of the desired distance and the desired communication quality of mobile IoRT throughout the simulation.

V. ADVANTAGES AND DISADVANTAGES

A. Advantages

- In IoRT applications such as smart agriculture, smart environment monitoring, smart exploration, smart disaster rescue etc.
- Usage of mobile robots which brings many advantages over one powerful IoRT robot.
- Performed as non-linear statistical model.
- Ability to detect all possible interactions.
- Takes less training instructions as it has independent variables.

B. Dis-Advantages

- As IoRT robots must be connected through their neighboring hops, the connectivity maintenance of all mobile robots is a crucial issue.

- Major problem in global connectivity maintenance is maximization of the network connectivity.
- VFA methods have limitations since there are situations that do not allow the systems to converge in a stable state. The connection to the central object is not always possible.

VI. CONCLUSIONS

Artificial Neural Network control scheme to maintain global connectivity among the multiple mobile robots. Virtual Force Algorithm (VFA) failed to capture the trade-off network between network coverage and communication quality expressed as Received Signal Strength Indicator (RSSI) level. With the intelligence of ANN IoT robot network is allowed to converge for a desired distance. Extended Virtual Force Algorithm (EVFA) is proposed through extensive simulation in terms of traveled distance and convergence time. It is worth to say that the global connectivity is reached with ANN approach as it was well trained and inherited the characteristics of IoT-based approach.

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