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A Stochastic Mobility Prediction Algorithm for finding Delay and Energy Efficient Routing Paths considering Movement Patterns in Mobile IoT Networks

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Abstract

In Mobile IoT Networks, the network nodes are constantly moving in a field, causing interruptions in the communication paths and, thus, generating long delays at the time of building a communication path from a source IoT node to the gateway (destination node). Communication interruptions affect the delay performance in delay-sensitive applications such as health and military scenarios. In addition, these IoT nodes are equipped with batteries, whereby it is also necessary to accomplish energy consumption requirements. In summary, a gateway node should not receive messages or packets coming from the IoT nodes with undesired delays, whereby it is pertinent to propose new algorithms or techniques for minimizing the delay and energy consumption experimented in the IoT network. Due to IoT nodes are attached to humans, animals or objects, they present a specific movement pattern that can be analyzed to improve the path-building with the aim of reducing the end-to-end delay. Therefore, we propose the usage of a mobility prediction technique based on a Stochastic Model to predict nodes' positions in order to obtain minimum cost paths in terms of energy consumption and delay in mobile IoT networks.

Our stochastic model is tuned and evaluated under the Markov-Gauss mobility model, considering different levels of movement randomness in order to test how the capability prediction of our proposal can impact the delay and energy consumption in mobile IoT networks in comparison with others routing algorithms.

Keywords: Markov Chains, Mobile IoT, Mobility Prediction.

1 Introduction

In Mobile Internet of Things Networks, the network nodes are constantly moving in a field, causing interruptions in the communication paths and, thus, generating long delays at the time of building a path from a source node to the destination node (the gateway node). These interruptions affect the delay performance in delay-sensitive applications such as health and military scenarios [3]. In addition, these IoT nodes are equipped with batteries, whereby it is also necessary to accomplish energy consumption requirements [1] [2]. In summary, a gateway node should not receive messages or packets coming from the IoT nodes with undesired delays, whereby it is pertinent to propose new algorithms or techniques for minimizing the delay and energy consumption in the IoT network [3][4].

According to the requirements described previously, new routing algorithms has been proposed [11] [12] [13]. In [13], the authors show a summary of algorithms in mobile wireless sensor networks, but no mobility prediction model is presented for a network that is entirely mobile. In [11], the authors present a proposal to assure that each source IoT node accesses a backbone node through a single hop with the aim of reaching a mobile sink. Nevertheless, a mobility prediction model is not proposed and just the sinks, not the rest of the network nodes, are moving in a field. Authors, in [12], present a multi-objective particle swarm optimization proposal for building the best path for data collection considering a mobile sink in a IoT network.

In summary, we use a mobility prediction model in a mobile IoT network. In detail, we propose to use a mobility prediction technique for building a path from a source IoT node and a gateway node (destination node) taking into account all network nodes are moving in a field and considering energy consumption and delay requirements. This mobility prediction technique is tunned to be evaluated under different levels of movement randomness in order to test how the capability prediction of our proposal can impact the energy consumption and delay in mobile IoT networks in comparison with others routing algorithms.

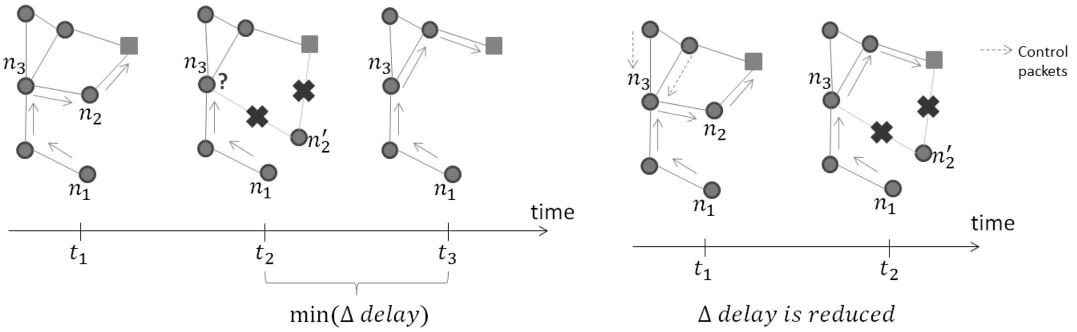
This paper corresponds to an extension of the work presented by us in [20]. This extension consisted of the following aspects:

- We evaluate more scenarios by testing different levels of movement randomness. That is, we vary the α parameter in equations 11 and 10 to analyze the positive or negative impact of movement randomness in our proposal.
- More specifications are presented for the movement considerations. In other words, theoretical details are described for the movement considerations.
- Our proposal is evaluated against a distance and a random algorithms enhanced to be applied in mobile IoT networks scenarios, which will be described later in the Results Section. In summary, the Distance and Random algorithms are evaluated under different levels of movement randomness in order to be compared against our proposal.

The remainder of the paper is organized as follows: Section II presents the problem requirements in order to propose in Section III an stochastic model based on Markov Chains to find optimal paths considering RSSI and energy consumption levels. In addition, this section shows details about the implementation in terms of simulations details, movement and energy consumption model of IoT nodes, and the proposals selected to be compared against our proposal. In Section V is presented the performance of our proposal in terms of delay and energy consumption. Finally, Section VI presents the conclusions of our proposal according to the performance obtained taking into account the evaluated scenarios.

2 Problem Formulation

In this section, we estimate future movements of nodes in a mobile IoT network by using a mobility prediction technique based on Markov Chains to determine if future movements will cause future communication interruptions for building paths. By determining future movements, the communication



(a) Problem

(b) Solution

Figure 1: Problem Definition

interruptions can be reduced, and then, the end-to-end can be decreased at the time of building a path between a source node and the gateway. The details of this estimation is described below:

In Figure 1.a, there is a mobile IoT network. Assume that at time t_1 there is a path between node n_1 (the source IoT node) and a gateway (squared node). Suppose that at time t_2, there is a communication interruption for carrying a data packet from the source IoT node to the gateway because node n_2 moved away from node n_3. When n_3 has noticed this interruption at time t_3, n_3 proceed to restore the path from n_1 to the destination node. However, these interruptions introduce undesired delays, at which in some applications they can be omitted because do not affect the general performance, but in delay-sensitive applications, they cannot be ignored due to they cause low values of the delay metric.

Described the problem previously, we propose to use a mobility prediction model referenced in figure 1.b [7][8]. This figure reflects a similar concern seen in figure 1.a; however, at time t_1, node n_3 is notified about that the node n_2 will be out of communication range at time t_2. According to this situation, at time t_1, n_3 is also determining which candidate node could substitute n_2 in the case of it will be incommunicated later. That is, at time t_2, if n_2 is incommunicated from n_3, this node at time t_2 could reestablish the path between n_1 and the gateway, decreasing the delay presented in figure 1.a.

In addition, we employ RSSI (Received Signal Strength Indicator) measurements to infer the distance measure between two nodes, with the aim of being aware of network movements. In detail, each IoT node predicts future distance (RSSI measurement) of neighbour nodes to estimate if they will be incommunicated later. The description of this method is shown in the following section.

3 Stochastic Model Proposal

Assume there is a network of two nodes: n_k and n_l, and that n_l is a neighbour node of n_k. Suppose that the node n_l, at time t_1, is at a specific distance from n_k, but at time t_2 we need to estimate if n_l will be incommunicated or not (or at the same distance in t_1) from n_k.

In addition, n_l can be positioned at a minimum and maximum distance to create a communication link with n_k. Node n_l will be at a maximum RSSI, $RSSI_{max}$, at a minimum distance. Likewise, n_l will be at a minimum RSSI, $RSSI_{max}$, at a maximum distance. In this sense, node n_l could be positioned between $RSSI_{min}$ and $RSSI_{max}$. Therefore, we have the aim of predicting the location of n_l in the future, that is, a position between $RSSI_{min}$ and $RSSI_{max}$. In order to propose a pragmatic model, we propose discrete locations equally spaced between $RSSI_{min}$ and $RSSI_{max}$. The positions, at which n_l could be located, are denoted as *states*. Thus, n_l could be located at S_1, S_2, S_r or S_G in the future, where G is the total number of states. The default probability of n_l to be at any state is $S_i = 1/G$, which is denoted as *Initial Probability Distribution of set S (π)*, and it is described as follows:

$$\pi = \{P_{s_1}, P_{s_2}, ..., P_{s_G}\} \tag{1}$$

The probability that state S_2has to go to state S_4 is calculated as follows:

$$P_{24} = \frac{N(S_2, S_4)}{\sum_{j=1}^{G} N(S_2, S_j)} \tag{2}$$

Where the number of times that state S_i follows state S_i is $N(S_i, S_j)$.

The previous equation could be used for the rest of probabilities as follows:

$$P_{ij} = \frac{N(S_i, S_j)}{\sum_{j=1}^{G} N(S_i, S_j)} \tag{3}$$

Given the probability that S_i has to go to any state S_j, all probabilities could be denoted in a matrix, named *Transition Matrix*:

$$T = \begin{bmatrix} P_{11} & P_{12} & ... & P_{1G} \\ P_{21} & P_{22} & ... & P_{2G} \\ . & . & ... & . \\ . & . & ... & . \\ P_{G1} & P_{G2} & ... & P_{GG} \end{bmatrix} \tag{4}$$

In this sense, suppose that n_l is at S_3 at the current time t_1. At a future time t_p, the future state of n_l is estimated as follows:

$$\pi_p = \pi * T^p \tag{5}$$

$$S_p = max\{\pi_p\} \tag{6}$$

$$S_p = max\{P_{s_1}, P_{s_2}, ..., P_{s_G}\} \tag{7}$$

Respect to 7, at time t_p, the most probable future state at which n_l will be is calculated by n_k. This calculation can be used by a routing algorithm or protocol to decrease the delay caused by communication interruptions. In other words, this information can be considered by the mobility prediction method to decrease the delay.

3.1 Mobility Prediction Algorithm

According to the previous described stochastic model, the pseudocode of the algorithm represents our method is shown below.

Algorithm 1 Prediction Algorithm Pseudocode.

```
Initialize Path = []
Initialize Sensor Nodes = [$N_1 N_2 ... N_n$]
Initialize Sink = [$S_1$]
for $t = 1$ to totalTimePeriods do
    if A packet arrived to a $N_i$ then
        Obtain list of neighbours $V$
        Obtain score of each $V_j$ based on Probability Transition
        Matrix and energy level
        if $|V| \neq 0$ then
            if $V_j$ is the sink $S_1$ then
                Send message to $S_1$
                Add $S_1$ to Path
            end if
            if $V_j$ is a connected node then
                Send message to the connected node $V_j$
            end if
            if $V_j$ is not a connected node nor the sink then
                Send message to the best $V_j$ based on its score
            end if
        else
            Store the message in the buffer until the next time
            period $t$
        end if
    end if
end for
```

The aim of this algorithm consists of determining the optimal forwarding node considering its probability to be incommunicated or not for building a communication from a source IoT node to the destination IoT node. At each period of time t, each node calculates its Transition Matrix to choose the best forwarding node with the aim of reducing the energy consumption and delay of the network.

The IoT nodes and the gateway are initialized in lines 1 to 3. For each time period (line 4 and line 5), it is necessary to identify in which IoT node is the message to be sent across different forwarding nodes (neighbour nodes V) to achieve the gateway. In lines 7 and 8, from that list of neighbour forwarding nodes, the best of them is selected by using the Transition Matrix. In lines 9, and 20 to 23, if there are not neighbour nodes, the data packet is stored for the next time period. In lines 10 to 13, if the gateway is among the neighbour nodes, the gateway receives the data packet and thus, from a source IoT node to the gateway has been established a path. This steps are repeated until the gateway is reached and, then, the algorithm finishes.

3.2 Energy Model

When a node needs to transmit a data packet of K bits to another node at a distance D, the next expressions are required to be considered for calculating the energy consumption in the transmitter and the receiver. For the transmitter, the energy consumption corresponds to $E_{elec} + E_{amp}$, at which E_{elec} is the energy consumption for codification, modulation and filtering. E_{amp} is the energy consumption for the *Transmitter Power Amplifier*. Likewise, the energy consumption for the receiver is E_{amp}. In summary, the energy consumption at the transmitter and the receiver are:

$$E_{tx} = (E_{elec} + E_{amp}) * K * D^2 \tag{8}$$

$$E_{rx} = E_{amp} * K * D^2 \tag{9}$$

Expression 8 represents more energy consumption than expression 9 due to for transmission is necessary more energy for modulation, filtering and codification (E_{elec}) than the energy consumption required for signal amplification in the receiver (E_{amp}).

3.3 Mobility Model

In relation to the movement of the network nodes, our proposal is evaluated taking into account the Gauss-Markov mobility model [9]. This mobility model was tuned to be not-entirely random for generating predictable movement patterns. In detail, the movement of the network nodes should be predictable because the IoT nodes are tied to humans, animals or objects, showing not entirely randomized movements. In other words, particular movement patterns are presented by these nodes.

In these expressions, at each instant, each node calculates its mobility speed and movement direction based on the the previous instant.

$$\theta_n = \alpha\theta_{n-1} + (1-\alpha)\overline{\theta} + \sqrt{(1-\alpha^2)}\theta_{x_n-1} \tag{10}$$

$$v_n = \alpha v_{n-1} + (1-\alpha)\overline{v} + \sqrt{(1-\alpha^2)}v_{x_n-1} \tag{11}$$

At time interval n, the new direction and speed of a particular node is θ_n and v_n, respectively. α is the random movement degree and it is between 0 and 1. $\overline{\theta}$ is the expected value of the direction and, $\overline{v}$ is the expected value of the speed, while θ_{x_n-1} and v_{x_n-1} are Gaussian distributed random variables with zero mean and unit variance. These random variables are independent of θ_n and v_n, respectively. By varying α, we can define different levels of movement randomness. For example, if α is 0, each movement is totally random following a Gaussian-Markov random process, that is, it is highly difficult to predict the movement trajectory of nodes. In contrast, if α is 0, each movement is the same as the previous one, generating a linear trajectory for all nodes, and in this sense, it would be very easy to predict the movement trajectory of nodes. Finally, the higher α is, the more difficult it would be to predict the movement trajectory of nodes. In other words, the lower α is, the easier it would be to predict the movement trajectory of nodes. In this sense, our prediction algorithm should obtain better results as α decreases, which will be shown in the Results Section.

Locations given by the mobility model were employed to determine distances, useful to calculate RSSI values, as the following expression describes[18]:

$$RSSI_d = RSSI_{d_0} - 10n * log_{10}\left(\frac{d}{d_0}\right) \tag{12}$$

In Equation 12, n, d_0 and $RSSI_{d_0}$ are known values, and configured for outdoor environments [18], where n is the path loss coefficient, d_0 is a distance of reference, and $RSSI_{d_0}$ set the RSSI level at the distance reference d_0. In summary, for a particular distance d, the RSSI level is calculated by using the previous information.

4 Results and Discussion

The energy consumption and delay metrics were considered to evaluate our mobility prediction algorithm in comparison to other routing algorithms, as described as follows:

- Distance Algorithm: The forwarding selected node for building a communication path from a source IoT node to the gateway corresponds to the forwarding node with the shortest distance to the current node. The current node corresponds to the one that has the message.
- Random Algorithm: The forwarding selected node for building a communication path from a source IoT node to the gateway corresponds to a random forwarding node connected to the current node. The current node corresponds to the one that has the message.

These algorithms (the Distance and Random algorithm) were designed and implemented by us to be compared against our prediction mobility algorithm.

The following table summarizes the most important parameters assumed in the simulations:

Table 1: Simulation parameters

Parameters	Value	Parameters	Value
Work Area	100x100[m^2]	r_c	20[m]
Eamp	100[pJ/bit/m^2]	Eelec	50[nJ/bit]
Number of Gateways	1	Number of simulations (for each figure data point)	1000
Number of IoT nodes	10-50	Number of sources nodes	1

Our mobility prediction algorithm was implemented in MATLAB as well as the Distance and Random algorithms.

Figure 2 shows the delay performance for each network size (10, 20, 30, 40 and 50 nodes) of each solution.

In figure 2, our Mobility Prediction algorithm always achieved the best delay result independently of the network size in comparison with the Distance and Random algorithms. In this sense, using a mobility prediction method is very suitable for building fastly a path minimizing the energy consumption. The performance difference between the prediction algorithm and the other algorithms was lesser as the network size decreases. Therefore, our mobility prediction algorithm is suitable for scarce networks because the prediction method does not require many neighbours nodes to build reliable communication paths (low amount of communication path disruptions) to achieve the gateway. However, for finding a communication path to the gateway, the Distance and Random algorithms require many opportunities (many neighbors nodes). In summary, our prediction algorithm is suitable for establishing reliable forwarding neighbour nodes, building fastly a path to the gateway .

Additionally, the performance of the Distance and Random algorithms is closer to our Mobility Prediction algorithm as network size increases because many nodes represents more probability to find a forwarding neighbour node and, therefore, decreases the probability to generate interruptions causing extra delays.

According to the level of movement randomness (α), when α is a low value ($\alpha = 1/3$), this indicates there is a low level of movement randomness, whereby the movement of nodes is more predictable and, thus, is easier for our prediction algorithm to build quickly reliable paths to the destination node. More reliable paths mean less interruptions, thus, causing less delays for building a path to the destination node. Given the previous reasons, it is understandable that our prediction algorithm obtains better values of delays for each network size when α decreases. According to the Distance and Random algorithms, despite not having a prediction method for forecasting future interruptions, they also obtains better values of delays when α decreases because the network is less chaotic (less level of movement randomness), that is, the network is more stable, and then, causing less communication interruptions that could affect the delay for building a path to the destination node. In other words, if α is a high value ($\alpha = 2/3$), this means there is a high level of movement randomness, causing that the movement of nodes will be less predictable, that is, more difficult to handle by our prediction algorithm because there will be more interruptions that will cause more delays for building a path to the destination node. Likewise, for the Distance and Random algorithm will be the same, that is, due to the network is more chaotic, there will be more interruptions causing more delays affecting the building of a path to the destination node.

In figure 3, for each network size (10, 20, 30, 40 and 50 nodes) is presented the performance of the algorithms in terms of energy consumption. The energy consumption by our mobility prediction algorithm is clearly less than the Distance and Random algorithms. In relation to the Random algorithm, its randomness allows it to explore many forwarding nodes before to determine a communication path to achieve the gateway. Because of this exploration, this algorithm processes more transmission and reception of packets, causing an extra energy consumption. According to the Distance algorithm, its performance tends to be equal to the Mobility Prediction algorithm performance as network size increases because there are more chances (more forwarding nodes) to achieve the gateway. In contrast, if the network has few nodes, the performance of the mobility prediction algorithm in terms of energy consumption is much less than the other algorithms.

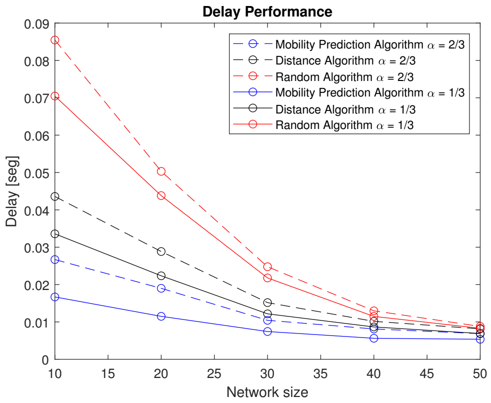


Figure 2: Delay Performance for all algorithms.

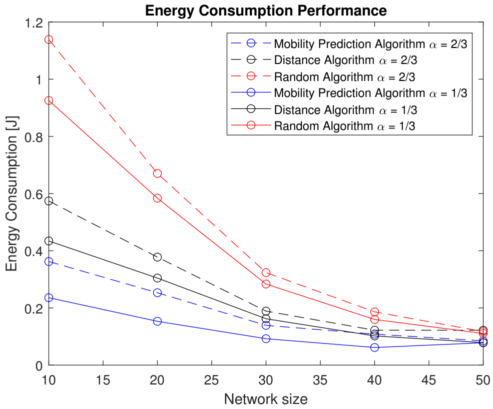


Figure 3: Energy consumption for all algorithms.

5 Conclusions

A mobility prediction distributed routing algorithm based on a stochastic model has been proposed for establishing a path from a source IoT node to a gateway (destination node) considering all nodes are moving in a field and that they have different levels of movement randomness. This proposal is evaluated against two proposals: the Distance and Random algorithms, also proposed by us to test the performance of our mobility prediction algorithm.

We observed that, when the movement of nodes was more predictable, it was easier for our prediction algorithm to build quickly reliable paths to the gateway. That is, more reliable paths were possible for avoiding more communication interruptions and, then, less delays were suffered in the network. In this sense, our mobility prediction algorithm obtained the best solutions in terms of delay and energy consumption compared against not using prediction techniques (the Distance and Random algorithms) independently of the number of network nodes and the level of movement randomness.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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