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# A Human Mobility Model in Shipyards

Dat Van Anh Duong and Seokhoon Yoon\*

Ph.D Student, Department of Electrical and Computer Engineering, University of Ulsan, Korea Associate Professor, Department of Electrical and Computer Engineering, University of Ulsan, Korea datdva@mail.ulsan.ac.kr, seokhoonyoon@ulsan.ac.kr

#### Abstract

Shipyards are potential environments for using IoT services, sensor networks, and delay tolerant networks. Simulations of those services and networks strongly rely on human mobility models. Results obtained with an unrealistic model may not reflect the true performance of applications, protocols, and algorithms in a shipyard. A lot of synthetic models for human movements have been studied but most of them are generic and focus on the daily movements of humans on city scales. Nevertheless, workers in shipyards have unique movement characteristics such as movement speed, pause time, and attractions places. For instance, workers usually move to some places, where they work, and rarely move to other places in the factory. Movement characteristics of workers not only depend on workers but also on tasks, which they do. For instance, workers, who paint ships, have similar movement speed and pause time. Hence, in this paper, human movements in shipyards are studied. We propose a new human mobility model called the human mobility mode in shipyards (MIS). In MIS, workers are classified into multiple types. Movement characteristics of a worker are similar to other workers in the same type. Based on the visiting probability, workers have some places, where they frequently visits, and some places, where they rarely visit. We analyze real mobility traces and studie to achieve human movement characteristics from real traces. The results show that MIS provides a well-match to the movement characteristic from real traces.

Keywords: Movement Speed, Pause Time, Visiting Probability, Wireless Networks, Human Movement Characteristics.

# 1. Introduction

In shipyard, there are a lot of IoT services, wireless networks, and automatic systems [1, 2]. Those networks and systems should be simulated and evaluated before applying to real factories. To do that various realistic human movement patterns should be considered because human movement patterns are a key component for validating the performance of such networks and systems. However, there are limited available real mobility traces since collecting real mobility traces is highly time-consuming and costly. Hence, synthetic models should be studied.

A lot of mobility models have been proposed. For instance, the random direction model [3] and the

Tel: +82-52-259-1403, Fax: +82-52-259-1687

Manuscript Received: August. 17, 2020 / Revised: August. 20, 2020 / Accepted: August. 23, 2020 Corresponding Author: seokhoonyoon@ulsan.ac.kr

Associate Professor, Department of Electrical and Computer Engineering, University of Ulsan, Korea

Markovian waypoint mobility model [4] were based on a pure random generation of movements without consideration of human movement characteristics. Therefore, those models could not reflect realistic human movements. In home-cell community-based mobility model [5] and the sociological orbit aware location approximation and routing mobility model [6], social contexts are considered to generate human movements, while human mobility models in [7-9] have studied to capture human movement characteristics such as inter-contact time, pause times, and flights. For instance, the simple model to generate small mobile worlds [7] have considered the distribution of inter-contact times in real traces. The self-similar least action walk [8] and the urban context aware mobility model [9] have studied more the realistic distributions of flights and pause times. In [10], the mobility model takes both social relationships among people and human movement characteristics into account. Nevertheless, such mobility models only consider the general situation of the daily human movement in city areas. None of them focus on the characteristics of human movements in shipyards. Hence, real contexts of human movements and realistic movement patterns in a shipbuilding factory could not be represented in those models.

In order to fully reflect realistic human movements in shipyards, we propose a new human mobility model called the human mobility mode in shipyards (MIS). First, the movement area of workers is considered in a shipyard. The layout of the shipyard is based on the study in [11]. There are subareas in the shipyard and a subarea is partitioned into multiple units. Each stage of shipbuilding production is processed in a subarea. Workers in a subarea are divided into some types based on their work. For instance, in a subarea, workers, who paint ships, are grouped in a type, while workers, who drive trucks or forklift trucks, are grouped in another type. Based on the real context that workers, who do the same work, have similar movement speed and pause time. Those characteristics of workers in the same type are set to similar. The realistic movement speed and pause time of people could be obtained by analyzing real mobility traces. In order to reflect the real context that a worker visits a unit could be calculated based on the movement information of the worker in the past. By using this probability to select the next unit to visit, some units with a high visiting probability will frequently be visited and units with a low visiting probability are rarely visited.

There is no available trace of workers in shipyards. Hence, we analyze real mobility traces in other areas. Akaike information criterion [12] is used to determine the best fitting distribution of movement speed, pause time, and the visiting probability in real traces, and then those distributions are used in the simulation of MIS. The human movement characteristics from MIS are compared with real traces. The obtained results indicate that MIS accurately reflects realistic human movement characteristics.

The rest of this paper is organized as follows. First, the system model is described in Section 2. Then, Section 3 presents the mobility model. The evaluation results are discussed in Section 4. Finally, we conclude this paper in Section 5.

#### 2. System Model

In this section, the system model is presented. First, a shipyard, which is the movement area, is described. Then, workers, who work at the shipyard, are discussed.

#### 2.1 Shipyard Layout

In this subsection, the layout of the shipyard is presented in detail. Based on the study in [11], a shipyard (size 2150m  $\times$ 1350m) is designed as shown in Figure 1. There are twelve subareas (i.e., plate stock (PS), treatment shop (TRE), cutting shop (CUT), fabrication (FAB), unit assembly (UA), sub assembly (SA), grand

assembly (GA), outfitting (OUT), painting shop (PAINT), pre-erection (PE), dock 1, and dock 2) in the shipyard.

A subarea is used for one or some stage in the shipbuilding process. For instance, plates and sections are made and stored in plate stock; panels are formed in the sub assembly; blocks are painted in the painting shop. The shipyard layout is designed based on shipbuilding processes and material flow in the shipbuilding factory. A subarea has several gates to move out and in, and it is divided into multiple units. A unit is a place of a machine (e.g., cutting machine, lifting crane) or a part of the ship, which is processing. Workers move between units through routes.

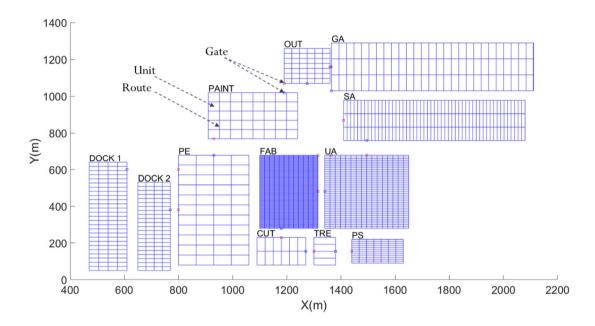


Figure 1. Shipyard layout

In the case of a dock, where the ship is constructing inside, multiple layers are considered. The first layer presents the floor of the dock and the other layers are desks of the ship. Each layer also is partitioned into units and some units are locations of ladders, where workers move between layers. Figure 2 shows an example of layers in a dock. In this figure, three layers of a dock are presented and there are units in each layer.

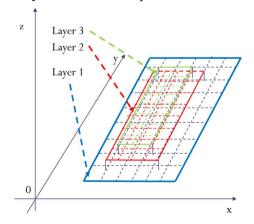


Figure 2. Multiple layers in a dock

#### 2.2 Worker in Shipyard

The workers in the shipyard are described in this subsection. Specifically, there are a number of workers in each subarea and workers, who do the same job, are classified into a type of worker. Then, the subarea might have one or several types of workers. For example, in the treatment shop, workers, who drive forklift trucks, are worker type 1. Workers, who control cranes to move items, are worker type 2. Workers, who cut and weld steel, are worker type 3. The number of types of workers depends on the number of tasks that are processed in the subarea.

# 3. Human Mobility Model in Shipyard

The proposed human mobility model is discussed in this section. First, we present how to select a destination to visit. Then, the movements of workers are described. Finally, the movement characteristics of the workers are discussed.

#### 3.1 Selection of The Destination to Visit

Workers in a type might only move in their subarea or in several subareas. For instance, worker type 1 (who drive forklift trucks) move between the treatment shop and the cutting shop to move the material between two subareas, while worker type 3 (who cut and weld steel) only moves between units in the treatment shop. Therefore, the movement areas are determined for each type of worker. As a result, a worker has a set of units, where the worker can visit. Let *i* be a worker in the treatment shop and  $S_u^i$  be a set of units.

$$\mathbf{S}_{u}^{i} = \{u_{1}, u_{2} \dots, u_{m}\}$$
(1)

In equation (1), units from  $u_1$  to  $u_m$  are the places, where the worker *i* can visit.

We assume that the probability that the worker i visits a unit could be achieved from the movement information of the worker in the past. In this paper, the real mobility traces at Dartmouth college [13] are analyzed to obtain the visiting probability for all people in the real trace. We plan to collect the real mobility trace in a shipyard and analyze the visiting probability for each type of worker in future work. The Akaike information criterion (AIC) [12] is used to find the best fitting distributions of the visiting probability from the real trace. A lower AIC value indicates that the distribution is a better fit for the visiting probability.

Table 1 shows AIC values of the visiting probability from the real trace with distributions. AIC values in Table 1 indicates that the visiting probabilities from the real trace fit better to a lognormal distribution. Therefore, the visiting probability of worker i with units in set  $S_u^i$  could be generated by using a lognormal distribution. Based on the generated visiting probabilities, a unit is selected to visit. Units with higher visiting probabilities to be selected. That reflects the real context that a worker usually visits some places and rarely visits other places. Finally, a position in the selected unit is randomly chosen as the destination to visit.

Table 1. AIC values of the visiting probability from Dartmouth real trace with distributions

|     | Normal distribution   | Exponential distribution | Truncated power-<br>law distribution | Lognormal distribution |
|-----|-----------------------|--------------------------|--------------------------------------|------------------------|
| AIC | -4.88×10 <sup>6</sup> | -8.92×10 <sup>6</sup>    | -9.79×10 <sup>6</sup>                | -1.11×10 <sup>7</sup>  |

#### 3.2 The Movement of Workers

In this subsection, we describe how a worker moves to a selected destination. First, the case that workers move between units of a subarea is considered. For example, Figure 3 shows how worker i moves between units in plate stock. In order to move from the current position to the destination, the shortest path is found by using Dijkstra's algorithm [14], and worker i will move on this path.

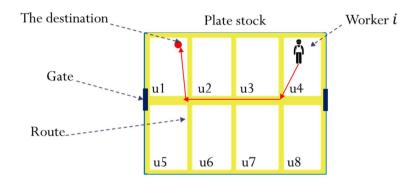


Figure 3. Worker *i* moves in plate stock

In the case of worker moves between subareas, for example, Figure 4 presents how worker i moves from plate stock to treatment shop. Worker i firstly needs to move to the gate of the plate stock, which nearby the gate of the treatment shop, and then go to the gate of treatment shop before moving to the destination. The shortest path also is also found by Dijkstra's algorithm and used in this case.

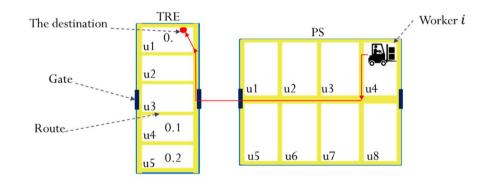


Figure 4. Worker *i* moves between plate stock and treatment shop

#### 3.3 The Movement Characteristics of Workers

In the real life, movement characteristics such as movement speed and pause time of a worker are similar to the worker in the same type (who do the same task in the shipbuilding process). Based on that context, workers in a type are setup to have similar movement speed and pause time. We assume that the distributions of movement speed and pause time could be obtained from the movement trace of workers in the past and set for each type of worker. In our future work, mobility traces in a shipbuilding factory will be collected. Then,

the movement speed and pause time of each type of worker could be achieved.

In this work, we analyzed the real mobility trace of Disney World theme park in Orlando [15] to obtain the distributions of movement speed and pause time of all people in the trace. Table 2 presents AIC values of movement speed and pause time from the real trace with distributions. As shown in the table, the movement speed is well-match to a lognormal distribution, while the pause time has a truncated power-law distribution.

 Table 2. AIC values of movement speed and pause time from Orlando real trace with distributions

|                        | Normal distribution  | Exponential distribution | Truncated power-law<br>distribution | Lognormal distribution |
|------------------------|----------------------|--------------------------|-------------------------------------|------------------------|
| AIC for movement speed | 1.09×10 <sup>5</sup> | 5.00×10 <sup>4</sup>     | 4.00×10 <sup>4</sup>                | 3.81×10 <sup>4</sup>   |
| AIC for pause time     | 4.80×10 <sup>4</sup> | 3.90×10 <sup>4</sup>     | 3.10×10 <sup>4</sup>                | 3.57×10 <sup>4</sup>   |

# 4. Evaluation Results

In this work, Matlab was used to simulate MIS. First, based on human movement characteristics in real mobility traces (i.e., the distributions of movement speed, pause time, and visiting probability), movement characteristics of workers are setup. Then, the human movement characteristics generated by MIS are compared with real mobility traces.

### 4.1 Simulation Setup

The total number of workers in the shipyard is set to 3000 and the number of workers for each type in subareas is set up as in Table 3. The movements of workers are generated for 50 hours.

| Subarea              | The number of workers  |  |  |  |
|----------------------|--|--|--|--|
| Plate stock (PS)     | Type 1: 50 workers; Type 2: 30 workers;  |  |  |  |
| Treatment shop (TRE) | Type 3: 30 workers; Type 4: 20 workers;  |  |  |  |
| Cutting shop (CUT)   | Type 5: 30 workers; Type 6: 30 workers; Type 7: 100 workers;   |  |  |  |
| Fabrication (FAB)    | Type 8: 40 workers; Type 9: 30 workers; Type 10: 150 workers;  |  |  |  |
| Unit assembly (UA)   | Type 11: 40 workers; Type 12: 30 workers; Type 13: 200 workers;  |  |  |  |
| Grand assembly (GA)  | Type 14: 50 workers; Type 15: 40 workers; Type 16: 250 workers;  |  |  |  |
| Sub assembly (SA)    | Type 17: 40 workers; Type 18: 30 workers; Type 19: 200 workers;  |  |  |  |
| Outfitting (OUT)     | Type 20: 30 workers; Type 21: 20 workers; Type 22: 100 workers;  |  |  |  |
| Painting (PAINT)     | Type 23: 30 workers; Type 24: 20 workers; Type 25: 100 workers;  |  |  |  |
| Pre-erection (PE)    | Type 26: 50 workers; Type 27: 40 workers; Type 28: 250 workers;  |  |  |  |
| Dock 1               | Type 29: 40 workers; Type 30: 30 workers; Type 31: 350 workers;  |  |  |  |
| Dock 2               | Type 32: 100 workers<br>Type 33: 30 workers; Type 34: 30 workers; Type 35: 300 workers;<br>Type 36: 90 workers |  |  |  |

# Table 3. The number of workers for each type in subareas

In this work, all workers in the shipyard are set to be the same human movement characteristic. Based on the results obtained from real mobility traces, movement speeds of workers are set to follow a lognormal distribution, *Lognormal*(-0.684, 0.97<sup>2</sup>), pause times of workers follow a truncated power-law distribution with a range of values from 0.5 to 227 minutes, and visiting probabilities are set to follow a lognormal distribution, *Lognormal*(-5.30,  $1.9^2$ ).

#### 4.2 Simulation Results

In this subsection, the human movement characteristics generated by MIS are compared with the real traces. Figure 5 shows the distributions of speed, pause time, and visiting probability from MIS and real traces. The results indicate that human movement characteristics obtained from MIS are closed to the characteristics in the real life.

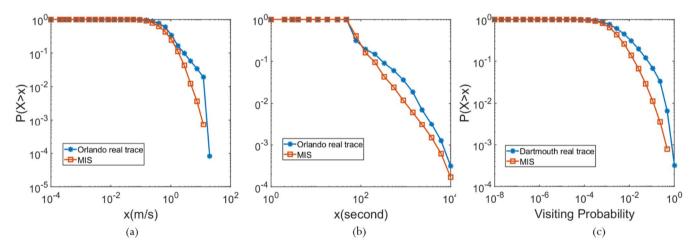


Figure 5. The distributions of human movement characteristics from MIS and real trace data (a) Speed distributions. (b) Pause time distributions. (c) Visiting probability distributions.

To validate the distributions of human movement characteristics obtained from MIS, AIC criteria is used. Table 4 presents the results from AIC between a truncated power-law distribution (denoted as Pow), a normal distribution (denoted as Nor), a lognormal distribution (denoted as Log), and an exponential distribution (denoted as Exp) over pause times, movement speeds, and visiting probabilities. The results from the synthetic trace of MIS are the same as the real traces. Specifically, pause times follow truncated power-law distributions, while movement speeds and visiting probabilities fit better to lognormal distributions.

| Table 4. Results from AIC for pause time, speed, and visiting probability |     |                    |         |  |  |
|---|-----|--------------------|---------|--|--|
|   | MIS | Orlando real Trace | Dartmou |  |  |

|                       | MIS           |       | Orlando real Trace   |               | Dartmouth real trace |                      |
|-----------------------|---------------|-------|----------------------|---------------|----------------------|----------------------|
| -                     | Pause<br>time | Speed | Visiting probability | Pause<br>time | Speed                | Visiting probability |
| Selected model by AIC | Pow           | Log   | Log                  | Pow           | Log                  | Log                  |

# 5. Conclusion

In this work, we proposed a human mobility model in shipyard. In order to obtain the realistic movement area of workers, a shipyard layout is considered. Based on contexts in the real life, workers, who do the same task, are grouped in the same type and have similar movement speed and pause time. The visiting probabilities are used to select the visiting unit in subareas. A unit with a higher visiting probability is frequently visited and a unit with a lower visiting probability is rarely visited by the worker. We also analyze real mobility traces to obtained movement characteristics. Those characteristics are used for the configuration of workers' movements. The movement speeds, pause times, and visiting probabilities generated by MIS are approximate real human movement characteristics. In future work, to make movement characteristics more realistic, we plan to collect mobility traces from shipyards and analyze the traces to obtain the different characteristics for different types of workers.

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