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Clustering of distance sensors to transfer training data for relative position and orientation measurement devices

Sogo Amagai*, Qiwei Ye, Yuji Fukuoka, Shin'ichi Warisawa and Rui Fukui

Abstract

Car-sharing services have recently attracted considerable attention. We proposed a platooning system to reduce the number of vehicle distributors. The platooning system uses a measurement device embedded with low-cost infrared distance sensors to measure the relative position and orientation of vehicles. The relative positions and orientations are obtained from the training data. However, preparing training data is time consuming. In this study, a sensor clustering method that selects sensors with similar output characteristics is proposed. Consequently, a set of training data are used repetitively for all relative positions and orientation measurement devices embedded with sensors with similar output characteristics. The verification experiment of the sensor clustering revealed that the calculation range restriction is the key technique. Platooning has been successful in various courses by using sensors with similar output characteristics. Based on the results, the proposed clustering method can effectively collect sensors with similar output characteristics and it realizes the training data transfer to the newly manufactured devices. In addition, it has the potential to improve production efficiency for the mass production of relative position and orientation measurement devices.

Keywords: Sensor clustering, Infrared distance sensor, Platooning, Autonomous vehicle

Introduction

Recently, one-way car sharing has been spreading rapidly, and is expected to become an effective means of transportation in urban areas in the future[1, 2]. However, it faces the following challenges: high labor costs for vehicle distributors and imbalance between supply and demand for vehicles [2–5]. To reduce the number of vehicle distributors and their burdens, we proposed a platooning system [6, 7] for urban areas. As shown in Fig. 1, multiple unmanned vehicles follow a manned vehicle. However, some research on the realization of autonomous vehicles (AV) in urban areas has revealed that the social implementation of AV is challenging owing to safety issues [8–11] and low social acceptance [12–14]. Hence, platooning can be an effective means of transportation in urban areas because the social implementation of platooning is easier than that of AV. The proposed platooning system offers four advantages over conventional platooning systems [15–17].

1. Configuration of the platooning system is simple and inexpensive because the relative position and orientation between vehicles can be measured using only low-cost distance sensors.
2. Because communication is not necessary between vehicles, it remains uninterrupted even when driving in poor communication environments.
3. Because the pin operates inside the ring, it is not affected by the external environment, such as rain and snow.

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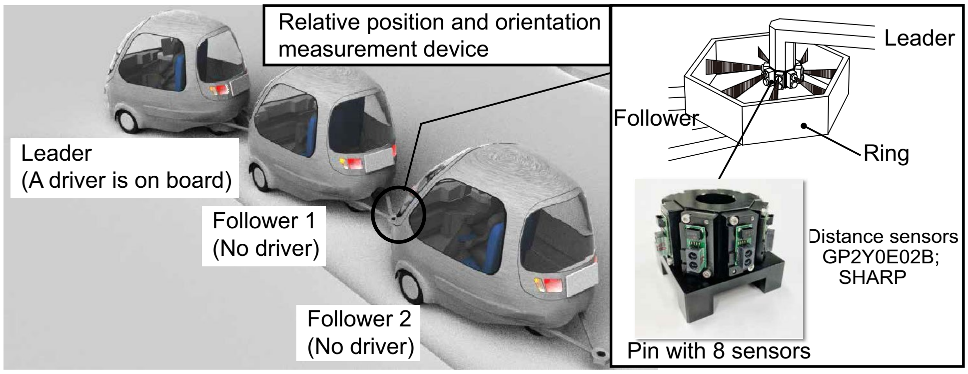

Fig. 1 Overview of proposed platooning system

4. When the follower runs out of control, the pin and ring restrict the movement of the follower.

In addition, the relative position and orientation between vehicles are measured using the relative position and orientation measurement device shown in Fig. 1. The device consists of a leader octagonal pin with multiple distance sensors (GP2Y0E02B, SHARP [18]) and a follower hexagonal ring. In a previous study [7], we developed a relative position and orientation measurement device for use in actual vehicles. The hardware in the loop simulation (HILS) using the developed device proved that the following four cars can follow on five courses. The five courses are as follows.

- Circular operation
- Lane changing
- Slaloming operation
- Pulsed steering
- Accelerated start.

To measure the relative position and orientation, the relative position and orientation measurement device requires training data. First, distance data $\boldsymbol{L}$ should be obtained using distance sensors at various relative pin-ring positions and orientations (x, y, θ). Second, training data should be created by combining (x, y, θ) and $\boldsymbol{L}$. In the relative position and orientation measurement device shown in Fig. 2, the relative position and orientation (x, y, θ) are calculated using $\boldsymbol{L}$ from the training data. However, a previous study [7] clarified that approximately 360,000 training data points are required to achieve the accuracy of the relative position and orientation that enables successful platooning. Consequently, the creation of training data, which requires approximately 8 hours, is an obstacle to the mass production of relative position and orientation measurement devices. Therefore, in this study, we proposed a sensor clustering method that enables the transfer of training data to newly manufactured relative position and orientation measurement devices, and then verified its performance in order to lead the mass production of the relative position and orientation measurement devices.

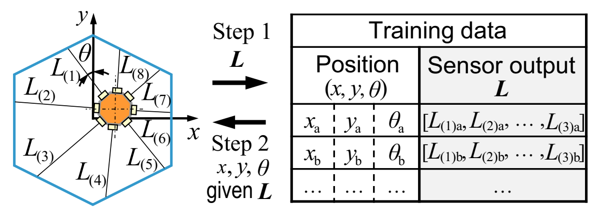

Fig. 2 Measurement of relative positon of pin and ring

In addition, this study contributes to the possibility of using multiple low-cost sensors without complicated calibration, by selecting sensors with similar output characteristics through sensor clustering. First, sensor clustering could be applied not only to relative position and orientation measurement devices for platooning, but also to other systems. Sensor clustering method is realized by acquiring sensor output characteristics readily and clustering algorithms based on the sensor output characteristics. Relative position and orientation measurement devices and sensor clustering method are independent from each other. Therefore, it is highly likely that sensor clustering method is applicable to other applications besides relative position and orientation measurement devices. Second, sensor clustering method is a novel approach of finding similar sensors. Since sensor clustering method does not require calibrating each sensor individually, it is time-efficient and effectively applicable to IoT system [19] that use a large number of sensors such as sensor network systems [20].

This paper is organized as follows.

- Approaches and technical issues of sensor clustering for transferring training data
- A sensor output characteristic acquisition device developed to realize sensor clustering and its performance evaluation
- Experiment to decide threshold for selecting sensors with similar output characteristics
- Verification experiment of sensor clustering
- An approach to the calculation range restriction of sensor dissimilarity for the realization of platooning and the changes in clustering results
- Verification experiment with sensor selection method suitable for platooning
- Findings and results of this paper

Concept

Transferring training data of a reference device to newly manufactured relative position and orientation measurement devices

As shown in Fig. 3, the distance to the measurement object d and the tilt of the measurement object φ affect the output of the distance sensors used in the relative position and orientation measurement device. The output characteristics of the sensors that vary with distance d and tilt φ are defined as $L = f(d, \varphi)$. L is the output value of the sensor. However, the distance data $\boldsymbol{L}$ for calculating (x, y, θ) are different from the training data because the output characteristics L of each sensor are different. Therefore, (x, y, θ) and $\boldsymbol{L}$ of the training data become less relevant. Consequently, the training data cannot be directly transferred to newly manufactured relative position and orientation measurement devices because the accuracy of the relative position and orientation is sharply reduced.

If the output characteristics of all sensors can be matched through rigorous calibration [21, 22] of the individual sensors, the training data can be directly transferred to newly manufactured relative position and orientation measurement devices. The self-calibration method [21], which uses two sensors of the same type for calibration, does not require a highly accurate comparison standard; however, calibration is time consuming when several sensors are involved. Thus, conventional calibration methods, such as self-calibration, are not suitable for multiple sensors.

Sensor clustering for transferring training data

Therefore, we proposed a sensor clustering method that does not require complicated calibration of each sensor. As shown in Fig. 4, sensor clustering divides all sensors into k clusters according to the dissimilarity in the sensor output characteristics. The relative position and orientation measurement device is composed of only sensors attributed to the same cluster. Sensors in the same cluster have similar output characteristics, thus each distance data $L_{(1)}$-$L_{(8)}$ are similar. (x, y, θ) and $\boldsymbol{L}$ of the training data remain relevant. Therefore, training data created using sensors in the same cluster may be transferred to newly manufactured relative position and orientation measurement devices using other sensors in the same cluster.

In the above implementation method, all sensors used in all relative positions and orientation measurement devices that transfer training data must belong to the same cluster. Therefore, a cluster must contain many sensors; hence, numerous sensors must be prepared. To address, this problem,we propose an equipping method in which the sensors that comprise a single relative position and orientation measurement device can be selected from eight clusters as shown in Fig. 5. In the proposed method, all sensors belonging to the same cluster have the same position index. (x, y, θ) and $\boldsymbol{L}$ of the training data are relevant because of the similarity in the sensor output characteristics at the same position index. Therefore, sensors from eight clusters are used in a relative

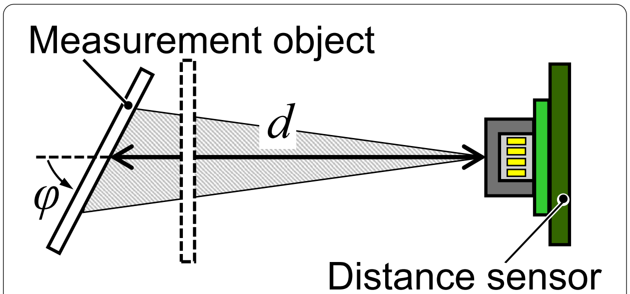

Fig. 3 Definition of distance d and tilt φ

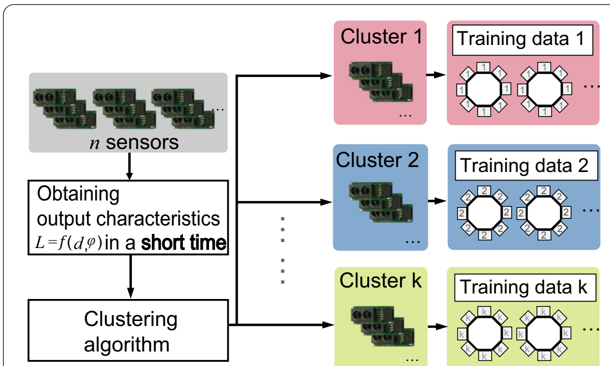

Fig. 4 Overview of sensor clustering

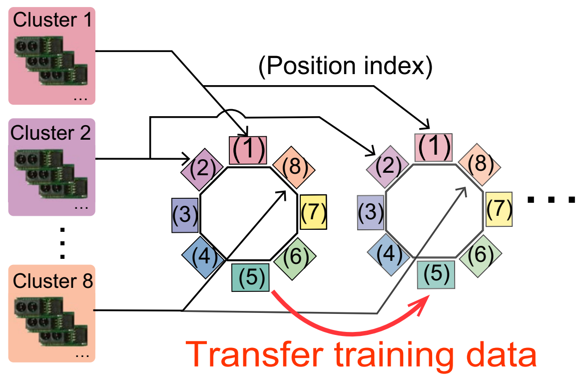

Fig. 5 Proposed equipping method for relative position and orientation measurement devices

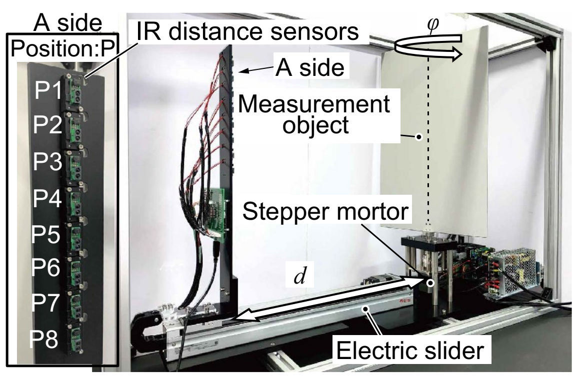

Fig. 6 Sensor output characteristics acquisition device

position and orientation measurement device with eight positions. The proposed equipping method is expected to be as effective as the case in which all the sensors that are composed of the relative position and orientation measurement device belong to the same cluster.

For sensor clustering, it is important to obtain a sensor output characteristic $L = f(d, \varphi)$, thus we developed a sensor output characteristic acquisition device shown in Fig. 6. Three functions were required for this device.

1. High reproducibility of measurement: Small variation of measurement output under the same conditions
2. High stability for sensor removal: Small variation of measurement output when a sensor is attached and detached at the same measurement position
3. High stability for sensor position exchange: Small variation of measurement output when a sensor is at the different measurement position

In addition, it is necessary to clarify the similarity of sensor selection with similar output characteristics. The normalized distance is used to evaluate the similarity. Sensor p and sensor q at distance d_i ($1 \leq i \leq N_i$, N_i is the total number of points of distance measured) and tilt φ_j ($1 \leq j \leq N_j$, N_j is the total number of points of tilt measured) are acquired output characteristics. Next, the difference between the output values of sensors p and q ($e_{p,q}(d_i, \varphi_j) = L_p(d_i, \varphi_j) - L_q(d_i, \varphi_j)$) is calculated and normalized for each distance d_i. Thereafter, the normalized distance D_{normal} is calculated as the root mean square error of the normalized output values of sensors. (Eq. (1))

$$D_{\mathrm{normal}}(p, q) = \sqrt{\frac{1}{N_i N_j} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \left(\frac{e_{p,q}(d_i, \varphi_j)}{d_i} \right)^2} \quad (1)$$

The normalized distance is smaller when the sensor outputs are similar for distance d and tilt φ. The calculation range of the normalized distance is $d = 95$-445 mm and tilt $\varphi = 30$–150 deg.

The range was determined empirically from HILS data. In practice, distance d and tilt φ used to calculate the normalized distance include a range that is not required for platooning. Therefore, distance d and tilt φ used for platooning are calculated from the HILS data, and then used as the range for calculating the normalized distance. By calculating the range restriction of the normalized distance, sensors with similar output characteristics will be selected for platooning. This is expected to improve the accuracy of vehicle position and orientation measurements when transferring the training data.

Development and evaluation of sensor output characteristics acquisition device

Overview of sensor output characteristics acquisition device

The developed sensor output characteristic acquisition device is illustrated in Fig. 6. Eight sensors were installed on P1 to P8 on side A to obtain the output characteristics. The distance d between the sensor and measurement object is changed by an electric slider, and the tilt φ of the measurement object is changed by a stepper motor. The electric slider has a repetitive positioning accuracy of ± 0.02 mm, and running parallelism of 0.03 mm, which allows the system to reproduce the relative positions of the measured object and sensor with high accuracy. The angular positioning error of the stepper motor is ± 0.067

deg, and the relative angles between the measured object and the sensor can be reproduced with high accuracy. The surface of the measurement object is a matt finish and white anodized to prevent specular reflection of infrared light.

Reference for evaluation of the device

The dissimilarity of different sensors was measured as a reference for the evaluation of the sensor output characteristic acquisition device. We randomly selected 8 sensors measured at P8, as shown in Fig. 6.

The results in Fig. 7 show the normalized distances between different sensors at P8. S1–S8 represent the eight randomly selected sensors. The minimum normalized distance between the sensors was 0.015, the maximum was 0.043, and the mean of the normalized distance of the eight sensors μ_{sensors} was 0.029, which was used as a reference for the evaluation of the device. In the following sections, an evaluation of the sensor output characteristic acquisition device is described.

Measurement reproducibility

The sensor output characteristic acquisition device must have a high reproducibility of measurement under the same measurement position and same sensor used. Sensor S1 was measured at P8 three times.

The matrix shown in Fig. 8 indicates the normalized distance between each trial, with the number of trials ranging from T1 to T3. The mean of the normalized distances between the three trials, μ_{repeat}, was 0.0063. Compared with μ_{sensors} (0.029), μ_{repeat} is sufficiently small. Therefore, the sensor output characteristic acquisition device has sufficiently high measurement reproducibility.

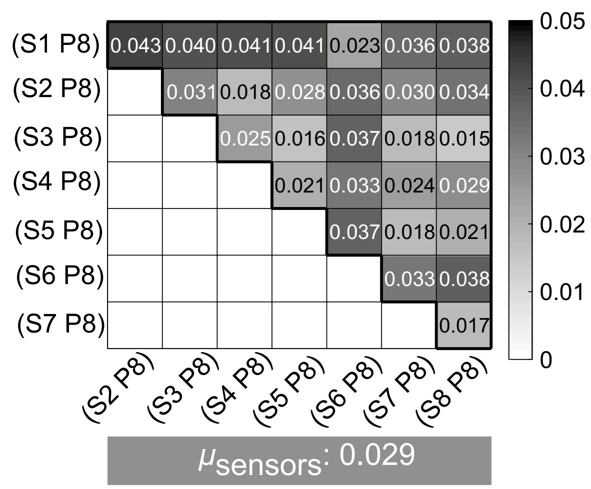

Fig. 7 Dissimilarity of different sensors

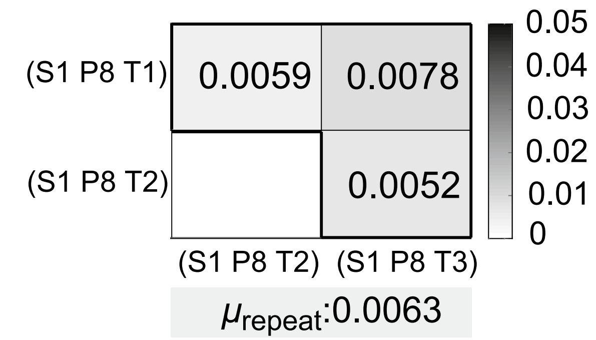

Fig. 8 Measurement reproducibility

Stability against for attach and detach of sensors

The same sensor output characteristics must be obtained when the same sensor is reattached to the device and measured. The same sensor was detached from the device, reattached, and measured three times. The sensor used was S1, and the measurement position was P8.

The matrix shown in Fig. 9 illustrates the normalized distance between each trial, with the number of trials ranging from T1 to T3. The mean of the normalized distances between the three trials, μ_{remove}, was 0.0066. μ_{remove} is fully small compared to μ_{sensors} (0.029). Consequently, the sensor output characteristic acquisition device has a high stability against the attachment/detachment of sensors.

Stability against for position change

To verify the stability against sensor position change, the same sensor S1 was sequentially installed and measured at P1–P8 shown in Fig. 6, and the normalized distances of the eight measurement data were calculated.

The matrix shown in Fig. 10 indicates the normalized distance between P1 and P8. The mean of the normalized distances measured at different positions $\mu_{\text{positions}}$

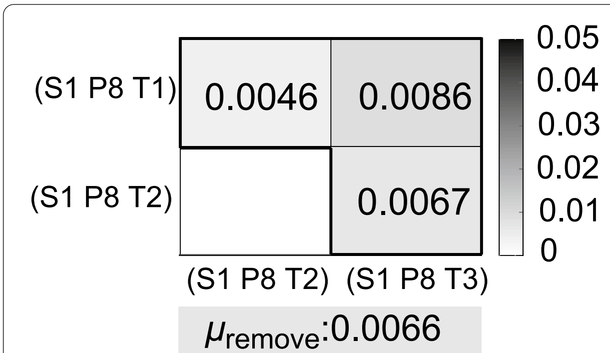

Fig. 9 Stability against for attach and detach of sensors

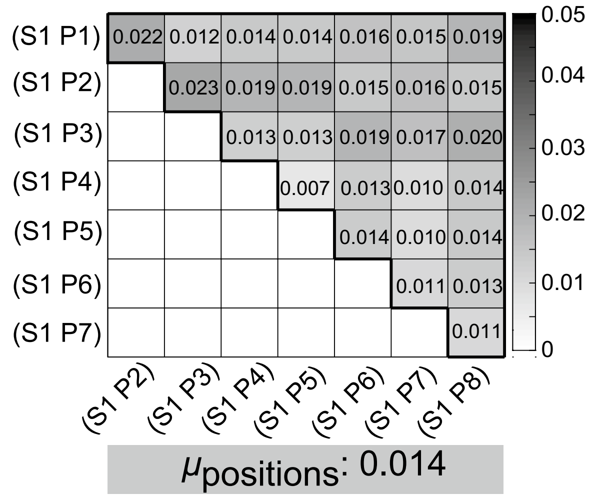

Fig. 10 Stability against for position change

was 0.014. $\mu_{\text{positions}}$ is less than half that of μ_{sensors} (0.029). Therefore, the sensor output characteristic acquisition device has high stability against position change.

Deciding threshold of sensor clustering

Distribution of normalized distance of 132 sensors

The sensor dissimilarity threshold was determined to select sensors with similar output characteristics. Sensors with dissimilarities below the threshold are defined as similar sensors.

First, the output characteristics of 132 sensors were obtained and the normalized distances between them were calculated. The distribution of normalized distances is shown in Fig. 11. The normalized distances for the majority of the sensor pairs are between 0.02 and 0.03. There are a few distributions with normalized distances below 0.02 or 0.03. Based on this result, sensors that have normalized distance around 0.016, which is approximately the top 10 % of the distribution of normalized distance of 132 sensors, are classified as“Good”. Sensors that have normalized distance around 0.02, which is close to the mode value in the distribution, are classified as “Fair”. Sensors that have normalized distance around 0.03, which is approximately the bottom 20 % of the distribution, are classified as “Poor”.

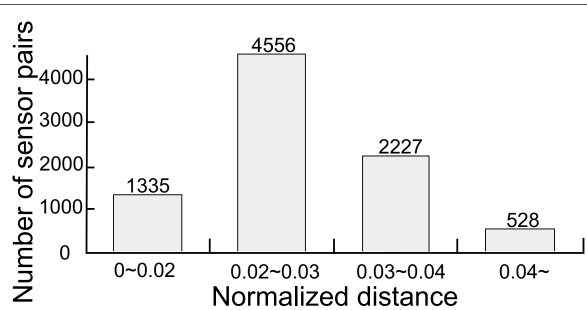

Fig. 11 Distribution of normalized distance of 132 sensors

HILS for deciding threshold of sensor clustering

An overview of the experiment to determine the threshold is shown in Fig. 12. Eight randomly selected sensors were used as the reference sensor groups. For each position index, a sensor was selected that satisfies the criteria of “Good”, “Fair”, and “Poor” in terms of normalized distance from the reference sensor. Each of the three selected sensor groups was used to configure the relative position and orientation measurement device. In this experiment, the reference sensor groups used in a relative position and orientation measurement device were employed to create the training data. The training data was transferred to a relative position and orientation measurement device consisting of three sensor groups selected from the “Good”, “Fair”, and “Poor” groups. Platooning was experimentally verified using the HILS. The objective of this experiment is to narrow the range of sensor dissimilarities that can achieve platooning when transferring training data based on platooning by HILS. Five different courses were used for HILS in a previous

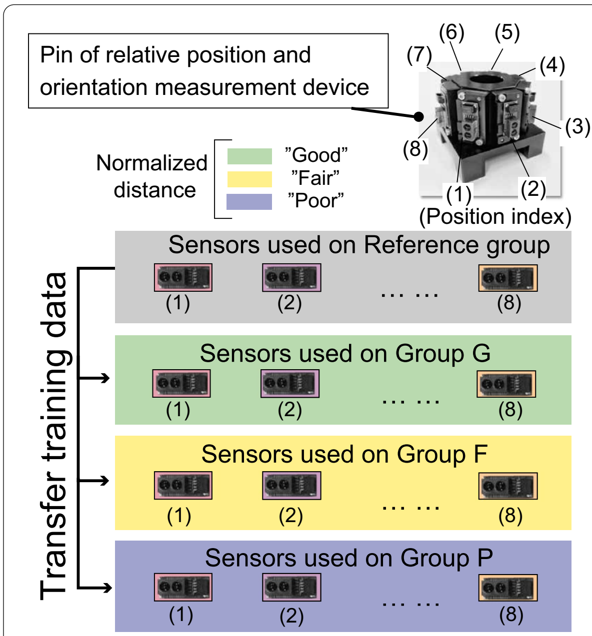

Fig. 12 Overview of experiment for deciding threshold

study [7]. The Reference group (Ref.) is defined as the vehicle using the relative position and orientation measurement device consisting of a group of reference sensors. Group G, Group F, and Group P are defined as the groups of vehicles using the devices consisting of the sensor groups selected according to the "Good", "Fair", and "Poor" respectively.

The HILS results are presented in Table 1. Group G maintained the highest number of platooning vehicles in each course, except for group P's circular operation. However, even in Group G, only one following vehicle could maintain platooning in the circular operation, and the following vehicle failed in the lane changing course as well as in accelerated start course. Therefore, the experimental results show that the normalized distance that can be successfully platooned when transferring training data is less than 0.016.

Verification experiment for sensor clustering

Sensor clustering uses hierarchical clustering (Algorithm 1) and the distances between clusters are calculated using the furthest neighbor method [23]. Out of the ${}_{132}C_2$=8,646 pairs of normalized distances for 132 sensors, only 273 pairs had normalized distances less than 0.016, thus clusters containing many sensors were not generated. As shown in Fig. 5, in the verification experiment, a relative position and orientation measurement device was configured by selecting the sensors from eight clusters.

Clustering was performed by setting the sensor dissimilarity threshold T, which is an index of merging stops, to 0.016, 0.015, 0.014, and 0.013, sequentially using Algorithm 1. From the clustering results, when the sensor dissimilarity threshold T is less than 0.015, most clusters contain only one sensor, thus the training data cannot be transferred. Therefore, in this experiment, we set the sensor dissimilarity threshold T to 0.015. The results of sensor clustering, in which similar sensors with dissimilarities below a threshold are collected, are shown in Fig. 13.

The sensor groups used for the sensor clustering validation experiment, selected from the dendrogram, are shown in Table 2.

The reference group is defined as a group of platooning vehicles using a relative position and orientation measurement device, which is composed of a reference sensor group used to create the training data. A group of platooning vehicles using a device composed of similar sensors and training data transferred from the reference group is defined as a transfer group (Trans.).

Figure 14 shows the results of the HILS of the four followers of the circular operation for the reference and transfer groups. The graph on the left in Fig. 14 shows the temporal variation in the distance between the center of the pin and ring of the relative position and orientation measurement device. The graph on the right in Fig. 14 shows the relative trajectories of the pin and ring. In the transfer group, when the leader entered the curve 2 seconds after departure, the distance between the centre of the ring and pin of follower 1 swung drastically. This vibration was transmitted to vehicles 2, 3, and 4 with amplification, resulting in platooning failure. The sensors used in the transfer group were not sufficiently similar to maintain the correspondence of the training data, which caused a decrease in the accuracy of the relative position and orientation measurements, resulting in platooning failure. The HILS for each course in the transfer group was conducted three times. In the pulsed steering and accelerated start, all the following vehicles were successfully maintained in all trials. In addition, at least two following vehicles were maintained in all courses. Based on these results, the use of similar sensors prevents a undesirable decrease in the accuracy of the relative position and orientation measurements, which occurs when the training data is transferred.

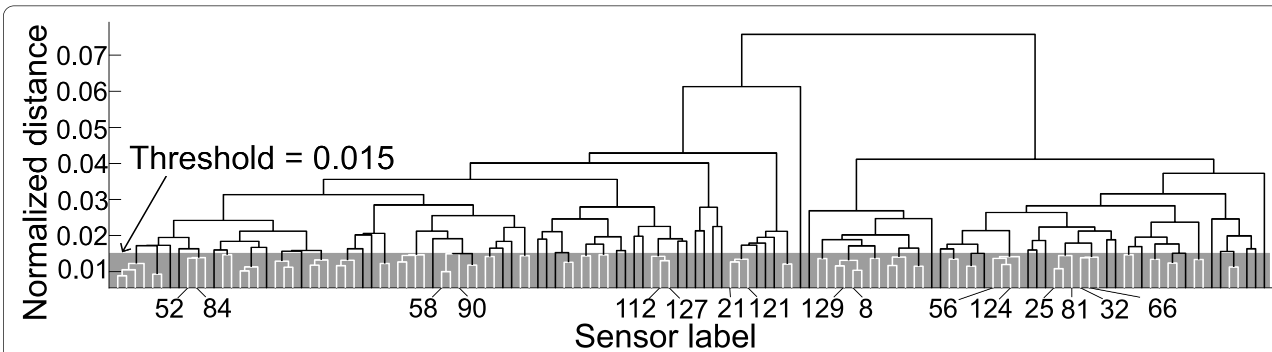

Fig. 13 Dendrogram of sensor clustering

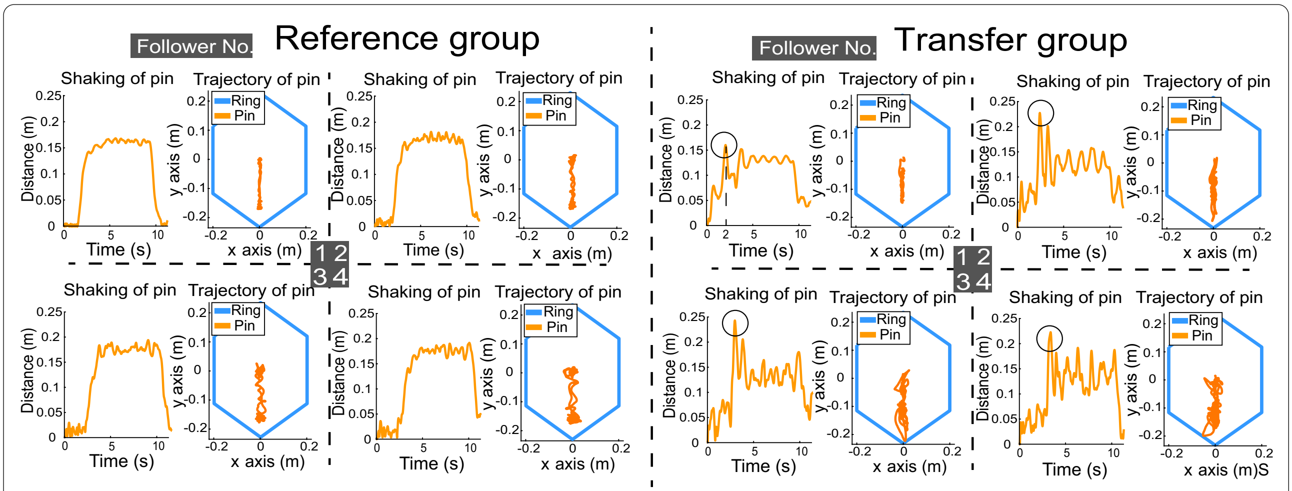

Fig. 14 Result of HILS on circular operation

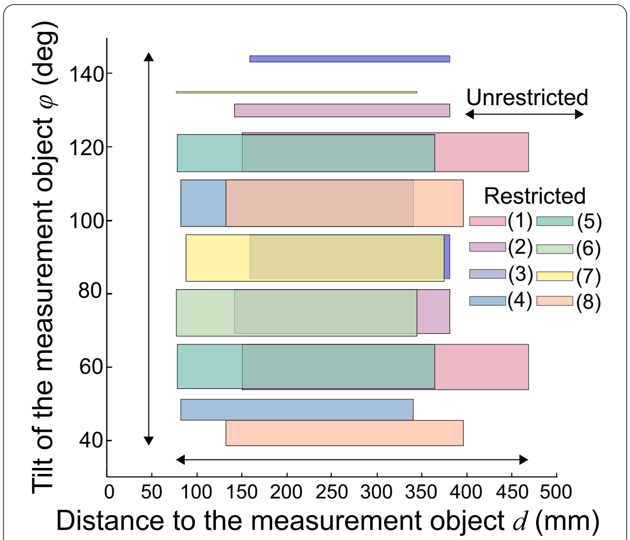

Fig. 15 Result of calculation range restriction for each position

However, it is important to select more similar sensors to further improve the accuracy of relative position and orientation measurements. As the range of distance d and tilt φ used to calculate the normalized distance may not be suitable for platooning, the calculation range of the normalized distance must be restricted to those used for platooning.

Table 3 illustrates number of followers maintained in platooning by each group in the verification experiment.

Sensor clustering using calculation range restriction

Deciding calculation range on each position index

From the output values $L_{(1)}$-$L_{(8)}$ of the reference sensor group and the pin trajectory, distance d and tilt φ between the sensor and the measurement object (the ring wall of the relative position and orientation measurement device) were calculated at each position index, and then used as the calculation ranges of the normalized distance. The result of the calculation range for each position index is shown in Fig. 15. "Unrestricted" illustrated by the arrows contains the range of minimum to maximum values of the output distance d and tilt φ of all sensors equipped with the relative position and orientation measurement device during HILS. On the other hand, "Restricted" illustrated by the rectangles of each color contains the minimum to maximum range of the output distance d and tilt φ of the sensor attached to each position index shown as (1)–(8) in Figure 5 during HILS. It was found that distance d and tilt φ between the sensor and the object to be measured during platooning differed significantly depending on the position index.

As the range used to calculate the normalized distance for each position index is different, it is expected that the normalized distance and clustering results will vary for each position index. In this section, normalized distance calculation and clustering are performed for each sensor position index. As shown in Fig. 15, when the calculation range of the normalized distance is not restricted, the

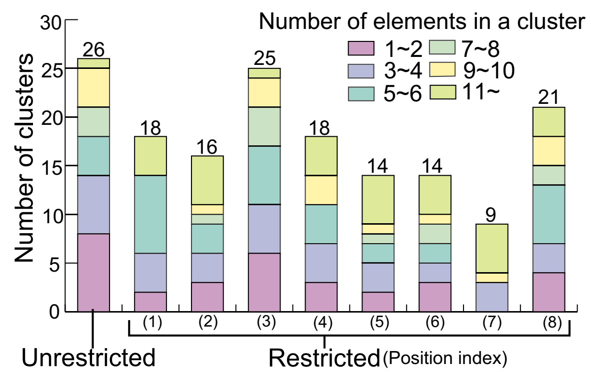

Fig. 16 Number of clusters and elements in a cluster

calculation range is defined as the minimum-to-maximum value of the calculated distance d and tilt φ.

Result of sensor clustering using calculation range restriction

Normalized distances were calculated using the calculation range restriction for each position index (Fig. 15). The clustering conditions were the same as those described in the previous section. Unrestricted range indicated by the arrows includes all of the distance and tilt used when HILS. Restricted range indicated by bars illustrates the range of distance and tilt during HILS for each sensor position. A comparison of the number of clusters generated and the number of sensors in a cluster with and without the calculation range restriction is shown in Fig. 16. The number of clusters generated tended to decrease with calculation range restriction. The number of clusters containing one or two fewer sensors decreased, whereas the number of clusters containing eleven or more sensors increased.

The difference in the distribution of the normalized distance, with and without the calculation range restriction, is shown in Fig. 17. The distribution with the calculation range restriction shows the results for position index (3) with the largest number of clusters, and position index (7) with the smallest number of clusters. The number of sensor pairs with normalized distances between 0 and 0.01 increased by a factor of approximately five. Owing to the characteristics of the infrared distance sensor, a large tilt φ of the object caused a larger sensor output error and affected the normalized distance calculation results. The calculation range restriction is believed to have increased the distribution of small normalized distances, and decreased the number of clusters because the output characteristics for an unnecessarily large tilt φ are not used.

Adequate sensor selection method for platooning

The results of sensor clustering using the calculation range restriction suggest that it may be possible to select sensors that are more similar to each other for platooning.

Therefore, we proposed an adequate sensor selection method for platooning, as shown in Fig. 18. The adequate method uses a sensor with the shortest Euclidean distance from the reference sensor in the two-dimensional feature space of the normalized distance, with and without restriction. The method is expected to select a sensor with a good balance measurement accuracy between the range frequently used in platoons and that in the entire ring.

Verification experiment for adequate sensor selection method

The training data generated by the reference sensor group were transferred to the adequate sensor group selected using the adequate sensor selection method, and the performance of the platoon was verified using HILS. The vehicle group using the reference sensor was the reference group. Similarly, the group of vehicles that used the adequate sensor group was designated as adequate (Adq.) group.

The number of successful platooning vehicles in each group is provided in Table 4. The adequate group

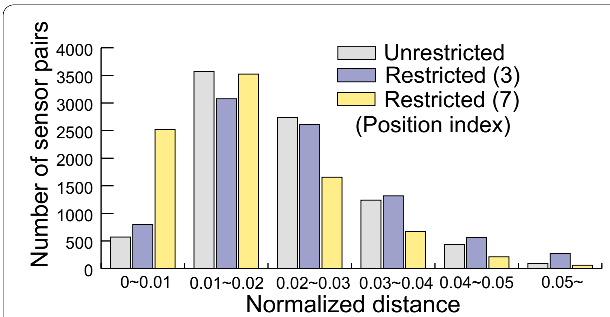

Fig. 17 Comparison of distribution of mutual normalized distance

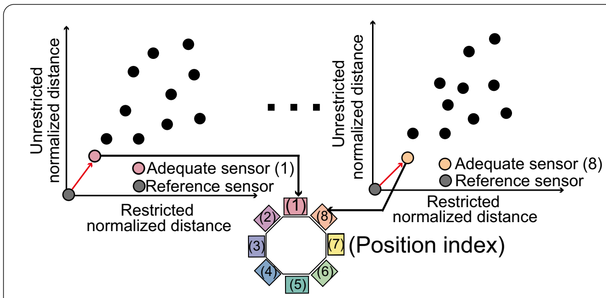

Fig. 18 Adequate sensor selection method

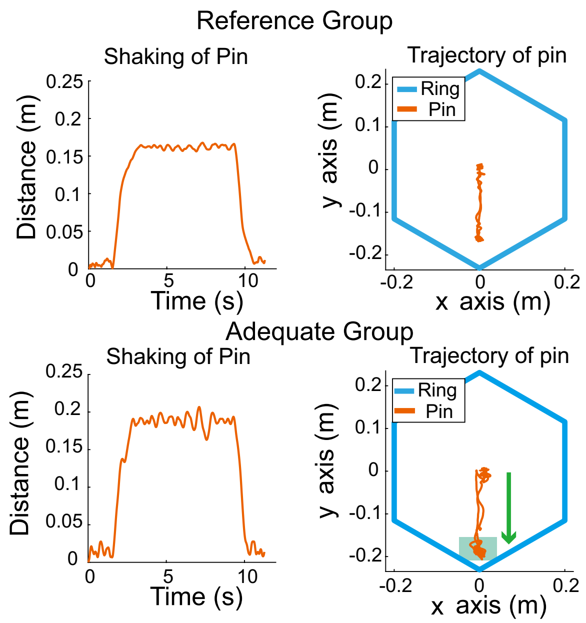

Fig. 19 Optimized experiment result of HILS on circular operation (follower 1)

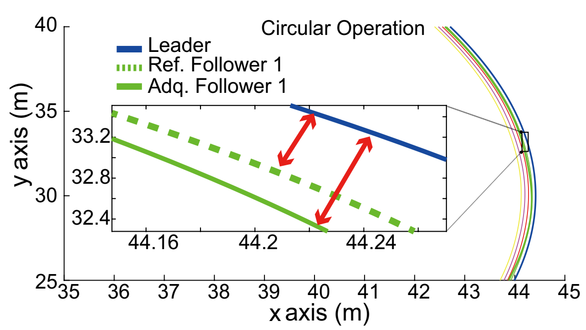

Fig. 20 Path error on circular operation

Table 1 Number of successful platooning vehicles on experiment for deciding threshold

Course	Group			
	Ref.	G	F	P
Circular operation	4	1	0	3
Lane changing	4	3	2	1
Slaloming operation	4	4	0	1
Pulsed steering	4	4	2	2
Accelerated start	4	3	1	1

successfully ran all courses except for the circular operation. The trajectory of the pin in the ring, and the shaking of the pin during the platooning of follower 1 are shown in Fig. 19. The pin of follower 1 shaking in the adequate group increased than that of follower 1 in the reference group. In addition, as the pin trajectory diagram on the right side shows (Fig. 19), the pin moves near the apex of the ring. The cause of the failure of the platooning in the circular operation is the deviation of the path from that of the leader owing to the measurement error of the orientation θ. Fig. 20 is the path of each group while driving on the circular operation. The enlarged figure shows that follower 1 of the adequate group turns on the inside of the curve compared with follower 1 of the reference group (Fig. 20). Consequently, the pin moved near the apex of the ring and failed platooning. To maintain the platoon during circular operation, it is necessary to reduce the measurement error of the orientation θ and to drive on a trajectory close to that of the leader.

Even when the training data were transferred, platooning was successful in all courses except for the circular operation using the adequate sensor selection method for platoons. We showed that this method can select a sensor with similar output characteristics that are suitable for maintaining platooning. However, even with an adequate sensor group, path errors owing to measurement errors in the attitude θ axis caused a failure of platooning on the circular operation.

Conclusions

In this study, we proposed a sensor clustering method for the transfer of training data required for relative position and orientation measurement devices. We developed and evaluated a sensor output characteristic acquisition device that can acquire sensor outputs at high speed, and has high reproducibility and stability against sensor removal and position changes.

Sensor clustering was verified using HILS by transferring the training data to a relative position and orientation device consisting of similar sensors. Four followers were successful in the two courses. These results reveal that, by selecting similar sensors through sensor clustering, it is possible to use multiple inexpensive distance sensors without complicated calibration. There were trials in which the four following vehicles could not be successful on the other courses. This maybe owing to the inability to use a sensor with sufficient similarity to the relative position and orientation measurement device to maintain the platoon.

Next, we showed that the number of clusters generated by clustering decreased, and the number of sensors in each cluster increased when the calculation range of the normalized distance was restricted. Therefore, we proposed an adequate sensor selection method that considers two features of the normalized distance with and without restriction. Platooning using the device with

Table 2 Sensors used on verification experiment

Sensors used on Reference group								
Sensor label	52	112	8	21	56	25	58	32
Sensors used on Transfer group								
Sensor label	84	127	129	121	124	81	90	66
Normalized distance	0.014	0.013	0.014	0.013	0.014	0.015	0.014	0.013
Position index	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

Table 3 Number of successful platooning vehicles on verification experiment

Course	**Ref.**	**Trans. trial**			**Mean of 3 trials**
		1	**2**	**3**	
Circular operation	4	4	2	2	2.67
Lane changing	4	2	3	2	2.33
Slaloming operation	4	4	4	3	3.67
Pulsed steering	4	4	4	4	4
Accelerated start	4	4	4	4	4

Table 4 Number of successful platooning vehicles on experiment for validation of appropriate sensor groups

Course	**Group**	
	Ref.	**Adq.**
Circular operation	4	1
Lane changing	4	4
Slaloming operation	4	4
Pulsed steering	4	4
Accelerated start	4	4

sensors selected based on this method was successful in various courses, even when the training data were transferred. It was demonstrated that the adequate sensor selection method for platooning can be used to select sensors with similar output characteristics. As a result, the training data can be used repeatedly for newly manufactured relative position and orientation devices. The results suggest that sensor clustering has the potential to increase the efficiency of production for the relative position and orientation measurement devices.

Furthermore, it was found that it is important to reduce the measurement error of orientation θ rather than positions x, y to maintain platooning. Future work will involve creating training data and applying an algorithm to measure the relative position and orientation to reduce the measurement error of orientation θ.

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Author contributions
SA, QY, and RF mainly contributed to the development of devices and the implementation of software. SA also mainly wrote the manuscript. YF was responsible for the critical revision of the manuscript. RF and SW supervised and advised on the concept and implementation of the study. All authors read and approved the final manuscript.

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Declarations

Competing interests
The authors declare that they have no competing interests.

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