Wide-ranging Registration Using LRF and PDR for MR Road Maintenance

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ABSTRACT
We have been developing a mixed reality system to support road maintenance using overlaid visual aids. Such a system requires a positioning method that can provide sub-meter accuracy even if the appearance of the road surface changes significantly caused by many factors such as construction phase, time and weather. Therefore, we are developing a real-time, wide-range worker positioning method that can be applied to these situations by integrating laser range finder (LRF) and pedestrian dead reckoning (PDR) data. On actual road maintenance sites, multiple workers move around the workspace. Therefore, it is necessary to determine corresponding pairs of PDR-based and LRF-based trajectories. In this study, we propose a method to calculate a similarity between trajectories and a procedure to integrate corresponding pairs of trajectories to acquire the position and movement direction of a worker.

Author Keywords
Mixed reality, geographic information systems.

ACM Classification Keywords

INTRODUCTION
In order to maintain the safety of public infrastructures such as roads, bridges, and tunnels, maintenance of them are essential. Because the objects of maintenance are so large, effective way of maintenance is required.

We have been developing RoadMR, a prototype mixed reality system for supporting road maintenance [1]. It measures and records position of a worker during the inspection and visualizes the detected damaged area intuitively. Figure 1 shows the system overview of RoadMR. RoadMR visualizes and damaged spots detected by road inspections. A user can see the inspection results interactively with tablet device. HMDs are also available to see the result more intuitively. A laser range finder (LRF) is used for sensing position of workers with sub-meter accuracy even in road maintenance filed where lighting conditions and appearance of the objects are drastically changes.

RoadMR provided three perspectives: egocentric, ego-impression, and exocentric, i.e., MR with mobile camera view (Figure 2C), MR with fixed camera view (Figure 2A), and MR with pseudo overhead view (Figure 2B) respectively. A user can choose an appropriate viewpoint to identify the position of damaged spots. When the user changes the viewpoint, two views are interpolated using animation not to lose track of the correspondence. In tablet camera view shown in Figure 2C, workers can interact with visual indicators of a damaged spot and view history images and annotated information.

RoadMR Also provided several methods for data visualization (Figure 3). Gradation, threshold filter of damaged spots, data interpolation and 3D graph are available in RoadMR.
POSITIONING METHODS IN ROADMR
Sensing of user position and orientation is fundamental function of mixed reality (MR) and augmented reality (AR). Especially, it is always challenging that sub-meter accuracy sensing in outdoor environments such as road maintenance site where lighting conditions and appearance of the objects are drastically changes. Basically, it is very difficult to use vision-based positioning methods in this situation.

GPS and Vision-based Tracking
In several marker-less outdoor MR maintenance support systems, GPS is used to estimate the position of the user. However, it is difficult to get sub-meter accuracy using present GPS. In addition, GPS does not work in occluded environments such as maintenance site under bridges and in tunnels.

Vision-based tracking has been used to obtain user positions and orientation in most AR/MR systems. Vision-based positioning errors are in cent metric order. However, vision-based method is not effective for homogeneous textures (e.g., most road surfaces) and performs poorly when the appearance of recognition targets has changed. Road surfaces are completely different in each construction phase, and the appearance of a road surface will be affected by time and weather. These factors indicate that vision-based positioning is unsuitable for an MR road maintenance system.

Vision-based positioning is also not effective for wide range and long distance use. In most vision-based tracking systems, position errors is accumulated until next recognition point. In addition, user has to maintain the database of images for recognized position before using it.

LRF and PDR Positioning
To overcome the limitations of GPS and vision-based camera tracking, we used laser range finders (LRFs) to obtain the worker’s position in real time in our first prototype system. We designed a system to analyze scan data from an LRF sensor (Figure 4A) and calculate a worker’s current position in real time (Figure 4B). We uses a LRF that has a wide-range and long distance (>50m, based on sensor module) sensing area. It can detect a worker’s position within 20 cm, which is an acceptable error range for use in a road maintenance MR system.

However, LRF cannot obtain a unique ID for tracked people. Therefore, the system does not recognize which worker is operating the RoadMR system if multiple people are moving in the detection area (Figure 4C).

Many other positioning methods such as pedestrian dead reckoning (PDR) can specify a unique ID for all tracked candidates. However, the accuracy and error range of PDR-based trajectories are insufficient to display MR visual indicators in our proposed system. PDR errors depend on walking distance after initialization. The error range in a road maintenance system should be less than 25 cm.

Methods to Integrate Heterogeneous Trajectories
To overcome these problems, we propose a method for integrating an LRF-based trajectory and a PDR-based trajectory that incorporates their advantageous characteristics, i.e., low error and unique ID (Figure 5). Specifically, we implemented a method for calculating the similarity between the trajectories and then determine corresponding ID to LRF trajectories from the paired PDR trajectory.
CALCULATE THE SIMILARITY BETWEEN LRF-BASED AND PDR-BASED TRAJECTORIES

The proposed method uses common feature values to verify the correspondence between multiple trajectories by a numerical indicator. We used relative feature values (e.g., speed and angular velocity) and absolute feature values (e.g., position and absolute angle) to compare trajectories (Figure 5). These feature values are selected considering the characteristics of LRF and PDR (Figure 5).

One PDR trajectory is compared with one or multiple LRF trajectories (Figure 7). All LRF trajectories are compared with a PDR trajectory to obtain a similarity score. The LRF trajectory with the best similarity score is considered a paired trajectory of a PDR trajectory. A corresponding pair is regarded as two trajectories originated from the same worker.

Calculation of similarity score is divided into two parts as relative part and absolute part. Relative part only uses relative feature values to calculate its similarity score. Moreover, absolute part uses additional absolute feature values to consider the existence probability of each PDR trajectories (e.g. by referencing external absolute positioning methods like BLEs, UWB and GPS etc.). After the calculation of relative and absolute parts, final similarity score is the sum of them (Figure 8). In our definition, higher score means higher similarity.

In addition, calculation of the relative part is the minimum requirement of our algorithm and absolute part is optional.

Algorithm for Calculate Similarity Score

Calculation of relative part are (a) compare their speed, (b) to compare their relative walk direction and (c) to compare their angular velocity. In addition, Calculation of absolute part are (d) compare their absolute position and (e) compare their absolute walk direction. Additionally, the weight value (0.0 to 1.0) of each feature amounts are variable.

In the equation (1), we defined \( V_L \) and \( V_P \) as the speed of LRF and PDR at the number \( i \) of coordinates. \( \omega_{weight} \) indicates weight value for speed. \( \theta_L \) and \( \theta_P \) means the relative walking direction calculated with positions on \( i \), \( i-1 \), and \( i-2 \). For example, if the walk direction of a pedestrian is 0 degree (i.e. facing to north) at the coordinate \( n \) and it is 30 degrees at coordinate \( n+1 \), his/her relative walking direction at coordinate \( n+1 \) is 30 degrees to right. Using the difference of relative walking direction between LRF and PDR trajectories helps the algorithm to give a good score when they have same action patterns (e.g. turn right or left).

\( \omega \) indicates difference of angular velocity calculated by equation (3). \( \omega \) is inversely proportional to the sum of angular velocity and proportional to the difference of angular velocity. \( \omega \) will close to zero when the angular velocity of PDR and LRF are high and similar.

In the equation (2), \( \alpha \) means the weight of LRF trajectory length. We considered a very short LRF trajectories are not reliable even their speed and walk direction are similar with PDR trajectories.

Finally, a similarity is calculated as the difference of common feature values between LRF and PDR trajectories using equation (1). After the calculation, a reasonable threshold for pairing trajectories should be determined based on the environment factor.

\[
\text{Similarity score} = \sum_{i=1}^{n} \left( \left| V_L - V_P \right| \times \text{Weight}_{\text{speed}} + \left| \theta_L - \theta_P \right| \times \text{Weight}_{\text{theta}} \right)
\]

\[
\alpha = \frac{\text{LRF trajectory length}}{\text{avg length of all LRF trajectories}}
\]
LRF track length = \sum_{j=1}^{n} d(L_j, L_{j-1})

\omega = \sum_{k=1}^{n} \frac{|\theta_{Lk}-\theta_{Pk}|}{(|\theta_{Lk}|+|\theta_{Pk}|)×n}

(3)

Evaluation of Pairing Accuracy
To verify the efficacy of the purposed algorithm, an offline experiment has conducted. The followings show the conditions of the experiment.

- Four subjects participated.
- A PDR sensor module is attached to each subject.
- Experimental tasks are (A) Free walk and (B) course walk. In task A, subject walk freely around the experimental area simultaneously. Subjects may walk along or together with other subjects, and also allowed to stop for a while. In task B, subjects are required to walk along an established course.
- All subjects are required to perform two different experiment tasks for 5 times.

Experimental Result
Table 1 shows the result of the experiment. Pairing accuracies are 88.4% in task A and 90.0% in task B. These results also show number of LRF trajectories in task A are more than those in task B. This is due to trajectories are separated into several parts when the subject is occluded by obstacles or columns.

<table>
<thead>
<tr>
<th>Task</th>
<th>Num. of LRF Trajectories</th>
<th>Num. of Right Answers (Candidate Num.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>60</td>
<td>23(26) Accuracy=88.4%</td>
</tr>
<tr>
<td>B</td>
<td>24</td>
<td>18(20) Accuracy=90.0%</td>
</tr>
</tbody>
</table>

Table 1. Experiment result of pairing accuracy.

Evaluation of Display Position Errors of CG Image
To evaluate the display position errors of CG Images in a wide range and long distance environment, we performed an indoor experiment (Figure 9).

Makers are placed on the floor at 1.5m, 5m, 10m, 20m, 30m, 40m and 50m points from the origin. A user walked from the origin to the end of corridor and the position errors of visualized CG Images placed on for each marker.

Experimental Result
Table 2 show the results of position errors. All position errors are less than 20cm. These results show our positioning methods and attitude estimation methods are high precision, wide-ranging and also satisfied the requirement to use in road maintenance service.

<table>
<thead>
<tr>
<th>Distance</th>
<th>Position Error of CG Image</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.5m</td>
<td>12cm</td>
</tr>
<tr>
<td>5m</td>
<td>8.5cm</td>
</tr>
<tr>
<td>10m</td>
<td>4.6cm</td>
</tr>
<tr>
<td>20m</td>
<td>11cm</td>
</tr>
<tr>
<td>30m</td>
<td>20cm</td>
</tr>
<tr>
<td>40m</td>
<td>17.6cm</td>
</tr>
<tr>
<td>50m</td>
<td>12.4cm</td>
</tr>
</tbody>
</table>

Table 2. Experiment result of CG display position errors.

CONCLUSIONS
We proposed a method for calculation of similarity of two trajectories in order to determine correspondences between multiple trajectories acquired by heterogeneous measurement methods. We also proposed a method to integrate a pair of corresponding trajectories.

We have performed two experiments for verifying accuracy of pairing LRF/PDR trajectories and display position errors of CG Image. Experimental results show pairing accuracy is over 88.4% and display position errors are less than 20cm even at 50m away from the LRF. These results fulfill the requirement of road maintenance MR systems.

To realize our final objective—developing a real-time positioning method for an MR road maintenance system—we plan to improve the accuracy of corresponding pair identification and integrate online trajectories.

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REFERENCES