Interconnecting robots using IoT for multi-agent patrolling

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Abstract

In this paper, we investigate the decentralized multi-agent patrolling problem for covering large areas using the Internet of Things (IoT) framework. We use a network of stationary and moving IoT devices to aid patrolling agents in satisfying the primary objective of uniform patrolling of an environment. The approach uses minimal resources on an IoT device that ensures secured message exchange through one-to-one communication, conveys relevant information through minimal message exchange, and uses simple tricks for keeping relevant information for coordination and decision making for moving vehicles. We propose a novel local, reactive, decentralized patrolling strategy 'MRPP-IoT' Algorithm which functions concurrently on these IoT devices. We implement and test the algorithm on a realistic simulation framework built using SUMO and ROS. Extensive performance analysis based on an evaluation metric for patrolling and IoT device failure cases confirm that decentralized multi-agent patrolling has prospects in the IoT framework. A comparative study with benchmark algorithms conveys that our novel algorithm for decentralized multi-agent patrolling satisfies the primary objective of uniform patrolling and robust against new issues on faults in IoT devices or requirement of every functional IoT device.

1 Introduction

Patrolling is a key part of any security protocol as it can both prevent as well as detect the acts of crime. It has been already established ([13]) that the presence of security personnel in a particular area/locality deters criminals or other bad actors from carrying out violence. In addition, patrolling also helps in identifying suspects by observing unusual behaviours. This task is inherently multi-agent as, traditionally, *Policemen* (either in groups or individually) visit different places in a defined schedule under the jurisdiction of their local unit. Given the advancements in the fields of autonomous driving and computer vision, today we can explore the possibility of automating the patrol process and eliminate humans. Various Multi Robot Patrolling Problems (detailed in Section 2) have been developed to automate the patrolling process.

The Multi Robot Patrolling Problem (MRPP) deals with planning of traversal strategies for multiple autonomous vehicles patrolling a given environment. A patrol strategy is said to be effective if the vehicles visit different locations in the environment as often as possible. For the first time, the multi-agent patrolling using an IoT (Internet of Things) methodology is investigated through this work. More specifically, we propose a decentralized network of interconnected IoT [15] devices that would support coordination among patrolling vehicles. While the concept of IoT is new, its core is interconnection and extracting useful information from this interconnection.

The majority of the relevant literature develops the MRPP problem from an agents' point of view. In particular, various possibilities of communication and capabilities between the agents (vehicles) have been explored. While this is an important direction, offloading the computations through a decentralized strategy has the obvious advantage of avoiding dependency on a centralized station. However, a decentralized MRPP strategy for patrolling an outdoor campus-like environment using agents (vehicles) cannot assume complete communication between the vehicles distributed all around the campus as the extent of patrol is spread over several square kilometers of area. To develop decentralized MRPP, in this work, we suggest an alternate approach by setting up a network of IoT devices of limited communication range and processing capabilities which help patrolling agents in carrying out their task. While the patrolling agents carry out surveillance, this network aids in decision-making for these agents. The devices in this network communicate locally amongst themselves and with the patrolling vehicles in their visit to the place of IoT device, thus maintaining the benefits of secured one-to-one communication and decentralized approach. While IoT supports coordination among agents, it must facilitate high-level decision-making for uniform patrolling by multiple agents. In reverse, the use of IoT introduces a dependency on information exchange on these devices. Therefore, a detailed study is needed to evaluate the patrolling performance under device failures. Analyzing various cases of device failures also mimics the scenario of identifying the redundancy in deployed devices.

In this work, we investigate the use of IoT for providing a solution for decentralized MRPP and summarize our contributions as follows:

- Proposed a novel technique for Multi Robot Patrolling using IoT devices for a secured, decentralised decision making and robust solution against device failures.
- Developed a local, reactive, decentralized algorithm (MRPP-IoT) to minimize Graph Idleness (defined in Section 3) with IoT devices at Junctions as the decision making units.
- Analyzed patrolling performance of MRPP-IoT algorithm based on extensive and systematic set of simulations carried out on SUMO (a traffic simulator). Comparison of the MRPP-IoT algorithm with two state of the art strategies - Conscientious Reactive as well as Reactive with Flags

[8] demonstrate the possibility of decentralised solution for MRPP that maintains the uniformity of patrolling even during device failures.

The rest of the paper is organized as follows - Section 2 presents related works from the literature on MRPP and multi-agent system based IoT development. With the aim of connecting IoT devices with one-to-one communication possibility to develop a decentralized MRPP solution, the problem setting and objectives are formulated in Section 3. In Section 4, the proposed MRPP-IoT algorithm is developed that renders the algorithms for IoT device and agents. A systematic simulation results are presented in Section 5 to facilitate analysis on patrolling performance of MRPP-IoT algorithm. As this work presents the opportunity to use IoT for decentralized multi-agent patrolling, various directions to further explore the benefits of edge computing are discussed in Section 6.

2 Related Works

The investigation into MRPP started in the early 2000s, due to a confluence of factors like, increase in computational power, increasing maturity of the Multi-Agent domain, and others. MRPP can also be seen as a natural extension of mapping and other coverage tasks, where the objective is to visit (cover) all the locations (area) in the environment. In MRPP, the task of visiting all the locations is to be done repetitively preferably not in the same sequence.

Different heuristics [8] under varied problem setups (for example, level of communication between the agents) has been developed using the term *Idleness*. Though the work in [8] is pioneering in many aspects, the empirical validation of the strategies are done under ideal conditions. In [3], the area is discretized into grids, and the agents negotiate to divide the grid cells amongst themselves. Each grid cell has a priority associated with it specified using probability of an event occurring at that location. Two strategies [6] based on dynamic task assignment have been developed, the second of which is an auction based mechanism.

The objective of a generalized partitioning strategy [2] is to arrive at a minimum number of agents which can patrol the given environment constrained by minimum frequency of visits. Each partition is assigned one or more agents. Though the partitioning is possible in polynomial time, the strategy is valid only for Outer planar Graphs. A graph partitioning based algorithm [11] partitioned the given environment into similar sized sub-graphs which are then allotted per agent. However, the partitioning method is not flexible for online applications. In [12], a Bayes' rule based strategy uses the conditional probability for traversing any particular edge depended on the idleness of the node, the number of visits to the node as well as how frequently that edge was traversed in the recent past. In [16], the problem is formulated as an MDP and Q-learning is used to obtain a strategy which reduced the idleness.

There have been many works in the sub-domain of *adversarial* patrolling [1], [19]. The objective in adversarial patrolling is to make sure that the adversary (intruder), cannot attack (intrude) the given environment. The perimeter

setting is considered and probabilistic guarantees in terms of detecting the intrusion have been obtained. In [1], realistic assumptions are made in terms of evolution of events (intrusion), non-deterministic nature of observability by the sensors, etc. A few works (notably [9] and [10]) have also focused on setting up their problem in realistic scenario, such as considering localization and sensing issues, non-uniform performance of different agents etc. In [4], the objective is to find the minimum number of agents which can be successful in intrusion detection. The environment is described as a grid with different *penetration time* for some *target* cells. A probabilistic guarantee is achieved that the *target* cells can be reached before its *penetration time* by at least one of the robots. However, the task of patrolling is not an object of interest.

The existing works under the ambit of MRPP have varied both in scope as well as the extent to which they address the task. A few axes along which the state-of-the-art techniques can be distinguished are as follows -

- Implementation - Online ([8, 6, 12]) vs Offline ([5], [11], [1])
- Environment Description - Perimeter ([9], [1]), Area ([3]), Graph ([5], [6])
- Problem Setting - Adversarial ([1], [19]) vs Non-adversarial ([2], [4])
- Coordination - Centralized ([11], [1]) vs Decentralized ([6], [3])
- Approach - Graph Theoretic ([5], [2]), Heuristic ([8]), Task Assignment ([6], [10]), Negotiation Based ([3]), Learning Based ([12], [16])
- Results - Deterministic ([11], [5]) vs Probabilistic ([1], [4])
- Bounds and Limits - Theoretical ([5], [11], [1]) vs Statistical ([12], [6], [16])

In the last decades, many IoT applications are emerging out, and it is indeed the future of communication that has transformed Things (Objects) of the real world into smarter devices. There are multi-agent scenarios that are being explored to take advantage of the IoT framework. The similarities in dealing with the interconnection of multiple agents or devices enable such an opportunity [18]. Multiple UAVs are explored as edge IoT devices [17] for restoring network under emergency situations. Edge IoT concept is further used for offloading computations [**Shen˙2019˙ACM˙Sensor˙Network**] from the data intensive centralized computations. Investigation of MRPP from IoT gives an opportunity to explore decentralized and secured implementation of local (range-based) communication protocol. The information exchange about visited along with visiting areas, and accordingly, decision making for each patrolling agent are the key for effective patrolling. The IoT devices will make it easier, secured, deployable and fault-tolerant solution in real scenarios. We can use the same IoT network for smart city monitoring [14] or managing any other natural or man-made catastrophe that warrants action to save lives and to protect property, public health, and safety. To the best of our knowledge, no work has analysed the MRPP from IoT perspective and provided meaningful information on system performance due to faulty devices.

The decentralized approach for solving MRPP has a possibility of deployment over large area with secured communication links between IoT Devices. The direct implementation of existing patrolling strategies under decentralized methodology is to be explored and a detailed comparative analysis of these direct implementations in IoT framework is fruitful to quantify system performance for effective patrolling.

3 Problem Formulation

We represent the patrolling environment using a directed graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ where each junction is represented by a node $v \in \mathcal{V}$ and each road segment from junction v to junction w by an edge $(v, w) \in \mathcal{E}$ [1]. For a node v, we denote the in-coming neighbours by $\mathcal{N}_{in}(v) = \{w|(w, v) \in \mathcal{E}\}$ and the out-going neighbours by $\mathcal{N}_{out}(v) = \{w|(v, w) \in \mathcal{E}\}$.

We use the time interval between consecutive visits to the nodes by patrolling vehicles as an evaluation criteria. For this purpose, we use the notion of *Idleness* (introduced in [8]) at time t defined as follows:

- The time elapsed since the last visit to a node $v \in \mathcal{V}$ by any patrolling vehicle is referred to as its *Instantaneous Idleness* (or simply, *Idleness*) and is denoted by $I_v(t)$.
- The *Node Average Idleness* (or simply, *Node Idleness*) $\bar{I}_v(t)$ of a node $v \in \mathcal{V}$ is given by,
$$\bar{I}_v(t) = \frac{1}{t} \int_0^t I_v(\tau) d\tau$$
.
- The *Graph Instantaneous Idleness* $I_{\mathcal{G}}(t)$ is given by,
$$I_{\mathcal{G}}(t) = \frac{1}{|\mathcal{V}|} \sum_{v \in \mathcal{V}} I_v(t)$$
.
- The *Graph Average Idleness* (or simply, *Graph Idleness*) $\bar{I}_{\mathcal{G}}(t)$ is given by,
$$\bar{I}_{\mathcal{G}}(t) = \frac{1}{t} \int_0^t I_{\mathcal{G}}(\tau) d\tau$$
.

Now, the patrolling objective is stated as follows: *For a given environment (represented by $\mathcal{G}(\mathcal{V}, \mathcal{E})$) with N patrolling agents, minimize the Graph Average Idleness $\bar{I}_{\mathcal{G}}(t)$ over the duration of patrol.*

We consider two sets of IoT devices in their minimal hardware requirement form for enabling one-to-one communication for security -

[1] We assume, for simplicity, that there exists only one road segment going from junction v to junction w

1. Junction Device: These are devices placed at each node v of $\mathcal{G}$ representing junctions in the road network. Each device has a minimal memory, processing and communication units. The memory unit stores the Idleness values of the neighbouring nodes. The on-board processor is able to carry out primitive operations like changing the values stored in memory and performing comparisons between different values. The communication unit has both transmitter and receiver to communicate with neighbouring junctions and the agent visiting the node v.

2. Agent Device: Each patrolling agent (vehicle) is equipped with a receiver unit which can receive instructions from the Junction devices. On reaching a particular junction, this device requests the corresponding Junction Device for the next edge to traverse. This next edge information is taken as an input by the vehicle's navigation system.

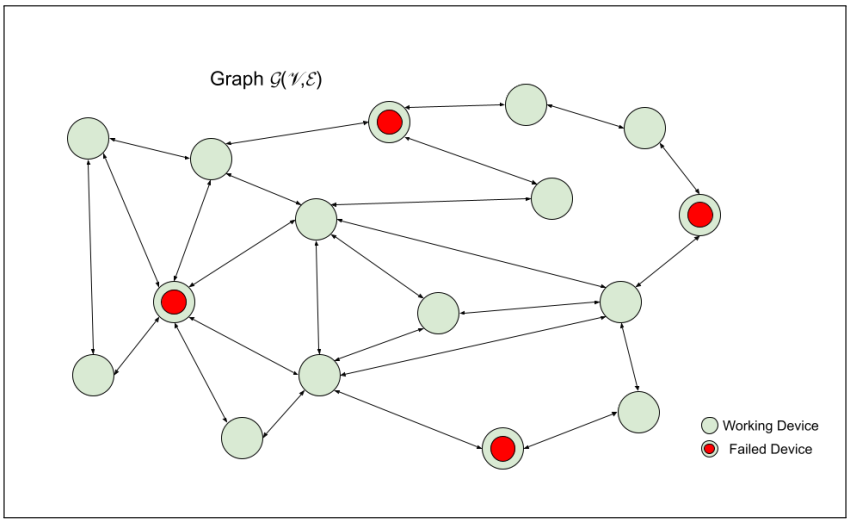


Figure 1: An illustration of directed graph representing an environment with Junction Devices placed at every nodes. Failed Junction devices are marked in red. Arrows show direction of traversal

In the suggested novel decentralized setting (more details in Section 4) wherein the decision making units are the stationary Junction Devices placed at the nodes. For each node $v \in \mathcal{V}$, the Junction Device at v maintains the Idleness of node v and nodes in $\mathcal{N}_{out}(v)$ based on agents' visits to these nodes. The information exchange between nodes is as follows - The Junction Device placed at node v receives data from $\mathcal{N}_{out}(v)$ and sends data to $\mathcal{N}_{in}(v)$. Such that each Junction Device obtains information about all of its out-going neighbours. Obtaining information from outgoing neighbors as against incoming ones is relevant as the patrolling agents (vehicles) visiting a node can go only to one of its out-going neighbours.

A failed Junction Device implies that it is not able to communicate either with those placed at neighbouring nodes or with the agents in its vicinity. Such failures can occur due to power failures or malfunctioning of the devices. It is important to accommodate for such failures in an algorithm which will be applied in realistic settings. Furthermore, analysing the effect of a few failed devices gives the possibility to reduce the number of IoT devices in the environment, thereby avoiding redundancy of IoT devices and the range limits of one-to-one communication. In particular, the requirement of placing IoT device at each and every junction and failures in the placed device need thorough investigation. Therefore, in our analysis, we also consider situations where the Junction Devices fail (refer to Figure 1). These failed Junction Devices can lead to drop in performance as per the evaluation metrics listed above. We do extensive simulations (elaborated in Section 5) to determine the effect of device failures on patrolling performance.

4 MRPP-IoT Algorithm

In this section we explain the proposed patrolling strategy - *MRPP-IoT Algorithm*. It is a decentralized strategy implemented using IoT devices placed at nodes in the environment as well as on the patrolling vehicles. These devices communicate amongst each other locally (recall from Section 3). While patrolling agents carry out the task of surveillance, the high-level decision making on the choice of edge traversal is offloaded to the IoT devices. Algorithms 1 and 2 correspond to parts of the algorithm running on Agent Devices and Junction Devices respectively. Figure 2 describes the communication protocol between these devices when a patrolling vehicle arrives at a node. The scenario is as follows - patrolling agent (say) a arrives at node v after traversing the edge (u, v). The in-coming neighbours of v are $\mathcal{N}_{in}(v) = \{u, w\}$ whereas its out-going neighbours are $\mathcal{N}_{out} = \{u, w, x\}$. Hence, the agent cannot come to node v directly after visiting node x. When the patrolling agent a visits the node v, following sequence of events are proposed and described using Figure 2:

1. It requests the Junction Device placed at node v for the next node to visit amongst the outgoing neighbours $\mathcal{N}_{out}(v)$. For this, the Agent Device a sends the message *NodeVisit* to Junction Device v.

2. The Junction Device at v (if active) responds with the message *NextNode*.

3. The Junction Device at v also sends message *NeighbourVisit* to in-coming neighbors nodes u and w in Figure 2.

With this simple communication protocol for the proposed decentralized MRPP solution, we next decompose the action sequences for Junction Device and Agent Device using Algorithms 1 and 2. *Each Junction Device computes and stores the Idleness values of its own and maintains the same of its out-going neighbors*

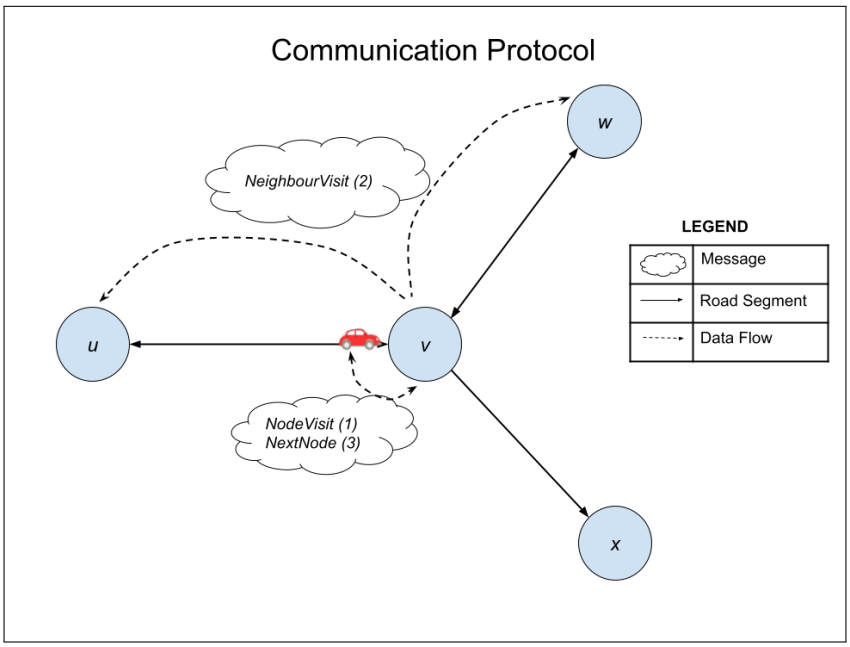


Figure 2: Communication protocols when a patrol agent a visits node v. The numbers in parenthesis in message box represent the order in which these messages are communicated.

In Algorithm 1, we describe the functioning of Agent Devices placed on patrolling vehicles. At the start of the patrol, we assume that the vehicles are placed at the junctions. Consider an agent a at junction v. The Agent Device a sends a message to Junction Device v (Line 2) $NodeVisit(a, v, t)$ and waits for instructions (Line 3) from the Junction Device v. Here, t denotes a's time of arrival at v. The Junction Device responds (Line 5) with $NextNode(a, v, u)$ where $u \in \mathcal{N}_{out}(v)$ is the out-going neighbour that a visits next (Line 6). We also have a fail-safe (Lines 8 - 11) if the Junction Device is malfunctioning. If the agent doesn't receive *NextNode* within a reasonable time (that is, if *timeout*), the Agent Device selects one of the out-going neighbours at random (Line 9) and the vehicle moves to that neighbour.

Algorithm 1 Agent Device(a)

1: **upon event** reach Node(v) **do**
2: send NodeVisit(a, v, t)
3: wait for NextNode
4: **upon event** receive NextNode(a, v, u) **do**
5: traverse (v, u)
6: **upon event** timeout **do**
7: $w \leftarrow$ *sample* $(\mathcal{N}_{out}(v))$
8: traverse (v, w)

In Algorithm 2, we describe the functioning of Junction Devices placed at the junctions in the environment. Consider the device placed at junction v. The internal clock is set to $t_c = 0$ (Line 2). We initialize a $|\mathcal{N}_{out}(v)| + 1$ sized vector I with zeroes (Lines 3-4). Each entry $I(w)$ gives the Idleness of node $w \in \mathcal{N}_{out}(v) \cup \{v\}$.

As described before, when agent a reaches junction v, it sends *NodeVisit*(a, v, t). When the Junction Device at v receives this message (Lines 5-14), it responds with an out-going neighbour (say) $u \in \mathcal{N}_{out}(v)$ that the agent is supposed to visit next. First, the Junction Device updates the vector I appropriately (Lines 6-8). Since, $(t - t_c)$ duration has elapsed, each entry in I is incremented by $(t - t_c)$. Then, the entry $I(v)$ is set to zero as agent a has visited node v. It, then, determines the out-going neighbour (say) v_{max} with highest Idleness value[2] and sends out *Next Node*(a, v, v_{max}) (Lines 10-11). Finally, the Idleness value of node v_{max} is set to zero (Line 12). This ensures that no two agents are assigned the same out-going neighbour consecutively. Finally, it sends a message (Line 13) *NeighbourVisit*(a, v, t) which is received by its in-coming neighbours.

When an out-going neighbour u is visited, Junction Device at v receives a message *NeighbourVisit*(a, u, t) signifying that agent a visited node u at time t (Lines 15-21). The Junction Device then updates its I vector (Lines 16-19) to account for this visit.

[3]

[2]if there are multiple nodes with equal Idleness values, one is selected at random

[3]Conflicting cases such as two agents visiting the same node is handled by serving each agent sequentially through the Junction Device and, equal Idleness values of more than two out-going neighbours is addressed by taking a random choice. Current proposal analyzes the MRPP-IoT technique using the updated information available from immediate neighbors. Future scope of this work can consider decision making by increasing the horizon of available information among neighbors.

Algorithm 2 Junction Device(v)

1: **procedure** INITIALIZE
2: $t_c \leftarrow 0$ ▷ Current Time
3: **for** $w \in \mathcal{N}_{out}(v) \cup \{v\}$ **do**
4: $I(w) \leftarrow 0$
5: **upon event** receive NodeVisit(a, v, t) **do**
6: **for** $w \in \mathcal{N}_{out}(v) \cup \{v\}$ **do**
7: $I(w) \leftarrow I(w) + (t - t_c)$
8: $I(v) \leftarrow 0$
9: $t_c \leftarrow t$
10: $v_{max} \leftarrow \max_{w \in \mathcal{N}_{out}(v)} I(w)$
11: send NextNode(a, v, v_{max})
12: $I(v_{max}) \leftarrow 0$
13: send NeighbourVisit(a, v, t)
14: **upon event** receive NeighbourVisit(a, u, t) **do**
15: **for** $w \in \mathcal{N}_{out}(v) \cup \{v\}$ **do**
16: $I(w) \leftarrow I(w) + (t - t_c)$
17: **if** $u \in \mathcal{N}_{out}(v)$ **then**
18: $I(u) \leftarrow 0$
19: $t_c \leftarrow t$

5 Performance Study using Simulation Results

In order to gain acceptance of IoT for high level autonomous system level task like decentralized multi-agent patrolling, the simulations are carried out in a systematic manner. The simulations setting and results are obtained to substantiate the following outcomes:

- A minimal IoT framework through proposed MRPP-IoT algorithm is capable of satisfying preliminary multi-agent patrolling objective of uniformity in visiting nodes.
- The need to develop novel IoT based multi-agent patrolling algorithm MRPP-IoT as the direct implementations of existing MRPP algorithm have a scope of performance improvements.
- The IoT devices may not be required to be placed at each and every junction for maintaining uniformity in patrolling. In other words, if the patrolling objective is still met with a few faulty devices.
- Observing interesting behaviors on patterns followed by the agents under the scenarios of fully-functional IoT and partially faulty IoT devices.

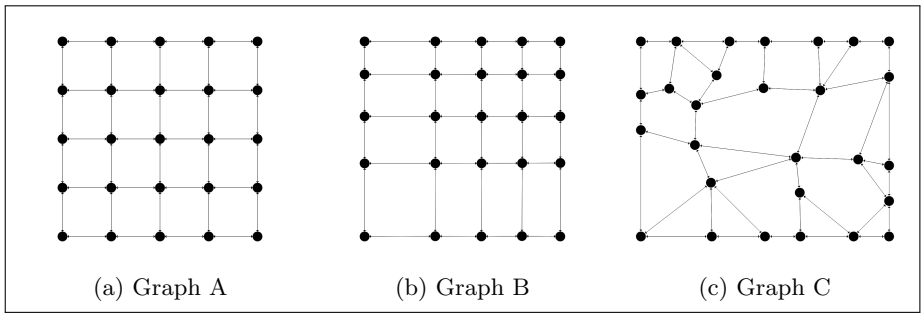
5.1 Simulation Setting

5.1.1 Simulator

We investigate the performance of the MRPP-IoT algorithm based on simulations carried out on 'Simulation of Urban MObility'(SUMO) [7], a realisitc traffic simulator. It is an open source, highly portable, microscopic and continuous traffic simulation package designed to handle large networks. We assume empty road scenarios with patrolling agents as the only vehicles traversing the road network. The Junction Devices are mimicked by software programs running concurrently and communicating with each other via Robot Operating System (ROS) [**quigley2009ros**]. The communication between these software programs and the agents in SUMO is done via Traffic Control Interface (TraCI), provided in SUMO.

5.1.2 Graph Layouts

The software program *netedit*, supplied with SUMO, is used to create the test layouts. Three representative graphs as shown in Figure 3 are used for analysing the results. Graph A is a symmetric graph with 25 nodes and equal edge lengths. Graph B also has 25 nodes but varying edge lengths with some uniformity. Graph C is asymmetric with 28 nodes and random edge lengths. Each edge on every graph is bidirectional, that is, for any pair of connected nodes, the agents can traverse in either direction.



(a) Graph A (b) Graph B (c) Graph C

Figure 3: Different layouts used for simulations

5.1.3 Patrolling Strategies for Comparison

As base cases, we chose two strategies from [8] - *Conscientious Reactive* (CR) and *Reactive with Flags* (RwF). When at a node, agents under Conscientious Reactive strategy choose the neighbour with the highest 'perceived' Idleness value. As agents do not communicate with each other, they do not know the 'true' Idleness values of the nodes. Whereas, agents under Reactive with Flags can communicate with each other and hence have access to 'true' Idleness values of the nodes. CR and RwF act as perfect benchmark strategies for our work

since we assume - (i) no communication amongst agents (directly), (ii) reactive decision making (that is, paths are planned one edge at a time).

In order to compare these strategies under the problem settings with failed Junction Devices, we modify them such that the agents get no information about nodes corresponding to the failed Junction Devices. We refer to the modified strategies, henceforth, as - *CR-Junction* and *RwF-Junction* respectively.

5.1.4 Simulation Parameters

We generate a total of 540 simulations with each simulation running for 30000s (CPU Time). For every graph layout in Figure 3, we run 60 simulations under each patrolling strategy (MRPP-IoT, CR-Junction, RwF-Junction). The number of patrolling agents in each run as well as the failed Junction Devices was fixed throughout the duration of that simulation. For every combination of graph layout and strategy, we had 15 runs each with 1, 3, 5 and 7 agents respectively. These 15 runs were further divided into 5 bins of 3 repetitions each with each bin corresponding to one of 0, 7, 12, 18 and 25 failed Junction Devices. In summary we had, $3(\textit{Repetitions}) \times 5(\textit{Device Failures}) \times 4(\textit{Agents}) \times 3(\textit{Strategies}) \times 3(\textit{Graphs}) = 540$ simulation runs.

At the beginning of each simulation, each agent is spawned randomly at the nodes and we assume Idleness value of each node is zero, as if they have just been visited. The patrol agents can attain a maximum velocity of 10 m/s, acceleration of 1 m/s^2, and deceleration of 5 m/s^2. Graph Idleness value is computed as Average of Instantaneous Graph Idleness over 30000s.

5.2 Result Analysis

5.2.1 Graph Idleness under MRPP-IoT Algorithm

Figure 4 illustrates the performance of MRPP-IoT algorithm under all the parameter settings. On each graph layout, the Graph Idleness value increased with increase in number of failed Junction Devices irrespective of the number of patrolling agents in the simulation. We also observed that the amount of increase in Graph Idleness reduced under higher number of agents. The Junction Device failure impacts highly for single agent scenarios (with Graph Idleness value increasing by a factor of $1.5\times$ to $2\times$ for 5 device failures). For 3 agents or more, the performance decays very gradually as the number of device failures increase. For Graphs A and B (refer to 3), 25 failed devices implies that the agents execute random sampling at each and every node. For simualations with 7 agents, the Graph Idleness value under the random sampling strategy is approximately $2\times$ that under MRPP-IoT algorithm executed at all nodes (that is, with 0 failed Devices).

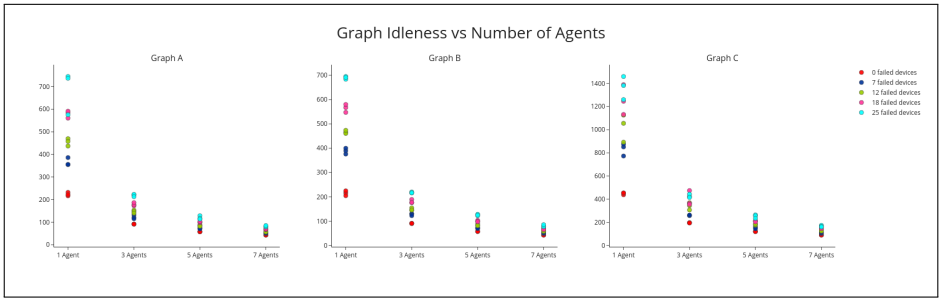


Figure 4: The plots of Graph Idleness values (in seconds) of each simulation runs under MRPP-IoT algorithm with different number of agents as well as different combinations of failed Junction Devices.

5.2.2 Temporal Analysis of Instantaneous Graph Idleness

Figure 5 contains plots of Instantaneous Graph Idleness values for a set of simulation runs on Graph C (refer to 3). We observed that even though the Instantaneous Graph Idleness varied over short periods of time, in the long run the values remained bounded in a particular range. In particular, with 0 Junction Device failures, the Instantaneous Graph Idleness varied in a cyclic manner implying that the agents' paths converged to cyclic patterns. As failure of Junction Device leads to random decision at the corresponding node (refer to Algorithm 1), the agents' path cannot converge to cyclic patterns and hence the Instantaneous Graph Idleness value is chaotic with time.

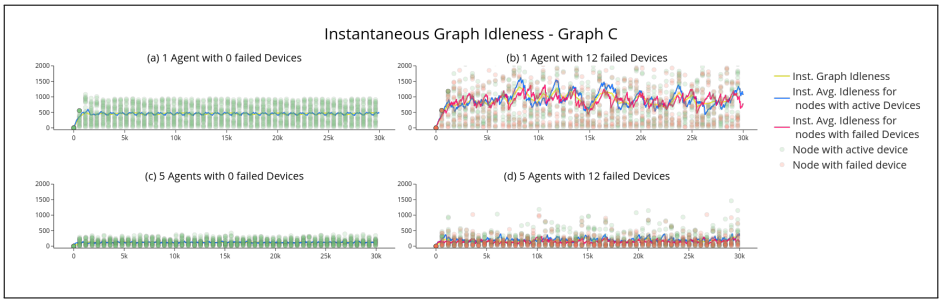


Figure 5: The plots of Instantaneous Graph Idleness values (in seconds) for simulation runs on Graph C under MRPP-IoT algorithm with (a) 1 Agent and 0 failed Devices, (b) 1 Agent and 12 failed Devices, (c) 5 Agents and 0 failed Devices, and (d) 5 Agents and 12 failed Devices.

5.2.3 Node Idleness under MRPP-IoT Algorithm

In Figure 6 [4], we depict the Node Idleness values observed for simulation runs on Graph C (refer to 3). The Node Idleness values of those in the center was consistently lower than those on the boundaries of graph, irrespective of number of agents as well as the combination of failed Junction Devices. The same was observed for each and every simulation run irrespective of the graph layout, the number of patrolling agents or the combination of failed Junction Devices. The results ensure uniformity in patrolling outcomes regardless of variations in number of agents, number of IoT Junction devices, and graph topologies.

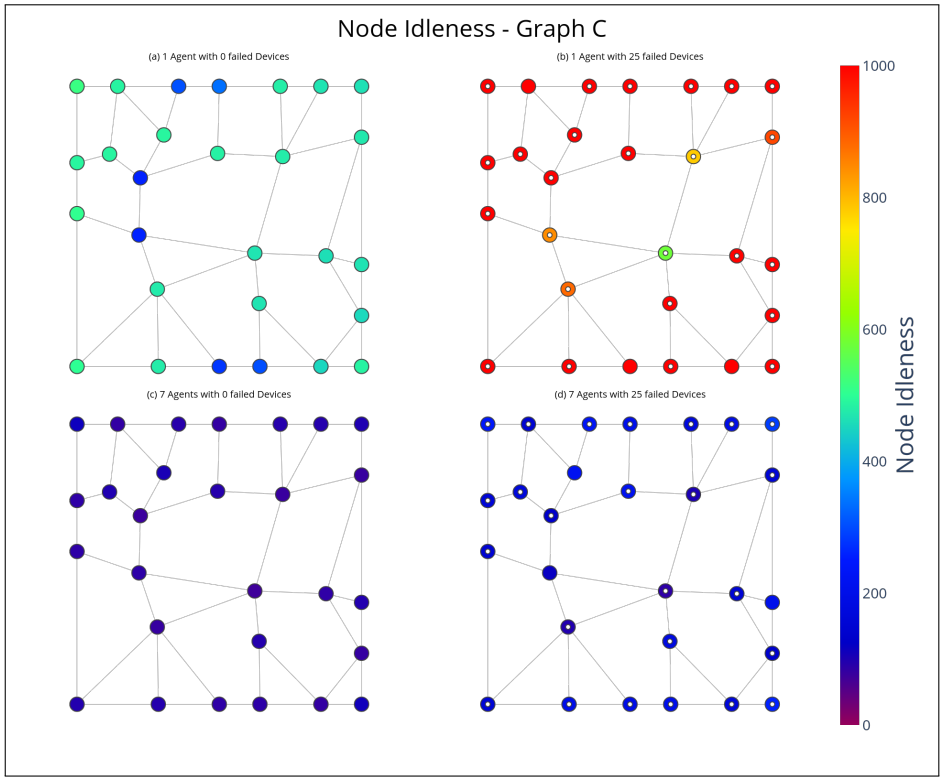


Figure 6: The plots of Node Idleness values (in seconds) for simulation runs on Graph C under MRPP-IoT algorithm with (a) 1 Agent and 0 failed Devices, (b) 1 Agent and 25 failed Devices, (c) 7 Agents and 0 failed Devices, and (d) 7 Agents and 25 failed Devices.

[4] In subplot (b), the Node Idleness values at some nodes reached more than 2000 seconds. For clarity and ease of comparison across the 4 plots, we have limited the color range to 1000 seconds

Table 1: Table of Graph Idleness values averaged over 3 simulation runs for each combination of simulation parameters.

# Agents	Graph A			Graph B			G	
	RwF-Junc.	CR-Junc.	MRPP-IoT	RwF-Junc.	CR-Junc.	MRPP-IoT	RwF-Junc.	CR
O Junction Device failures								
1	239	**220**	223	224	223	**215**	**444**	
3	119	120	**91**	118	120	**90**	450	
5	78	79	**57**	78	79	**57**	201	
7	59	60	**42**	59	60	**42**	156	
7 Junction Device failures								
1	9041	10522	**365**	7747	6931	**382**	6931	1
3	4920	6369	**122**	3800	5314	**127**	4496	
5	4008	7926	**72**	3890	4532	**71**	5948	
7	5606	2881	**51**	3211	3048	**50**	4670	
12 Junction Device failures								
1	1701	4780	**454**	2053	1197	**466**	2452	
3	1427	1551	**146**	1213	659	**148**	2014	
5	925	709	**84**	932	753	**84**	1545	
7	1489	920	**56**	1078	1061	**58**	1076	
18 Junction Device failures								
1	764	891	**578**	932	782	**564**	1732	
3	431	1272	**178**	225	256	**180**	780	
5	125	225	**100**	323	140	**100**	636	
7	91	137	**68**	285	482	**67**	379	
25 Junction Device failures								
1	693	**584**	685	**677**	697	689	1708	
3	**215**	230	218	**207**	223	217	530	
5	120	217	**119**	122	**121**	125	285	
7	**80**	80	81	82	**80**	80	186	

5.2.4 Comparison with state of the art strategies

As mentioned previously, we use Conscientious Reactive and Reactive with Flags patrolling strategies as base cases for studying our algorithm's performance. In Table 1 we have compiled the Graph Idleness values for every combination of simulation parameters we have tested on. Except for the case with 25 Junction Device failures, MRPP-IoT algorithm out performs both Reactive with Flags as well as Conscientious Reactive strategies. In fact, for 7, 12 and 18 Junction Device failures, both RwF-Junction and CR-Junction strategies fail spectacularly in comparison with MRPP-IoT algorithm. This is caused as under MRPP-IoT, the active Junction Devices account for the intent of patrolling vehicles (refer to Algorithm 2). They reset, in their internal memory, the Idleness value of the agent's next node of visit to zero. This minor modification accounts for significant improvement in performance under cases with Junction Device failures.

For fully functional IoT (zero failure in Junction Device) and more than one patrolling agents, MRPP-IoT algorithm performs better than RwF-Junction and CR-Junction consistently. While for the single agent case the three strategies are indistinguishable and hence the difference in values noticed in Table 1 is mainly due to varying initial conditions.

Figure 7 depicts the Node Idleness values for simulation runs on Graph C with 3 patrolling agents. The distribution of Node Idleness values under both RwF-Junction as well CR-Junction is almost identical to that under MRPP-IoT. Specifically, the Idleness of nodes in the center is less compared to those on the boundaries.

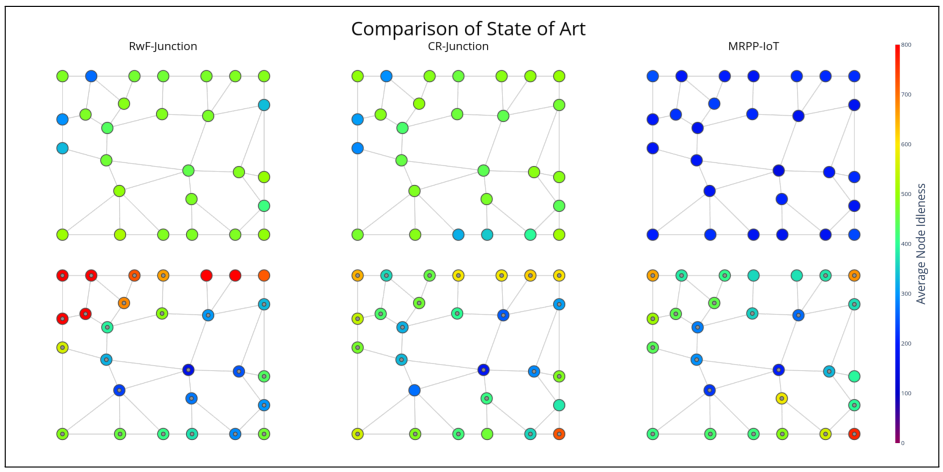


Figure 7: The plots of Node Idleness values (in seconds) for simulation runs on Graph C with 3 agents patrolling under different strategies. Plots in the top row are cases with zero device failures while those in the bottom row are cases with 25 device failures.

6 Conclusion

Through this paper, we present a novel approach to Multi Robot Patrolling Problem which is motivated to provide practical solution for city wide patrolling. Suggestion here is to set-up an IoT framework where Junction Devices are placed at every junction in the environment. These Junction Devices can be low-cost modular IoT devices which have minimal storage, basic computing powers and one-to-one communication capabilities. One-to-one communication with minimal message exchange is motivated to facilitate secured communication. We deviate from the conventional perspective of decentralized strategies with agent based decision making, as seen commonly in literature (refer to Section 2), and suggest the Junction Device based local decision making. The communication between Junction Devices and Agent Devices is assumed to be primitive (one message per decision) (refer to Section 3), our strategy can also be implemented

in an existing large scale patrolling setup involving human driven patrol agents by substituting the Junction Devices as decision makers rather than the policemen, thereby utilizing the benefit of both human intelligence gathering capabilities and bias-free objective decision making capabilities of an automated system.

In the Section 4, we have explained our proposed patrolling strategy 'Multi Robot Patrolling Problem - Internet of Things' (MRPP-IoT) algorithm. This algorithm consists of two parts - (i) Agent Device part and (ii) Junction Device part (refer to Algorithms 1 and 2) running concurrently on patrolling agents and junction devices respectively. The Junction Devices interact with each other locally to obtain *Idleness* information in their neighbourhood and then carry out reactive decision making providing the patrol agents with next node to visit.

We implement MRPP-IoT algorithm on a realistic simulation framework using SUMO and ROS. SUMO provides us with realistic motion simulation of patrolling agents while we use ROS to setup communication between different Junction Devices and Agent Devices. The performance study is presented in Section 5. We use two base case strategies - Conscientious Reactive and Reative with Flags (RwF) to benchmark our algorithm's performance. We analyze our algorithm's decay in performance to Junction Device failures and observe that with increasing number of patrolling agents, the strategy becomes more robust. MRPP-IoT outperforms both CR as well as RwF strategies under full communication as well as cases with failed Junction Devices. In fact, CR as well as RwF strategies fail completely under device failures (refer to Table 1 justifying the need for MRPP-IoT Algorithm.

The current work makes a base case for IoT to solve multi-agent patrolling. Various edge computing methods would certainly benefit in addressing challenging objectives of multi-agent patrolling. These objectives could be to solve prioritized patrolling, randomized patrolling or human-in-loop patrolling. While we have extensively studied the robustness against IoT device failures and developed MRPP-IoT algorithm, robustness against hacked IoT devices would bring interesting settings for the IoT based MRPP.

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