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Trajectory Estimation Using PDR and Simulation of Human-Like Movement

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***Abstract*—For the IPIN 2017 PDR Challenge in Warehouse picking, we propose a trajectory estimation method that combines Pedestrian Dead Reckoning (PDR) and simulation of human-like movement. In this competition, we can use Warehouse Management System (WMS) picking data with location. By using picking location information, we can estimate a rough trajectory of a picking worker between the consecutive picks. Because some records are deleted for the competition, we do not have all of the WMS data. So we have to check the continuity by using PDR. We also employ error models for PDR to compensate accumulated localization errors in PDR. By using the worker's movement simulation based on the optimal reciprocal collision avoidance (ORCA), we can generate human-like movement.**

***Keywords*—Pedestrian Dead Reckoning, PDR Challenge, ORCA, PDR Error Compensation**

I. Introduction

We propose a trajectory estimation method that combines Pedestrian Dead Reckoning (PDR) with simulation of human-like movement, for warehouse picking in The International Conference on Indoor Positioning and Indoor Navigation (IPIN) competition 2017 track4[1]. In our proposal, we create a human-like trajectory using simulation, and compare it with the trajectory estimated by PDR to improve the accuracy of trajectory estimation.

There are two advantages of combining PDR with simulation. First, we can estimate warehouse workers picking that is not recorded in the Warehouse Management System (WMS) data. The WMS data has warehouse worker's data when he or she pickup a goods, however some records are deleted for competition. By comparing a simulation results created by connecting between consecutive picking points in the WMS data with the trajectory estimated by PDR, we can detect workers picking points deleted from the WMS data.

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Second advantage is that we are able to create more human-like trajectory by calculate an optimal route between each picking points. The estimation error of PDR has a characteristic that the longer the path length, the larger the error. We thought that this error would be a problem to reproduce a human-like trajectory. Therefore, we calculate a trajectory that worker naturally avoids obstacles and other workers on simulation by using RVO2 [2]. RVO2 is a python library for simulating movement of people including collision avoidance with obstacles and other people, based on the optimal reciprocal collision avoidance (ORCA) formulation.

The contribution of this work is the combination method of the usual localization technique such as PDR and error compensation[7] with the method of simulation based generation of a human-like trajectory. Especially in this competition, the sensor data is the result of complicated movement of the warehouse workers, it is not easy to apply usual PDR techniques.

In the following, we first explain about the competition and our initial strategy in section 2. We explain how to create workers optimal route and calculate human-like trajectory by simulation in section 3, then how to estimate workers trajectory by our PDR algorithm and update error model using simulated trajectory in section 4.

II. PDR Challenge in Warehouse Picking

Detail of the challenge is described in [1]. At here we only explain the most important part of the challenge for us. For the competition, organizers prepare the following data sets.

a). Sensor data (Time, Angular velocity, Acceleration, Magnetism, BLE) for 7 subjects, 3 hours each.
b). WMS data (Time with picking shelf location).
c). Map/Obstacle/Shelf location information.

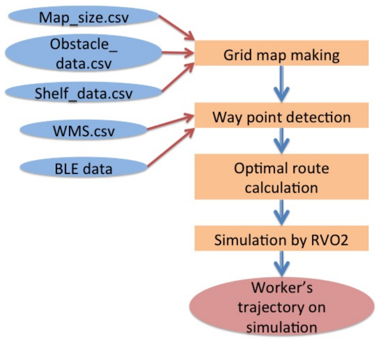

Fig. 1. Process of creating workers trajectory by simulation.

d). BLE location information.

The most difficult part of the competition is that we need to consider the effect of the variety of the worker's task such as picking, gathering, walking in a warehouse, carrying goods with carts and so on. In the beginning of the data analysis phase, we start from combining sensor data with WMS picking data. We try to calculate the each worker's average movement speed from the consecutive picking with location data. However, it seems most of the WMS picking data is not consecutive one because the time span of the two consecutive picking is too large for most of the data. So, we can only rely on the several picking data.

In the following, we start from a trajectory simulation using ORCA by using WMS picking data. Then we evaluate the data with PDR error compensation schema.

III. Trajectory Creation by Simulation

Workers simulation including collision avoidance among multiple workers has been studied. Antonini [3] probabilistically determines the moving direction and speed of the worker per unit time while considering collision avoidance with other workers and obstacles. Pars [4] express the three-dimensional environment as a two-dimensional walking space, and add information such as the direction the worker should avoid the obstacle to each obstacle. By doing this, simulation of obstacle avoidance close to more reality. However, these simulations do not propose an optimal route matching the each workers destination. Shao [5] combines the topological map and the occupancy grid map to calculate optimal path of the worker, and simulates worker's movement along that path.

In our case, information on picking in the warehouse is given as WMS data. However, we do not know from WMS data which route a worker has walked between each pick point. So, we calculate the optimal route between worker's each pick point in advance and simulate worker's move along the path.

In this section, we explain how to calculate the workers optimal route between each pick point from WMS data, and create a human-like trajectory by simulation using that route, following Fig.1.

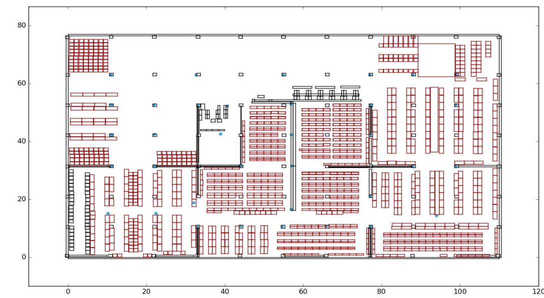

Fig. 2. Obstacles, shelves and BLE beacon

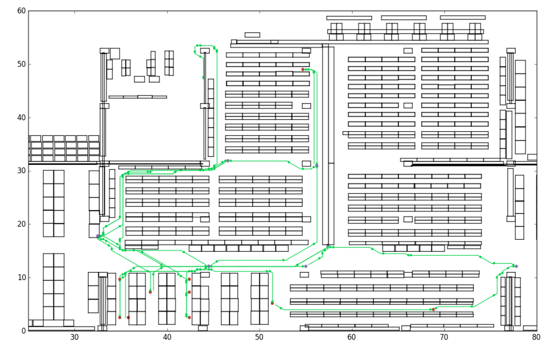

Fig. 3. Workers pickup point, passed point and calculated optimal route.

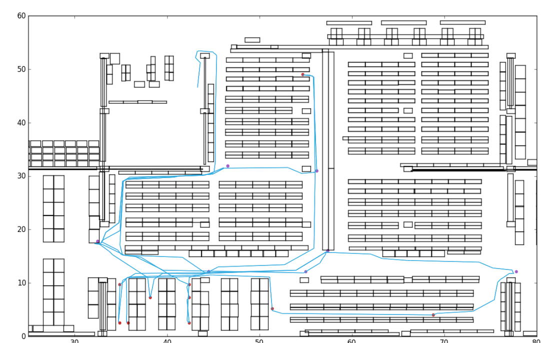

Fig. 4. Simulated worker's trajectory.

A. Grid map making

First, we get following map information from data set.

a). Map size and start point from Map_info.csv.
b). Each obstacle coordinates from Obstacle_data.csv.
c). Each shelf ID, coordinates and pick form from shelf_data.csv.
d). Each BLE beacon's coordinates from BLE_info.csv

Then, we make grid map as Fig.2 by dividing the map into 0.3m meshes and classifying each cell into, passable area, obstacles or shelves. In this figure, the black objects are obstacles such as pillar, wall and partition, red objects are shelves, and blue points are BLE beacon.

B. Way point detection

From received data of BLE, we detect the BLE beacon that worker would have passed by, and uses that information as the passing point of that worker. In received data, if Received Signal Strength Indication (RSSI) is higher than -65, the position of the BLE terminal having that MAC address is set to worker's way point.

C. Optimal route Calculation

From WMS data and way point list, we get list of passed point that worker would have picked or passed. Then, we create worker's optimal route between each way point using Dijkstra's algorithm like Fig.3 to minimize total cost of worker's movement on the grid map. This figure displays the calculated optimal route to the first 10 pick and way points in that way of terminal4. Red points are worker's pick points in WMS data and purple points are passed points in way point list of terminal4. Green line is path calculated optimal route that simply to connect between each pick point and way point. The cost of moving neighboring cell on the grid map is usually constant, but to make more human-like moving route, moving cost is increase with following conditions.

a). In case, the destination cell is close to any obstacle or shelf, the cost is increase according to its distance. This is because worker chooses a route that is not too close to the obstacles and shelves.

b). When worker moves to diagonal cell, the cost is increase according to its moving distance. This is because, movement distance in cross direction and diagonal direction are different.

D. Simulation by RVO2

Using RVO2, we simulate each workers movement following created optimal route. RVO2 is a python library for simulating movement of people including collision avoidance with obstacles and other people, based on ORCA formulation. In this simulation, we can obtain a human-like trajectory that avoids obstacles and other workers like Fig.3. This figure displays simulated trajectory of terminal4's first 10 pick points and way points in that way. Red points and purple points are pickup or passed point of terminal4 same as Fig.4, and blue line is worker's trajectory simulated by RVO2.

Our method basically uses the PDR algorithm of Ban et al. [6]. And We add compensation to PDR estimation [7]. Below, we explain each block individually.

IV. Estimate worker's movement

After create worker's trajectory, we estimate worker's movement from trajectory, BLE received signal and acceleration signal. In this section, we explain how to estimate the worker's movement, following Fig.5.

A. Step Detection

Our method uses the automaton created by Alzantot [8] as the step detection algorithm. The automaton has six states: stay, start of operation, observe maximum, observe minimum, complete motion, and detected steps. The state is transitioned if the norm of input acceleration satisfies the each threshold. We assume that the stride length is constant, and the movement distance is calculated by step number $\times$ stride length.

Then, we create the movement list that contains the start time and the end time of movement. Fig.6 shows the acceleration signal with the label of moving. The moving terms are shown in yellow. The start time is recorded at the time when a step is detected when the worker stays. Moreover, the end time is recorded at the time when a step has not been detected while one second from the previous step.

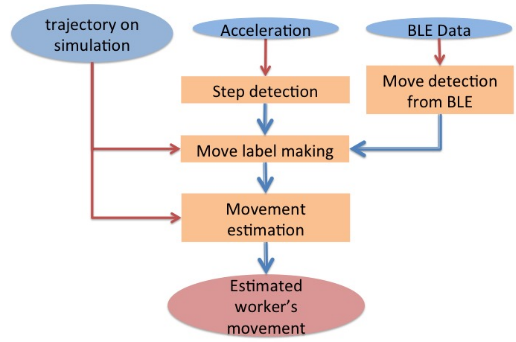

Fig. 5. Process of estimating workers movement.

Fig. 6. Acceleration signal with move label.

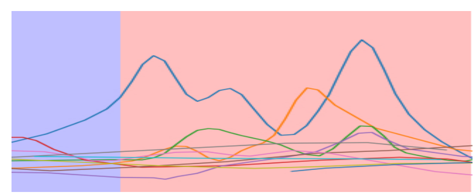

Fig. 7. BLE signal with unstable label.

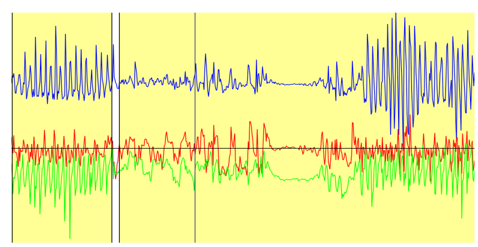

Fig. 8. Acceleration signal with move label added unstable label.

B. Move detection from BLE

To detect the workers movement when the sensor data is stable, we use BLE signal strength data. Firstly, to remove the fluctuation of the signal strength, the three-sample moving average operation is repeated three times. Secondly, the subtraction value d_t of the signal strength s_t and mean of $st_{t-8:t-1}$ is calculated to each beacon. Thirdly, based on the standard deviation σ of the subtraction values, the time t with $d_t >= 2.5\sigma$ is marked as the major change. Finally, stable section is labeled if no major change is in 20 seconds. Fig.7 shows BLE signal with the label of stable or unstable. In this graph, the signal intensity is taken on the vertical axis and time is taken on the horizontal axis. RSSI of each beacon received by the worker is plotted. Each signal has removed fluctuation by taking moving average. The stable terms are shown in blue and the unstable terms are shown in red.

C. Move label making

We estimate average velocity between each way points form length of trajectories created by simulation and moving time estimated by step detection. If average velocity exceeds 1.5 m/s, we assume that the moving time is not correctly detected from the acceleration alone, and the unstable section computed from the received data of the BLE is also considered as the moving time. Fig.8 shows the acceleration signal, same as Fig.6, with the label of moving expanded by unstable label in Fig.7. This figure shows that the move label which was not determined by step detection alone is expanded by the signal of BLE.

D. Move estimation

Finally, we calculate worker's move by combining simulated trajectory with move label, because move label is not taken into consideration in simulation. Then we Calculate how many steps on the simulator equivalent to 1 second in real time (1 step = 0.1 second in simulation). Move the worker so that the worker follows the trajectory according to the number of steps per second in the section moving on the label and keep the section not moving on the spot. Then, we calculate the worker's position every second and use it as the estimation result.

V. Conclusion and Future Works

In this paper, we present a warehouse worker's trajectory estimation method that combines PDR with human-like movement simulation. We calculate worker's optimal route from WMS data and way point list created from BLE received data, and create human-like trajectory using ORCA based simulation. Then we estimate worker's position using calculated worker's trajectory with acceleration data and BLE received data.

But this time, we have confirmed several problems through this trajectory estimation. In simulation, we forcibly trying to fit the trajectory to move label, there was several points that became an unnatural movement for human. In order not to do so, we should have considered move label at the time of simulation. It seems that worker's movement will be more human-like.

In the PDR part, we can only use the step detection for estimating the worker's sensor data this time. We could not estimate the pick points omitted for the competition because we were not able to detect the pick motion from sensor data. Also, the generation of the way point from the BLE received signal was made only when passing through the immediate vicinity of the beacon, so the number of way points generated was little. If it is possible to generate way points at constant time intervals, there is a possibility that a more accurate trajectory could be estimated.

As a future task, we try to estimate a combination of trajectory generated by combining PDR and map matching, and then correct trajectory with simulation result.

Acknowledgement

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