PIEM: Path Independent Evaluation Metric for Relative Localization

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***Abstract*—There are many methods for indoor positioning. These methods are divided into the relative localization and absolute localization. In the relative localization, one widely used method is Pedestrian Dead Reckoning (PDR). Relative localization estimates the moving distance, orientation, and height of the pedestrian. However, relative localization has a problem caused by an accumulated error: the longer the path, the worse the accuracy of relative localization. There is another problem in the existing evaluating metrics: they compare only the actual location and the estimated location of the destination. Relative localization also has this evaluation problem. We propose PIEM: Path Independent Evaluation Metric for Relative Localization. PIEM is a path independent evaluation metric, considering the complexity of the path; distance, orientation, and height. Then we evaluate these three factors of relative localization in addition to the position. Our proposed method showed more consistent results for the complexity of the path than the existing methods of relative localization evaluation.**

I. Introduction

There are several relative localization systems (such as PDR) in the market and research field[1][2][3]. However, they use different sensors and algorithms, so it is not easy to make a comparison among them. Because smartphones have become widely used, demand for relative localization for them is increasing. Therefore, comparison methods of relative localization for smartphones are also becoming important. One characteristic of relative localization is accumulated error. Relative localization cannot refer to any information of absolute location such as GPS, magnetism[4] and Wi-Fi fingerprints[5]. Positioning error of relative localization tends to increase in proportion to elapsed time. Therefore, positioning error depends on the length of the path. To achieve an accurate evaluation method, the method should not depend on path complexity because researchers cannot arrange an evaluation environment that has exactly the same path complexity as environments in other comparison research. Additionally, we think that path complexity, such as the number of corners and existence of rounded corridors, affects relative localization accuracy.

Conventional relative localization consists of the following three components: 1) distance estimation, 2) direction estimation, and 3) height estimation. In distance estimation, walking distance of the time period is estimated by using the detected number of steps and step length. In direction estimation, relative direction of the time period from the start direction is estimated. In height estimation, vertical movement, such as using stairs and elevators and the distance of the time period, is estimated. In addition to accuracy evaluation of positioning, evaluation measures for the above mentioned individual estimations should help discover the bottleneck of the relative localization algorithm. Also, their measures should help compare multiple relative localization algorithms in detail.

In this research, we propose a relative localization evaluation method that does not depend on path complexity. To evaluate accuracy of a total relative localization algorithm, errors of estimated positions are verified. To evaluate accuracy of individual estimation methods, errors of moving distance/orientation/height estimation are verified. To eliminate the dependency on path complexity from relative localization evaluation, we adopt the trend of error accumulation as the evaluation matric. Additionally, we compare multiple relative localization algorithms by using our proposed evaluation method.

The structure of the paper is the followings. We describe conventional relative localization evaluation methods and their problems in section 2. In section 3, relative localization evaluation methods are proposed. In section 4, we compare multiple relative localization algorithms by using our proposed evaluation method. Finally, we conclude the paper in section 5.

II. Related Work

Relative localization is often evaluated by average, standard deviation, and square mean value of error[6][7][8]. Likewise, the maximum and minimum value of error is used[9]. However, the walking path affects the evaluation matric. This is attributed to accumulate the error as relative localization accumulates the change of location. The numbers of turns and curved lines on the walking path affect the evaluation matric as well. The walking paths used to evaluate vary from research to research. For example, more than 1000m long path including some turns[10] and the path including stairs

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are used[11][12]. Therefore, we cannot compare the accuracy of relative localization.

Some researches showed graphically for evaluation. The vertical line shows the position error, and the horizontal one time. They often used for looking the spape of the graph[13].

Kourogi researched the estimation of relative localization[14]. They noted that the relative localization outputs the position coordinate and orientation at discrete time and evaluates the accuracy of position and orientation. The ratios of moving distance to position error and walking time to orientation error were used as evaluation matorics. This research did not evaluate the height.

Ross's research, obtained location using a sensor device on shoes[15]. The sensor estimates the error of the position, the length of step, and the orientation when a long or the short walking path is used. This research did not evaluate the height either.

Similar to Ross, Jimenez et al obtained location using a sensor device on shoes[16]. They prepared some relative methods to evaluate and compared the accuracy of these methods using the same path. The step length and the number of steps taken were the matrics. The evaluation paths were evaluated by plotting them in figures. This research evaluated the evaluation paths using not a numeric value but a subjective judgment. Furthermore, this research did not take account of the path complexity, specifically the moving distance and the change amount of an angle in the walking path.

III. Evaluation unaffected by complexity of path

Relative localization estimates the amount of position change and update location by the accumulation value. The amount of position change is obtained by the change of moved distance, orientation, and height. Thus, we evaluate three factors of relative localization (distance, orientation, and height) but not position. This enables us to evaluate both these three elements of relative localization and position estimation. Relative localization bottlenecks are easy to discover when we compare some methods. Also relative localization estimates a relative position. Therefore, it is characterized by accumulation of position, moved distance, orientation, and height errors. In this work, we propose PIEM: Path Independent Evaluation Metric for Relative Localization. PIEM is new relative localization evaluation matorics considered the complexity, which is defined by distance, orientation, and height, to reduce reliance on the walking path.

A. Positioning estimation evaluation

The position evaluation matric is the position error generated per second. Using only the finish position error ignores error on the walking path.

We derive position estimation evaluation as follows. First, we calculate the position error per second (Fig. 1). Second we create the scatter plot (Fig. 2). The vertical line shows the position error, and the horizontal one time. The errors of estimated positions per second are represented by the slope of the line regressed by using the least square estimate method,

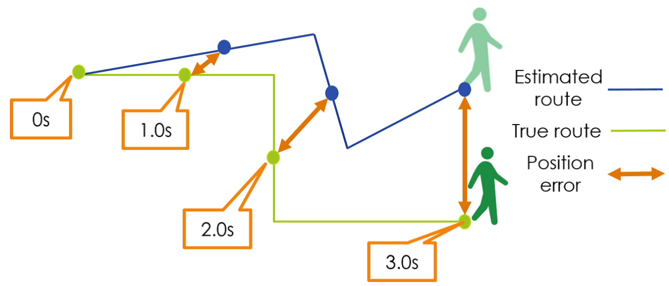


Fig. 1: Error used in position estimation evaluation

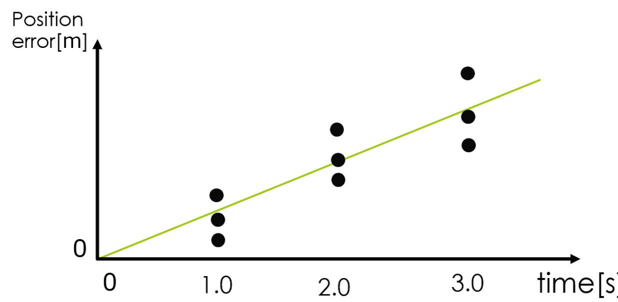


Fig. 2: Time-position error scatter plot

so we use linear regression. The smaller the value, the better the position evaluation. The green line in Fig. 2 shows the regression line. We prepare data being sprayed, N, and the i-th data is represented (x_i,y_i). The slope of the line regressed, a:

$$a = \frac{\sum_{i=1}^{N}(y_i x_i)}{\sum_{i=1}^{N}(x_i)^2} \tag{1}$$

We use the error per second for deriving position estimation evaluation. But we do not use the error per second for deriving moved distance, orientation, or height estimation evaluation. This is because path complexity influences relative localization accuracy. path complexity includes length, turning points, curved lines, and stairs on walking paths. Long and straight paths seem to have easier estimation and higher accuracy than short paths with that have many turning points and stairs. In the proposed method, we consider the complexity which is defined by the length, the orientation, and the height of the path in order to suppress variation in evaluation matorics of various paths.

B. Moving distance estimation evaluation

The moving distance estimation evaluation matric uses the length as path complexity, and moving distance estimation is evaluated by moving distance error generated per meter. We derive the moving distance estimation evaluation matric as follows. First, we calculate the moving distance error per second (Fig. 3). Second, we create the scatter plot (Fig. 4). The vertical line shows the moving distance error, and the horizontal one moving distance. The error of estimated moving distance per 1m is represented by the slope of the

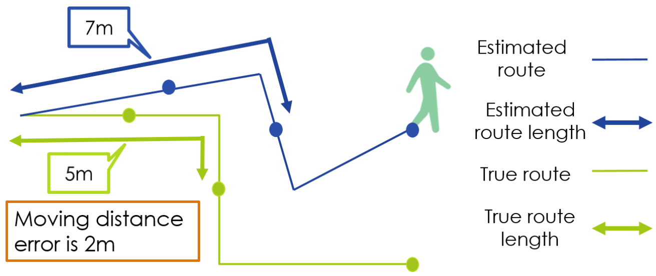


Fig. 3: Error used in moving distance estimation evaluation

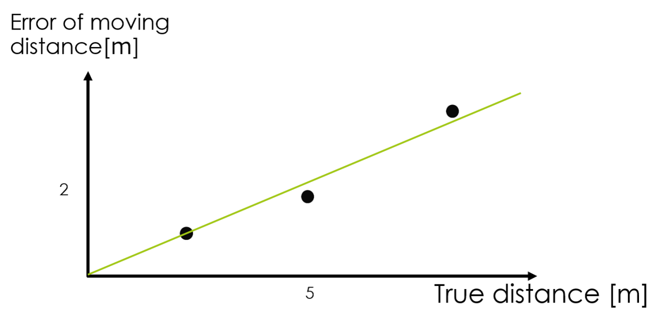


Fig. 4: Moving distance-moving distance error scatter plot

line regressed by using the least square estimate method. Therefore, we use the regression line in the same way as in position estimation evaluation. The slope on the graph is the moving distance estimation evaluation matric. The matric allows for the length of the path.

C. Orientation estimation evaluation

The orientation estimation evaluation matric uses the total angular change as path complexity. Orientation estimation is evaluated by orientation error generated per degree. We derive the orientation estimation evaluation matric by following the steps described below. First, we calculate estimated orientation, the accumulation of true orientation's change, true orientation, and per second (Fig. 5). Second, we create the scatter plot (Fig. 6). The vertical line shows the orientation error, and the horizontal one the accumulation of the true orientation's change. The error of estimated orientation per degree is represented by the slope of the line regressed by using the least square estimate method, so we use the regression line in the same way as previous methods. The slope on the graph is the orientation estimation evaluation matric. The matric allows for the accumulation of orientation's change of the path.

D. Height estimation evaluation

The height estimation evaluation matric uses the length as path complexity, and height estimation is evaluated by height error generated per meter. We derive the height estimation evaluation matric by following the steps described below. First, we calculate the height error and the accumulation of the true height's change per second (Fig. 7). Second, we create the scatter plot. The vertical line shows the height error, and the

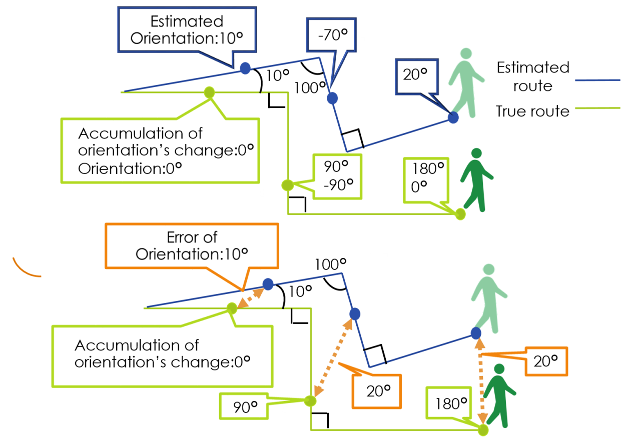


Fig. 5: Error used in orientation estimation evaluation

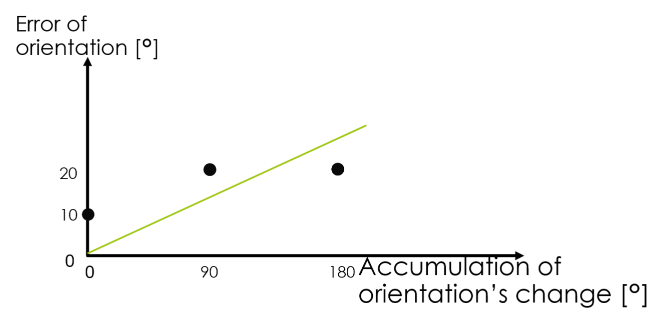


Fig. 6: Accumulation of true orientation's change-orientation error scatter plot

horizontal one the accumulation of true height. The error of estimated height per meter is represented by the slope of the line regressed by using the least square estimate method, so we use the regression line in the same way as previous methods. The slope on the graph is the height estimation evaluation matric. The matric allows for the height of the path.

IV. VERIFICATION EXPERIMENT

A. Verification with many relative localization methods

We verify how our proposed matrics are influenced by path complexity, which is defined by distance and orientation. First, we obtain estimated results from five relative localization

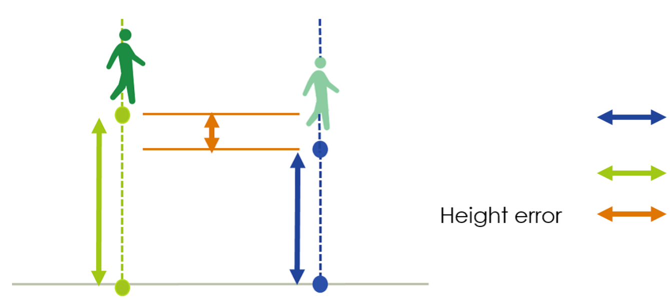


Fig. 7: Error used in height estimation evaluation

TABLE I: Characteristics of walking dataset

Average Walking Time[s]	114
Average Moving Distance[m]	133
Average Angular Change[$^\circ$]	896
Average Height Change[m]	7.5
Number of People	231

methods. We derive and compare proposed matrics and existing matrics from the results. We use five methods, their results, and walking datasets submitted to UbiComp/ISWC 2015 PDR Challenge[17]. Characteristics of the walking datasets are summarized in table I.

We propose the average and the standard deviation as existing matrics. These are used in UbiComp/ISWC 2015 PDR Challenge to estimate relative localization methods. We compute the average, e_ave, and the standard deviation using the last error of each paths, e_n[m] and the number of the paths, N.

$$e_{Ave} = \frac{\sum_{n=1}^{N} e_n}{N} \tag{2}$$

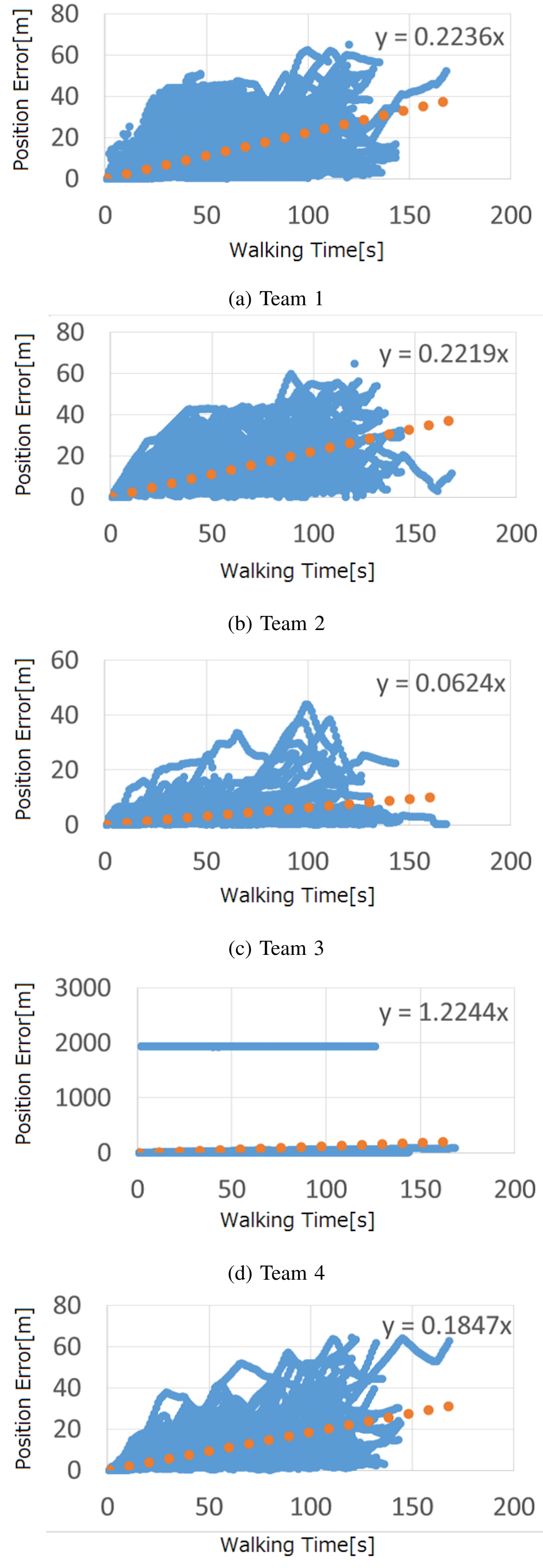
$$e_{SD} = \sqrt{\frac{\sum_{n=1}^{N} (e_n - e_{Ave})^2}{N}} \tag{3}$$

We compare proposed matrics with their matrics and consider the features of each relative localization method to consider the features of all matrics.

1) Positioning error: All matrics are summarized in table II. We show the scatter plot in figure 8. When all matrics are arranged from lowest to highest, the order in both proposed positioning error estimation evaluation matorics and existing estimation evaluation matorics is Team 3, Team 5, Team 2, Team 1, and Team 4. The proposed matric of position estimation evaluation plays a role of overall evaluation.

2) Moving distance error: We show the scatter plot in figure 9. When the proposed matrics are arranged from lowest to highest, the order is Team 3, Team 2, Team 1, Team 5, and Team 4. This order is not the same as that of the position estimation evaluation matorics. In the case of positioning estimation, Team 1 is better than Team 2, but in the case of moving distance estimation, Team 2's matric is smaller than Team 1's matric. It can be said that Team 1's method is better than Team 2's method in the case of moving distance. Team 2's method distinguishes between " normal walking " and "wandering." This enables us to accurately estimate stride length after the start and when passing someone. We discover new superiority of each relative localization method by using moving estimation evaluation.

3) Orientation error: We show the scatter plot in Fig. 10. When the proposed matrics are arranged from lowest to highest, the order is Team 3, Team 1, Team 5, Team 2, and Team 4. This order is not the same as those of the position estimation evaluation matorics and the moving distance estimation evaluation matorics. Team 1 pays attention to indoor walking paths composed of straight lines and right-angle turns, so Team 1's method changes exactly 90 degrees when it detects a corner. From Fig. 10(a), (c), and (e), we



(a) Team 1

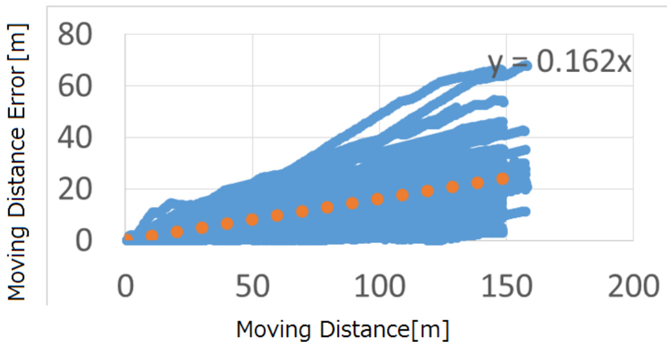
(b) Team 2

(c) Team 3

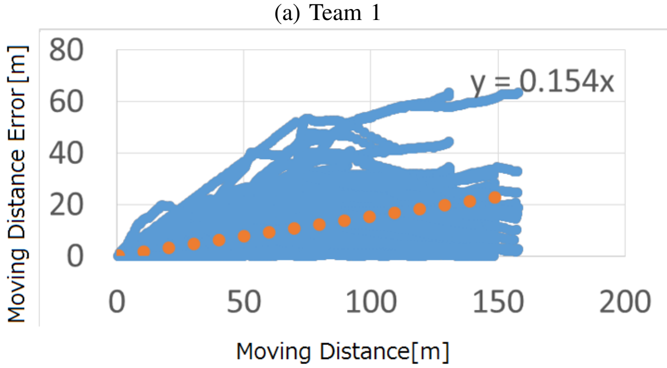
(d) Team 4

(e) Team 5

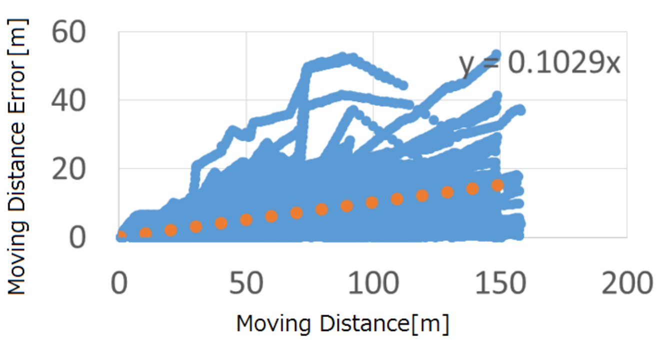
Fig. 8: Time-position error



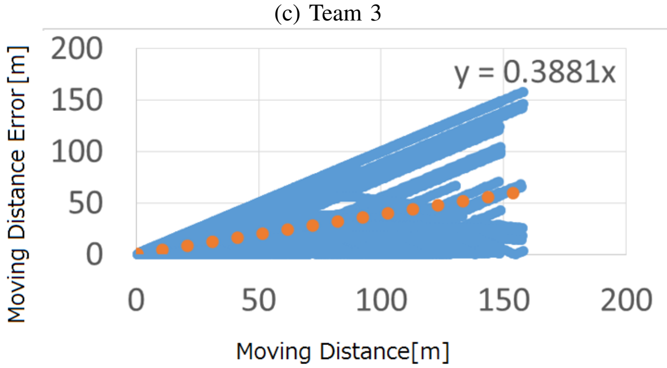
(a) Team 1



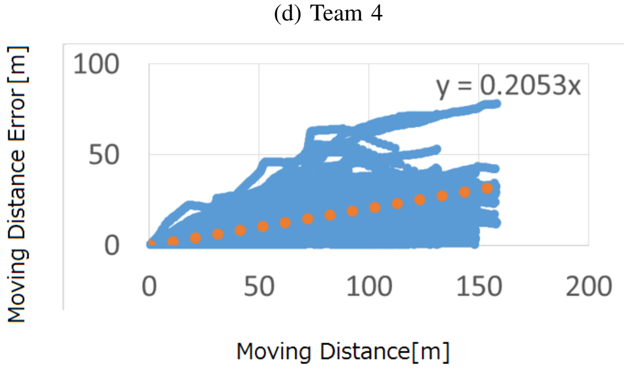
(b) Team 2



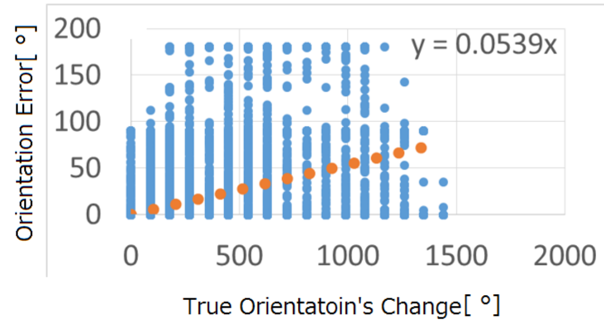
(c) Team 3



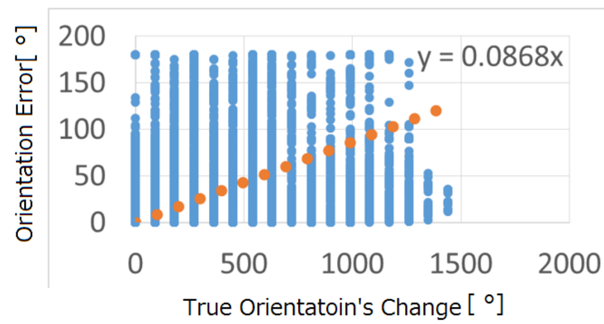
(d) Team 4



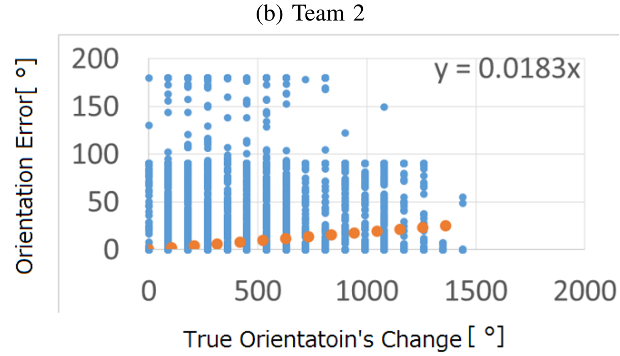
(e) Team 5



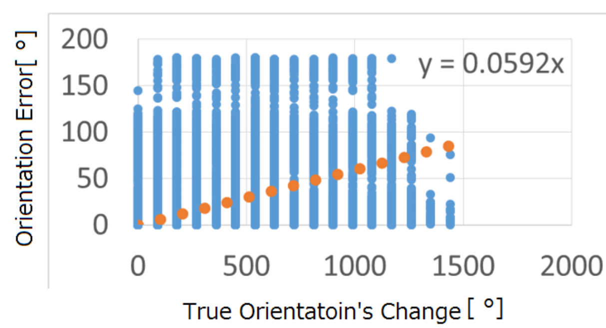
(a) Team 1



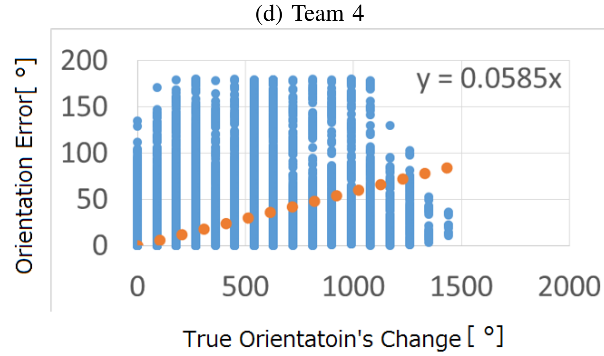
(b) Team 2



(c) Team 3

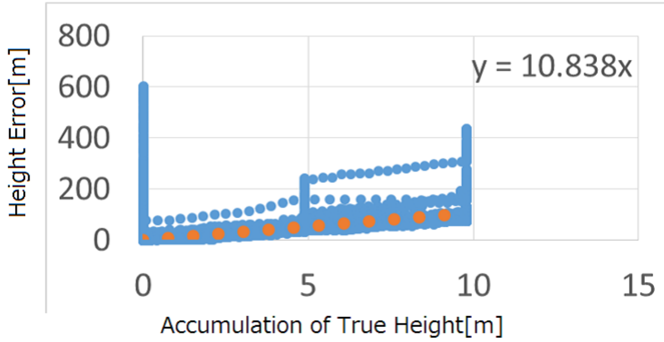


(d) Team 4

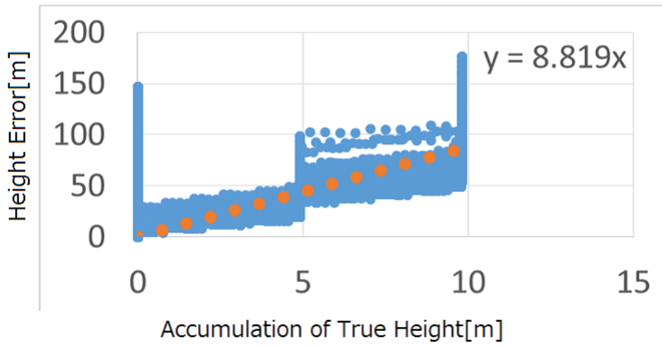


(e) Team 5

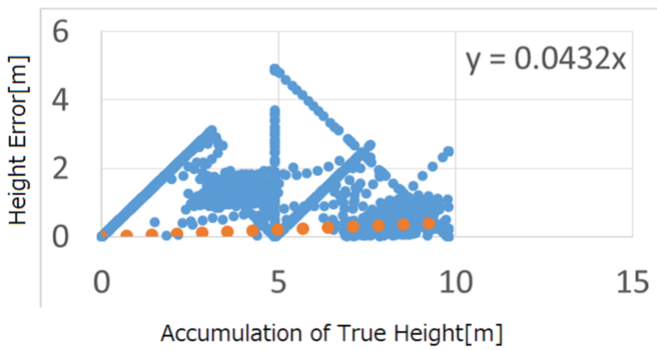
Fig. 10: Accumulation of true orientation's change-orientation error



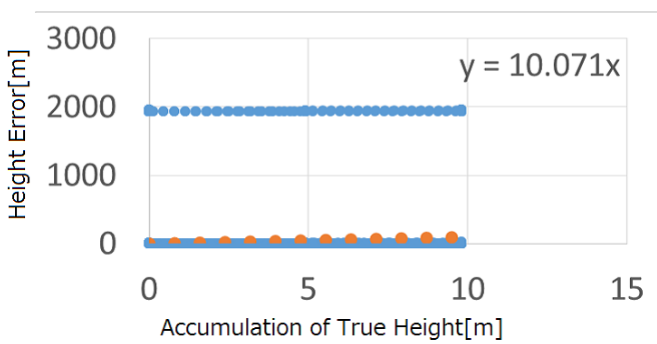
(a) Team 1



(b) Team 2



(c) Team 3



(d) Team 4

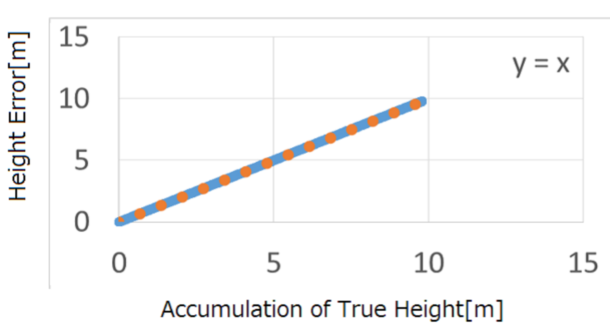


TABLE II: Estimation matrics

	Team 1	Team 2	Team 3	Team 4	Team 5
Position	0.21	0.22	0.062	1.22	0.18
Distance	0.16	0.15	0.10	0.39	0.21
Angle	0.054	0.060	0.018	0.087	0.059
Height	10.8	10.1	0.043	8.81	1.0
e_{Avg}[m/s]	13.0	13.1	3.5	46.93	10.7
e_{SD}[m/s]	9.21	7.78	1.69	9.37	6.5

TABLE III: Characteristics of dataset

	Set 1	Set 2	Set 3	Set 4	Set 5
Walking Time Avg[s]	58.2	85	117	126	132
path Length[m]	71	91	132	149	159
Angle Change [°]	270	630	630	1260	1080
Height Change[m]	0	0	9.8	9.8	9.8
Number of Samples	20	20	20	20	20

observe the following features. Figure 10(a) has many error values close to 0 and 90 degrees. We find the scatter plot reflects characteristics of relative localization methods.

4) Height error: We show the scatter plot in Fig. 11. When the proposed matrics are arranged from lowest to highest, the order is Team 3, Team 5, Team 2, Team 1, and Team 4. This order is same as that of the position estimation evaluation matorics. Team 5 does not estimate the height, so the slope in Fig. 11(e) is 1. We pay attention to the value of a coordinate on the vertical axis in Fig. 11(a), (b), and (d). The maximum values are 600, 180, and 2000m, much larger than those of the other two teams. Team 4's method uses the initial value of an atmospheric pressure sensor. The atmospheric pressure sensor of a certain terminal outputs an extremely small value. Thus, Team 4's method outputs a large error.

5) Consideration: The ranking of the proposed matric of positioning estimation evaluation is the same ranking of existing matrics used in UbiComp/ISWC 2015 PDR Challenge. On the other hand, the rankings of proposed matrics of moving distance and orientation are not the same as that of matrics of positioning estimation evaluation. Evaluating three factors of relative localization reveals a new bottleneck that position estimation evaluation does not. For example, height estimation is very inaccurate in Teams 1, 2, and 4. In summary, the proposed matrics enable us to compare four factors of relative localization: positioning/moving distance/orientation/height. Additionally, we can find which of the three factors (moving distance, orientation, and height) is a bottleneck of relative localization used by the proposed matrics.

B. Investigating dispersion of matrics

1) How to investigate: To verify the dependency on path complexity, we calculate the dispersion of the evaluation matorics. First, we input some walking datasets into relative localization. Then, we calculate the evaluation matorics from each estimated result and compare the dispersion of the evaluation matorics.

We use Team 3's algorithm due to its excellent accuracy evaluation of the total relative localization algorithm and indi-

TABLE IV: Proposed matrics

	Set 1	Set 2	Set 3	Set 4	Set 5	CV
Position	0.081	0.070	0.067	0.043	0.064	0.19
Distance	0.14	0.10	0.11	0.097	0.090	0.17
Angle	0.032	0.022	0.023	0.014	0.020	0.28
Height	0	0	0.052	0.038	0.044	0.83

TABLE V: Existing error:the error per second

	Set 1	Set 2	Set 3	Set 4	Set 5	CV
Position	0.032	0.045	0.031	0.024	0.018	0.29
Distance	0.15	0.12	0.11	0.09	0.09	0.20
Angle	0.042	0.028	0.080	0.029	0.13	0.62
Height	0	0	0.0013	0.0011	0.0002	1.10

vidual estimation methods. The walking datasets are obtained from UbiComp/ISWC 2015 PDR Challenge and grouped into walking paths. Table III shows the characteristics of the each dataset.

For the existing matrics, the location errors per meter of moving distance and per second are heavily used. Therefore, we compare the proposed matrics with the position/moving length/orientation/height errors generated per second and per meter. The matrics using the error per second are calculated by the last error of each path, e_n, the number of the paths, N, moving distance, r_n, and walking time, r_n, as

$$e_l = \frac{\sum_{n=1}^{N} \frac{e_n}{r_n}}{N} \tag{4}$$

$$e_t = \frac{\sum_{n=1}^{N} \frac{e_n}{t_n}}{N} \tag{5}$$

To verify the dispersion of the evaluation matorics due to path complexity, we need to use the dispersion matric independent of the evaluation matric value. Therefore, we use the coefficient of variation, CV. This is calculated from the standard deviation and the average.

2) Result: Table IV, V, and VI shows the value and the dispersion of each estimation evaluation matorics. Figure 12 shows the dispersion of each estimation evaluation matorics. The dispersion of proposed matrics is smaller than existing matrics in all. In the orientation estimation evaluation, we take into account total angular change as path complexity. As the result, we obtain dispersion of proposed matrics that is significantly smaller than that of existing matricers. The dispersion of height estimation evaluation matorics is a big value because the matrics are always 0 in two datasets.

From the above, we think that using the proposed method makes the dispersion of matrics small and reduces dependency on path complexity.

V. Conclusion

In this work, we propose new relative localization evaluation matorics considered the complexity, which is defined by distance, orientation, and height for reducing reliance on the walking path. The existing estimation evaluation uses the

TABLE VI: Existing error:the error per meter

	Set 1	Set 2	Set 3	Set 4	Set 5	CV
Position	0.026	0.036	0.030	0.022	0.015	0.28
Distance	0.13	0.093	0.11	0.079	0.073	0.20
Angle	0.033	0.019	0.068	0.026	0.10	0.63
Height	0	0	0.0012	0.0009	0.0001	1.13

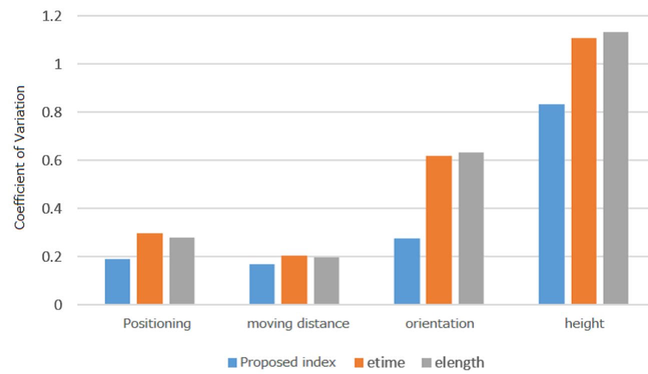


Fig. 12: Dispersion of each matrics（CV）

positioning error in the last part of the path. It does not take into account the error in the middle of the path or the accuracy evaluation of individual estimations of moving distance/orientation/height. In this research, we proposed relative localization evaluation methods that do not depend on path complexity. To evaluate accuracy of the total relative localization algorithm, errors of estimated positions are verified. To evaluate accuracy of individual estimation methods, errors of distance/direction/height estimation are verified.

We note that relative localization estimates positioning by using moving distance/orientation/height estimation, so we evaluate distance/orientation/height of relative localization but not position. First, positioning estimation is evaluated by the position error per second as the accuracy evaluation of the total relative localization algorithm. Next, errors of distance/direction/height estimation are evaluated as the accuracy evaluation of individual estimation methods. The moving distance estimation evaluation matric is moving distance error generated per meter, the orientation evaluation estimation matric is orientation error generated per degree, and height evaluation estimation matric is height error generated per meter. These three matrics are calculated from the slope of the line in a scatter plot in which the vertical axis is error and the horizontal one time. We use a dataset composed of 230 pieces of walking data and five relative localization methods. The data and method are collected from UbiComp/ISWC 2015 PDR Challenge. This enables us to evaluate the individual estimation methodS. Therefore, we can compare three accuracy evaluations (moving distance/orientation/height) in addition to accuracy evaluation of position in each relative localization method. The proposed method reveals the bottleneck of relative localization by focusing on the biggest matric. We show the relative localization method that has low accuracy overall does not always have low accuracy in individual estimations. To verify the dependency on path complexity, we calculate the dispersion of the evaluation matorics. Using the walking dataset obtained from UbiComp/ISWC 2015 PDR Challenge, we calculate the evaluation matorics from all estimated results and compare the dispersion of the evaluation matorics. The dispersion of the proposed matrics is smaller than that of existing ones in all evaluation points. The evaluation estimation of the more complex method including relative localization and the evaluation of the amount of electricity saved in addition to accuracy of position will be the subjects of further study.

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