Abstract

In this study, we aim to develop a new upgrading method of digital map content for automated driving on nationwide public roads. In general, a dense waypoint map based on a digital map is necessary to realize precise motion controls of intelligent automobiles. However, current preparation methods for digital maps have two problems for practical use on public roads in wide areas: the size of the map data for onboard storage and the monetary and human resources for manual mapping processes. To solve these problems, in our previous study, we proposed a new digital map called “LeanMAP,” which consists of elementary information about the road, and also proposed an upgrading method of its contents from the level of car navigation map to the level of quasi-precise map. Furthermore, in this study, we propose another upgrading method based on a virtual trajectory to reduce the number of resources necessary for the mapping process to as low as possible. First, we propose a lateral transcription method that generates a virtual trajectory of an adjacent lane. Although three or more driving data items are necessary in order to upgrade the LeanMAP contents in the previous method, the proposed method in this study requires only one item of driving data. Then, to evaluate the accuracy of the dense waypoint map based on the elemental information upgraded by the proposed method, we conduct an initial evaluation using actual driving data on a public road. As a result, we confirm that the proposed system satisfies the target value of less than 1 % lateral error. From this result, we confirm the feasibility that our proposed system can reduce the cost and manual operations of mapping a precise digital map.

Keywords: Automobile, Intelligent vehicle, Digital map, Virtual trajectory, Map deepening

1. Introduction

In recent developments regarding intelligent automobiles, the digital map is becoming one of the most essential components in realizing automated motion controls including advanced driver assistance systems and fully autonomous driving technologies (Bengler et al., 2014) (Kamijo et al., 2015). For dealing with the needs from various future applications, the digital map as a foundation of intelligent automobiles is necessary. Although there are many functions related to digital maps, localization that estimates the position of the vehicle on a digital map is a fundamental function for other functions regarding a digital map. Thus far, various methods of localization have been proposed considering related onboard sensors and the data structure of a digital map. For example, Omae et al. proposed an autonomous driving technology based on a digital map using the Real Time Kinematic Global Positioning System (RTK-GPS) (Omae et al., 2004). Because map data for localization using RTK-GPS contains a dense waypoint tightly coupled with precise GPS data, the amount of map data becomes relatively large. After the Urban Challenge in 2007 held by the Defense Advanced Research Projects Agency (Buehler et al., 2009), point feature based localization became popular. In existing studies, either Light Detection and Ranging (LIDAR) or a camera is typically used for such approaches. As an example of the former, Levinson et al. realized localization in urban environments using LIDAR (Levinson and Thrun, 2010). On the other hand, as an example of the latter, Ziegler et al. achieved autonomous driving by point feature based
localization using a camera (Ziegler et al., 2014 a) (Ziegler et al., 2014 b). Some of abovementioned methods have been developed in the research field of robotics. In contrast to field robotics, in the research field of intelligent automobiles, preliminarily prepared map data are usually used for such localization approaches. Thus, the abovementioned examples require a vast amount of point cloud data or feature point data for their digital maps because intelligent automobiles usually move in greater areas than field robots. Therefore, although these kinds of methods can be applied for intelligent automobiles at a research stage in a limited area, it seems difficult to practically apply them to great range of public roads owing to the size of the map data. In other words, the method of preparing the digital maps for great range of public roads by reasonable approaches which do not have any problems from the viewpoints of the size of map data and the necessary resources for map preparation is challenging point for future practical intelligent automobiles.

To reduce the amount of map data, recent precise digital maps sometimes consisted of vector data instead of point cloud data. In the vector maps, the road environments are expressed as combinations of vector data which consist of endpoints. On the contrary, in the point could maps, the road environments are expressed as aggregations of many points that 3D LIDARs measure. For example, Kato et al. developed Autoware, which is an open-source platform for autonomous driving (Kato et al., 2015). In their platform, a localization module can use a precise 3D map based on vector data as well as a point cloud map. Similarly, Kazama et al. proposed a localization method using multilayer LIDAR and a precise vector map (Kazama et al., 2017). Regarding the general creation process for a precise vector map, first, the Mobile Mapping System (MMS) (Puente et al., 2013) gathers dense point cloud data tightly coupled with precise GPS data (Ishikawa et al., 2007). Then, the map company conducts mapping processes of various content, which is represented by vector data, from the gathered point cloud data. In the latter process, because the preparation of vector data requires many manual operations and checks to enhance reliability, the cost is so high that preparation of precise vector maps for public roads in wide areas becomes difficult.

To handle the cost problem regarding manual operations of preparing vector maps, some countermeasures were proposed in existing studies. For example, Kojima et al. proposed an automatic map generation method using an onboard camera and GPS (Kojima et al., 2012) (Meguro et al., 2017) (Guo et al., 2016). In this method, first, many local maps, the target areas of which were limited in order to avoid accumulated errors, were generated by the driving data of a normal vehicle. Then, global maps were generated by combining many local maps. Similarly, Hara et al. proposed an automatic conversion method for edges of various objects on a road from a 3D point cloud to a vector map (Hara et al., 2016). These studies solved some parts of the existing problem regarding the manual operations of preparing a precise vector map. However, because even the data size of a vector map is still large, further reduction of the data size while considering the structure of map data is required to prepare digital maps for nationwide roads.

As discussed above, reducing the data size and manual operation during content preparation are necessary for a practical approach to creating a digital map for intelligent automobiles. In other words, we need to discuss two topics: the new data structure of digital map for reducing the data size, and the preparation method of digital map contents for the new data structure with reducing the manual operations. For the first topic, in our previous studies, we proposed LeanMAP, which is a new digital map framework (Ito et al., 2016). The LeanMAP framework does not preliminarily prepare the dense waypoint map which consists of many waypoints indicating the road shape; rather, it dynamically reconstructs the dense waypoint map from elemental information of the road shape on demand. This on-demand reconstruction of a waypoint map can reduce the data size of a digital map. For the second topic, we proposed a deepening method for LeanMAP content to reduce the manual process during the preparation of map content (Ito et al., 2018). This method realized an upgrade from car navigation map to quasi-precise digital map by referring to actual driving data. To be more precise, this approach realized improvement of accuracy of digital map contents from meter order to sub-meter order. In addition, this approach could prepare digital map contents that car navigation maps usually do not contain. In short, this approach could upgrade a digital map from temporary one to practical one from various viewpoints. Thus, because this approach was not only involved in the update and modification of values in the digital map, we called such an upgrade approach “deepening.” However, further reduction of various resources for map preparation is desirable. Thus, in this study, we aim to develop another deepening method for LeanMAP content based on a virtual trajectory by lateral transcription. In other words, dealing with the second topic moreover is the contribution of this study.

The following parts of this paper are organized as follows: details of the system design are described in chapter 2. An experiment and evaluation of the proposed system are described in chapter 3. Finally, conclusions and future works are described in chapter 4.
2. System design
2.1 Overview of LeanMAP

As discussed in the introduction, dense waypoint maps are generally required to precisely control the motion of intelligent vehicles, and can be used in various ways (e.g., a reference for precise path tracking, and a basic source combined with sensor-based detection results of coexisting traffic participants). In our LeanMAP framework, we reconstruct a dense waypoint map for each lane from the elemental information of road parts. Figure 1 shows a conceptual schematic of reconstructing a dense waypoint map. The left side shows an example of the target road, while the right side shows an example of the process that reconstructs a dense waypoint map. The database of LeanMAP only has information of curved parts of the road such as curves A and B shown in the figure, and does not have the information for the straight parts. The curve information consists of the following three elements:

- **Offset**: Position of the curve, which is expressed as the distance measured from the origin point along the road.
- **R**: Radius of the curve.
- **θ**: Angle of the curve.

Based on the information of the curved part, the waypoint map reconstructor considers other parts of the road as straight. Then, the waypoint map reconstructor alternately creates a dense waypoint map, as shown on the right side of the figure. More detailed explanations appear in our previous paper (Ito et al., 2016).

![Fig. 1 Conceptual schematic of reconstructing dense waypoint map in LeanMAP framework.](image)

Figure 2 shows a conceptual schematic of the coordinate system in the LeanMAP framework. A dense waypoint map consists of many waypoints. The position of each waypoint is expressed by four variables: x, y, θ, and offset. In this study, we reconstruct the waypoint map with a density of 0.05 m. The position of the vehicle is expressed by two kinds of coordinate system: an offset coordinate system and an X-Y coordinate system. The origin points of both coordinate systems are located at the entrance of the lane, which connects two crossings. In the offset coordinate system, the vehicle position is expressed by the deviation from the nearest waypoint. The deviation from the nearest waypoint is expressed by the lateral deviation (LD) and deviation angle (ϕ). The position of the nearest waypoint is expressed by the offset. Thus, position of the vehicle is expressed by a combination of the offset, LD, and ϕ. On the other hand, in the X-Y coordinate system, the position of the vehicle is expressed by a combination of x, y, and θ. The coordinate system of LeanMAP framework is apparently similar to the Frenet coordinate system (Werling et al., 2010) to a certain degree, but a bit different from it. One of different points is the consideration of deviation angle ϕ. Owing to this variable, we can simply combine the current vehicle state with information of forward waypoints that are used for some kinds of preview lateral motion controls.

![Fig. 2 Conceptual schematic of coordinate system in LeanMAP framework.](image)
The important point is that these expressions of the vehicle position in the LeanMAP framework are interconvertible. This interconvertible expression of the coordinate system has two merits. The first merit is that we can realize both preview lateral motion control (Inoue et al., 2017), and preview longitudinal motion control (Saito and Raksincharoen, 2016) separately with good harmonization. The second merit is that we can conduct lateral localization and longitudinal localization separately. In general, our localization system basically estimates the time series position by referring to information from the Inertial Measurement Unit (IMU) and Control Area Network (CAN). Regarding the lateral localization, the system occasionally corrects the error of the lateral position by using camera-based detection results of white lane marks. Regarding the longitudinal localization, the system occasionally corrects the error of the longitudinal position by using camera-based detection results of various landmarks such as diamond marks and speed limit marks (Nakamura et al., 2018). These separate architectures enable a localization system based on a lean sensor system, which does not require high-cost sensors such as multilayer LIDAR or RTK-GPS.

### 2.2 Overview and issue of LeanMAP deepening

In the first study of LeanMAP (Ito et al., 2016), we prepared the content of LeanMAP, such as the information of curves, by manually reducing a precise 3D map. However, this preparation method had a problem with regard to time and cost. Thus, we focused on the existing map data of a car navigation system, which already covered wide areas of public roads. Further, we proposed a method for upgrading the LeanMAP content from temporary content that was prepared from a car navigation map to quasi-precise content by referring to actual driving data (Ito et al., 2018). Figure 3 shows a conceptual sequence of the LeanMAP upgrade. First, we prepare the temporary contents of LeanMAP from a car navigation map through automatic processes. Because the information of road shape in a car navigation map is imprecise, the digital map through the first step has many temporary data items. We called this temporary situation a LeanMAP Float. Then, we upgrade the LeanMAP content based on actual driving data. We called the second upgraded step a LeanMAP Fix. Through the second process, for example, curve information such as offset, R, and θ, are upgraded. In addition, we named this upgrading method from temporary to quasi-precise as LeanMAP deepening.

![Fig. 3 Conceptual sequence of LeanMAP upgrade process.](image)

Figure 4 shows an example of information in a non-intersection curve. In the LeanMAP Framework, as shown in the figure, a curving road has some curve composition points, which have information of the offset, R, and θ. Because the car navigation map does not have precise information regarding R and θ, we assigned a temporary value to each curve composition point. For example, in the stage of LeanMAP Float, we assigned 10 m to R of all composition points, although this is not a precise value. To deepen this information, we optimized the curve information in sequential order from the first curve composition point by comparing the trajectory logs with candidates for the waypoint map. Figure 5 shows a conceptual schematic of deepening the curve information. Detailed explanations are provided in our previous paper (Ito et al., 2018). As a result of our previous and afterward studies, we confirmed that three or more driving data items can deepen the curve information while satisfying our target value, which was a 1% error. This indicates a lateral error of less than 1.0 m for 100.0 m of longitudinal driving in a non-intersection curve.
As mentioned in the above paragraph, our proposed method realized a relatively low-cost automatic preparation method for a digital map. However, because our proposed method referred the actual trajectories, we needed to gather the actual driving data. On this point, deepening the digital map based on fewer driving data items is more practical, although we cannot zero the number of driving data items. Thus, to reduce the number of gathered driving data items to as low as possible, we focus on another deepening process based on virtual trajectories.

### 2.3 Concept design of lateral transcription

Some roads consist of a single lane without a center lane mark, and other roads consist of two or more lanes with lane marks dividing them. Regarding the latter, the shapes of adjacent lanes are not exactly the same but are basically similar to a certain degree. Thus, once we deepen the curve information of a lane, the deepened waypoint map can become the source of virtual trajectories for side lanes. In this study, we call this approach a lateral transcription.

The basic process of deepening based on virtual trajectories by lateral transcription is as follows, and Fig. 6 shows a conceptual schematic of the process. In this explanation, we assume that there are two lanes: lane A and lane B. The lanes run opposite to each other, and lane B is the target of the lateral transcription.

1. We prepare the data of the LeanMAP Fix for lane A by deepening the curve information of lane A based on actual driving data for lane A.
2. We transcribe the imaginary curve composition points of lane B based on the actual curve composition points of lane A by considering the scaling of the road shape.
3. We generate a virtual trajectory for lane B by smoothly connecting the imaginary curve composition points of lane B.
4. We prepare the data of the LeanMAP Fix for lane B by deepening the curve information of lane B based on the virtual trajectory of lane B.

![Fig. 6 Conceptual schematic of deepening based on virtual trajectory by lateral transcription.](image-url)
curve composition points of lane B in step 4. Additionally, the origin point of each lane is located at a different point. Therefore, we cannot simply copy the information of curve composition points from lane A to lane B. Using the abovementioned process, we can copy the corresponding equivalent information from lane A to lane B through the process of lateral transcription. The merit of this approach is that we can reduce the number of necessary driving data compared to simple deepening approach proposed in our previous study. Although we need usual process of deepening for lane A, we can reduce the number of the necessary driving data for lane B through lateral transcription.

2.4 Implementation of lateral transcription

In the process of lateral transcription, steps 2 and 3 are newly proposed processes that were not used in our previous studies. Thus, detailed implementation is necessary. Regarding step 2, Fig. 7 shows a schematic for variables regarding the lateral transcription of the curve composition points. In this figure, P_i indicates the curve composition points of lane A, and Q_i indicates the transcribed imaginary curve composition points of lane B. Each P_i has position variables of x_i, y_i, and \( \theta_i \). W_1 and W_2 indicate the widths of lanes A and B, respectively. In this study, we assume a constant width for each lane. Based on these variables, each transcribed position of Q_i (t_{xi}, t_{yi}, and t\( \theta_i \)) is expressed as follows:

\[
W = (W_1 + W_2) \\
t_{xi} = x_i + W \cdot \cos(\theta_i - \frac{\pi}{2}) \\
t_{yi} = y_i + W \cdot \sin(\theta_i - \frac{\pi}{2}) \\
t\theta_i = \theta_i - \pi
\]

In this process, although we need to determine W_1 and W_2, these values in LeanMAP Float may not be accurate but temporary. Thus, we estimate both values from the camera-based detection results of lane marks. On this point, we need at least one driving data item of the target lane of the lateral transcription, although we wanted to reduce this process. Then, to handle a little waver of time series detection results, we estimate a stable value from the histogram of the detection results. Because typical road widths are defined from 2.75 m to 3.75 m in steps of 0.25 by the road structure ordinance in Japan, we set the conditions of the histogram bins to follow these values.

![Fig. 7 Schematic for variables regarding lateral transcription of curve composition points.](image)

Regarding step 3, we create the dense waypoint map as a virtual trajectory. To smoothly connect two transcribed imaginary curve composition points, we assume a simple arc for the partial waypoint map between two adjacent points. The process is as follows:

1. Based on t\( \theta_i \) and t\( \theta_{i+1} \), we judge whether this segment is a straight road, left-curving road, or right-curving road.
2. If the target segment is a curving road, we estimate the center point of the arc between Q_i and Q_{i+1} based on the intersection point of the normal vectors that start at Q_i and Q_{i+1}. At the same time, we estimate the radius of the arc.
3. Based on the center point and the radius, we create a part of the virtual trajectory as a certain density.
4. We repeat the above process for all \( Q_i \).

Through the above process, we can calculate the information of \( x, y, \) and \( \theta \) for each waypoint of the virtual trajectory. However, to deepen the curve information of the waypoint map, we need offset information of the virtual trajectory as well as \( x, y, \) and \( \theta \). Thus, we estimate the offset information of the virtual trajectory as follows:

1. Based on the boundary conditions, the starting point of lane A is located just next to the terminal point of lane B.
2. From the LeanMAP content, we determine the offset value of \( P_i \) in lane A, and the offset value of the terminal point of lane B.
3. The deviation offset between the starting point of lane A and \( P_i \) is equivalent to that between the terminal point of lane B and \( Q_i \). Thus, we can estimate the offset value of \( Q_i \).
4. Based on the offset value of \( Q_i \), we can estimate the offset values of all waypoints in the virtual trajectory.

Through the abovementioned processes, we can prepare a virtual trajectory for deepening the curve composition points of lane B. The remaining steps 1 and 4 are basically the same as those of the previously proposed method. The details regarding steps 1 and 4 are described in our previous paper (Ito et al., 2018).

3. Initial evaluation based on actual driving data on public road

3.1 Overview

To confirm the feasibility of the proposed system, we conducted an initial evaluation using actual driving data on a public road. Figure 8 shows our experimental vehicle. The vehicle was equipped with an IMU to estimate the vehicle trajectory, and cameras to detect landmarks and lane marks. Figure 9 shows an aerial photographic map of the evaluation course. This figure and the following figures are based on a map image published by the Geospatial Information Authority of Japan (Geospatial Information Authority of Japan, 2018). The course consisted of municipal roads in Susono city and Gotemba city in Shizuoka prefecture. There is a gradual downgrade from the left side of the figure to the right side along the road. In this evaluation, we set the road colored in blue, which we called lane A, as the source of lateral transcription. We set the road colored in red, which we called lane B, as the target of lateral transcription. In addition, we set the segment colored in orange, which is the first curve in lane A as well as the last curve in lane B, as the evaluation target. In this segment, the lane marks were basically well-maintained.

![Fig. 8 Appearance of experimental vehicle.](image1)

![Fig. 9 Aerial photographic map of evaluation course.](image2)

3.2 Deepening curve information of lane A

The first step is to deepen the information of curve composition points in lane A, which is a source lane. Based on our existing and afterward studies, we confirmed that three or more valid driving data items could deepen the information of the curve composition points. Thus, in this study, we collected three driving data items of lane A, and conducted the deepening process of lane A using this data. Figure 10 shows the deepened dense waypoint map of lane A. The black lines indicate the three trajectories used for deepening. The blue circles indicate the curve composition points of lane A. The blue line indicates the deepened dense waypoint map of lane A. The origin point of the figure is located at the position of the first curve composition point of lane A. As shown in the figure, because the blue line fit the black lines relatively well, we were successful in deepening the information of the curve composition points of lane A.
3.3 Lateral transcription of imaginary curve composition points

The second step is the lateral transcription of imaginary curve composition points. First, we estimated the width of lanes A and B, as discussed in section 2.4. Based on the detection results of the lane marks, which were originally detected for lane keeping, we made histograms for each lane. To estimate the width of lane B, we collected and used one driving data item of lane B. Figure 11 shows a histogram of the estimated lane width. Because the detection results contained abnormal values to a certain degree, the histograms did not show a concentric distribution. Based on the local maximum value, we determined the width of both lanes as 2.75 m. Then, based on the estimated lane width, we transcribed the curve composition points from lane A to lane B. Figure 12 shows the transcribed results. Blue circles indicate the original curve composition points in lane A, while black circles indicate the transcribed imaginary curve composition points in lane B.
3.4 Generation of virtual trajectory of lane B

The third step is the generation of the virtual trajectory of lane B. Based on the positions of the transcribed imaginary curve composition points, we generated a virtual trajectory by connecting the arcs between adjacent points. Figure 13 shows the generated virtual trajectory of lane B. The black circles indicate the transcribed imaginary curve composition points, while the black line indicates the virtual trajectory of lane B.

![Fig. 13 Generated virtual trajectory of lane B.](image)

3.5 Deepening curve information of lane B

The last step is to deepen the information of actual curve composition points in lane B, which is a target lane. Figure 14 shows the virtual trajectory and curve composition points of lane B. The black circles indicate the transcribed imaginary curve composition points of lane B, while the red cross marks indicate the actual curve composition points of lane B. The black line indicates the transcribed virtual trajectory of lane B. In contrast to Figs. 10-13, the origin point of the figure is located at the position of the first actual curve composition point of lane B. As discussed in section 2.3, the positions of the actual curve composition points were not necessarily located at the positions of the transcribed imaginary curve composition points. Actually, as shown in the figure, some points have no corresponding curve composition points. This is the reason why lateral transcription is necessary for deepening the information of adjacent lanes in the LeanMAP framework, which contains only elemental information for preparing a dense waypoint map. Then, based on the virtual trajectory and the positions of the actual curve composition points, we deepened the information of the actual curve composition points.

![Fig. 14 Virtual trajectory and curve composition points of lane B.](image)

3.6 Evaluation of reconstructed waypoint map of lane B

In the LeanMAP framework, the digital map information and sensor information complement each other. Thus, localization accuracy when the system ignores the sensor information represents the accuracy of the digital map. Based on this concept, in our previous study (Ito et al., 2018), we proposed an evaluation method of a deepened dense
waypoint map. Figure 15 shows a conceptual schematic of the evaluation method. Although the detailed methods are described in our previous paper, the summarizations of evaluation methods are as follows.

1. The localization system conducts the localization using information from the LeanMAP, IMU, and lane mark detection.

2. When the vehicle reaches the evaluation segment, which was the curving road in this study, we have the localization system ignore the information from the lane mark detection. Thus, the localization system conducts the localization using only information from LeanMAP and IMU during the evaluation segment. At this time, if the reconstructed dense waypoint map is not accurate, the estimated lateral localization error increases in accordance with the driving along the evaluation segment.

3. After the evaluation segment, we reactivate the sensor information of the lane mark detection. Then, the correction value before reactivation and after reactivation represents the accuracy of the deepened dense waypoint map. To be more precise, a smaller correction value indicates a more accurate dense waypoint map. Important point is that this method does not evaluate the whole shape of a dense waypoint map but evaluates the adequateness of elemental information regarding curve composition points by checking the correction value.

In this study, we followed the evaluation method proposed in our previous study. We set the start point of the evaluation segment at approximately 25 m before the first curve composition point. The total length of the evaluation segment was approximately 150 m. In this evaluation segment, we had the localization system ignore the lane mark information. As for the evaluation data, we collected nine actual driving data items for lane B. For each data item, we calculated the correction value after the evaluation segment using two dense waypoint maps: a dense waypoint map reconstructed from LeanMAP float, which was prepared from a car navigation map, and that from LeanMAP Fix, which was a deepened one by the virtual trajectory in this study. Figure 16 shows a comparison of the accuracy. Owing to the deepening process, the average lateral correction value, which represents the accuracy of the dense waypoint map, decreases from 7.12 m to 1.40 m. Regarding the LeanMAP fix, the 1.40 m lateral error for approximately 150 m of longitudinal driving achieved a lateral error of less than 1 %, which was the target value in our previous study.

![Fig. 15 Conceptual schematic of evaluation of deepened dense waypoint map.](image)

![Fig. 16 Comparison of accuracy of dense waypoint map between LeanMAP float and fix.](image)

© The Japan Society of Mechanical Engineers
To consider the accuracy furthermore, we compared the result in this study with the result in our previous study (Ito et al., 2018). The evaluation course that we used in this study was different from that in the previous study. In addition, the number of samples for deepening process in this study was smaller than that in the previous study. Thus, we could not directly compare the results. Therefore, we checked the lateral error rate as a relative comparison index. The lateral error rate in this study is 0.0093 (1.40 m / approximately 150 m), whereas that in the previous study was 0.0035 (0.42 m / approximately 120 m). Thus, the accuracy in this study was worse than that in the previous study. However, we considered that this result was appropriate. Because the whole process of lateral transcription includes the simple deepening process, the lateral error rate through the whole process of lateral transcription normally becomes larger than the lateral error rate through the simple deepening process in principle. However, we considered that even the lateral error rate through the whole process of lateral transcription satisfied the practical level. Important point is that the purpose of lateral transcription is not improvement of accuracy but reduction of necessary resources for digital map preparation. Thus, we considered that our proposed method could reduce the resources for map preparation with keeping practical accuracy.

4. Conclusion

In this study, we developed a new deepening method for LeanMAP content based on a virtual trajectory for realizing automated driving on nationwide public roads. First, by extending the deepening method proposed in our previous study, we proposed a lateral transcription method that generated a virtual trajectory based on curve composition points of adjacent lanes. Then, as an initial evaluation of the proposed system, we evaluated the accuracy of a dense waypoint map generated by the proposed system using actual driving data on a public road. As a result, we confirmed that the proposed system satisfied the target value of less than 1 % lateral error. From this result, we confirmed the feasibility that our proposed system could reduce the cost and manual operations of mapping precise digital maps by reducing the data collection of actual driving.

However, future work is needed. Because we focused only on a specific curving road as an initial evaluation in this study, we need to validate the proposed system on much more various roads. In addition, because we needed to determine the width information of the transcribed lane, we collected and used at least one set of driving data on a target lane for the lateral transcription. Although we reduced the number of necessary driving data items from three or more to only one by our proposed method, further reduction from one to zero is desirable. On this point, estimating the lane width of an adjacent transcribed lane from the original lane has the possibility of solving this problem. This trial is one of our future works.

Acknowledgement

This research has been conducted as a part of the research project “Autonomous Driving System to Enhance Safe and Secured Traffic Society for Elderly Drivers” granted by Japan Science and Technology Agency (JST), S-Innovation (Strategic Promotion of Innovative Research and Development). The authors would like to thank the agency for providing financial support.

The map data of test course were measured by the support of INCREMENT P CORPORATION. We deeply thank their contributions.

References


