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RESEARCH ARTICLE

Augmented Reality-Based Navigation Using Deep Learning-Based Pedestrian and Personal Mobility User Recognition–A Comparative Evaluation for Driving Assistance

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ABSTRACT Recently, research on augmented reality-based head-up displays (AR-HUDs) for driving assistance has been widely conducted in the automotive industry. The disadvantage of having to look away from the road while driving can be compensated by using AR-HUD-based visualization instead of an auxiliary display on the central dashboard. As the number of personal mobility users on the road increases, and their moving speed is considerably faster than pedestrians, personal mobility makes it more difficult for the driver to cope with dangerous situations. However, there is little research work for considering personal mobility users for driving assistance. This study aims to enhance the driver's situational awareness to respond to unexpected situation by providing driver assistance information on the AR-HUD by combining deep learning and AR. In particular, the deep learning-based anomaly detection method can recognize personal mobility users effectively. This study also investigates the driver's understanding of the relationship between the amount of prioritized information provided to AR-HUD and situational cognitive ability. This understanding can be used to adjust the amount of information displayed on the AR-HUD to maintain drivers' situational awareness. The proposed approach was evaluated through an online study. The results showed that the proposed deep learning-based AR-HUD system improved the driver's situational awareness and showed advantages in driving assistance compared to the typical system.

INDEX TERMS Augmented reality, head-up display, personal mobility user recognition, driving assistance.

I. INTRODUCTION

With the recent development of infotainment technologies, automobiles can provide drivers various functions and driving assistance information. For this reason, behavior other than driving increases, reducing concentration on driving and increasing the probability of missing objects in front of the driver. As the number of personal mobility users on the road increases, their moving speeds are considerably faster than those of pedestrians, making it more difficult for drivers to cope with dangerous situations. Therefore, it is challenging to effectively assist driving by quickly providing information on objects and persons that the driver may miss.

Previous studies were conducted to assist drivers using AR-based visualization. Gabbard et al. [1] presented the benefits of AR while driving and addressed the problems of drivers'

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perceptual and distraction issues inherent in AR systems. Rusch et al. [2] conducted a study to evaluate the effects of AR cues designed to direct the attention of experienced drivers to potential roadside risks in rural roadways. Schall Jr. et al. [3] showed the possibility of improving the safety of elderly drivers by increasing the possibility of risk detection without interfering with other driving tasks by using AR clues. Bauerfeind et al. [4] showed a reduced mental load using the AR-based display for surrounding information while driving in urban areas with ambiguous intersection conditions. Concerning previous studies, AR technology can support drivers in various ways.

Recently, some studies were being conducted to assist driving by applying artificial intelligence (AI) technology. Colley et al. [5] visualized driving information using semantic segmentation on the AR-based windshield and tablet PC. It was shown that AR-assisted visualization could reduce cognitive load during driving while increasing situational awareness (SA). Currano et al. [6] conducted an online study to evaluate the influence of head-up display (HUD) visualizations on drivers' situation awareness and perceptions. They showed that situational cognition decreased as the information provided to HUD increased. However, since the information displayed on the windshield and HUD was mainly the location information of the dynamic or static objects, such as pedestrians and cars, it is difficult for the driver to cope with a situation when the personal mobility user appears. For example, drivers can cope better with critical situations if they can predict the moving direction of the personal mobility user. In the case of the windshield, it is expensive to make the entire vehicle glass into a display, and if the position of the object on the display does not exactly match the real one, driving may be hindered. Concerning the current HUD, as the display size is small and the amount of information to be displayed increases, the complexity of understanding driving information increases. Therefore, the HUD should be able to provide only prioritized information to be visualized.

This study proposes and evaluates a new approach to recognizing pedestrians and personal mobility users and their moving directions using deep learning and providing driving assistance information in the AR-HUD. The proposed system consists of two main sub-systems: deep learning-based personal mobility user recognition and driving information visualization in the AR-HUD. The results of the deep learning-based sub-system are used to present pedestrian and mobility user information to the AR-HUD. The proposed approach is evaluated through an online study ($N = 87$) to analyze the usability and situation awareness of drivers and the relation between the amount of prioritized information provided to the AR-HUD and the driver's situational cognitive ability is sought. A further evaluation is performed according to the amount of prioritized information displayed in the AR-HUD. The comparative evaluation shows the advantage of the proposed method over the previous approach.

The contribution of this study that fuses deep learning and AR-HUD is as follows.

1) We propose a new approach that can detect pedestrians and personal mobility users using deep learning-based anomaly detection and visualize the detected information to the AR-HUD for effective driving assistance.
2) By incorporating a deep learning approach into the AR-HUD, it is more effective to identify even fast-moving personal mobility users.
3) An online study-based evaluation shows the advantage of the proposed system concerning driving assistance and situational awareness.

This paper is organized as follows. Section II explains related work. Section III presents the proposed method, and Section IV discusses the experimental design. Section V presents the results of the comparative experiment. Finally, Section VI concludes the paper with some remarks.

II. RELATED WORK

Augmented reality (AR) technologies have been applied to various fields, such as driving [1], [2], human-robot collaboration [7], surgical navigation [8], education [9], and manufacturing task assistance [10]. This section focuses on and reviews previous studies related to providing driving assistance information using AR-based visualizations.

Some previous studies conducted AR-based driving assistance for autonomous or conditional automation vehicles. Lindemann et al. [11] examined the effects of using an AR interface with world-registered visualization to assist drivers in the last moments before a takeover for conditional automation vehicles in an AR driving simulation environment. They simulated an AR-based windshield display and compared it with a conventional head-down display. They showed that the AR-assisted display enabled higher lateral performance and reduced workload. von Sawitzky et al. [12] mentioned that fully autonomous driving has far more functions than human drivers can achieve, but the unpredictable behavior patterns of autonomous vehicles can make passengers uncomfortable. Since autonomous driving information is not visible to the driver, the biggest problem is whether the user trusts the system. According to their study, when route information of autonomous vehicles is provided using AR technology, trust in autonomous vehicles can be improved. Wintersberger et al. [13] conducted a study to find whether AR assistance has the potential to increase user acceptance and trust by communicating system decisions. By conducting two driving simulator studies, they concluded that the application of AR is a good opportunity with high potential for automated driving. Chen et al. [14] stated that the existing semantic segmentation method could not be stably applied to the autonomous driving system because it ignores the importance of different grades for safe driving. For example, pedestrians, cars, and cyclists in the scene are much more important than the sky and buildings when driving a car. Thus, their segmentation should be as accurate as possible.

A large amount of data is currently generated in the infotainment device, causing driver confusion and increasing the probability of collision. Therefore, Charissis et al. [15] conducted a study to manage related information while safely displaying data in AR-HUDs and providing effective interaction methods. As a result of comparison with typical head-down display interface systems, accident avoidance capabilities are improved by 64%. Currano et al. [6] conducted an online study to evaluate the influence of HUD visualizations on drivers' situation awareness and perceptions. The study results showed that situational cognition decreased as the complexity of the driving situation increased, and situational cognition decreased even in the presence of HUD compared to the absence of HUD.

Several researchers evaluated AR-based windshield displays for driving assistance. Windshield displays are considered a promising technology for automated driving, as they can provide various information assisting drivers in non-driving-related activities. However, knowing whether drivers can use them effectively is still challenging. Riegler et al. [16] conducted a study to address user preferences for AR-based windshield displays and their potential to enhance user experience in automated driving. Colley et al. [5] compared windshield-based and tablet-based semantic segmentation visualization. The results showed that visualization with windshields increased situational awareness while maintaining a low cognitive load. However, in order to make the driving assistant information visible on the windshield, the display must be mounted on the glass of the existing car. This can rather cause the problem of increasing the price of a car. In addition, even if mounted, it may confuse the driver if the information displayed on the windshield does not exactly match the object in the real world. However, currently, there is no vehicle to support the whole windshield display, although we can expect those displays in the future.

III. PROPOSED APPROACH

Regarding previous studies, providing driving information using AR technologies can effectively assist drivers, but providing all the information can interfere with driving. Therefore, this study focuses on prioritized information such as personal mobility users and provides this information to drivers since they move faster than pedestrians. Since various personal mobilities come to the market, traditional object detection or semantic segmentation can partially recognize them or requires re-training whenever new models come to the market. However, there is little previous study on evaluating driving assistance by detecting personal mobility users and combining this information with the AR-HUD. We have conducted an online study to verify the proposed approach.

A. SYSTEM OVERVIEW

The proposed approach is composed of two main subsystems: deep learning-based personal mobility user recognition and AR-HUD-based driving information visualization, as shown in Fig. 1. The first sub-system is to recognize the locations and moving directions of pedestrians and personal mobility users by using deep learning-based anomaly detection and body orientation estimation, respectively. The second sub-system visualizes driving assistance information in the AR-HUD, where pedestrians and personal mobility users can be highlighted and focused.

B. DEEP LEARNING-BASED PERSONAL MOBILITY USER DETECTION AND MOVING DIRECTION ESTIMATION

Recently, the number of personal mobility users has increased enormously, and various types of mobilities have come to the market, which causes critical car accidents since mobilities move very fast. Thus, it is challenging to recognize mobility users in addition to pedestrians effectively. In this study, the deep learning-based personal mobility user recognition and direction estimation sub-system can detect pedestrians and personal mobility users and estimate their moving directions. In particular, personality user detection comprises three modules: human detection, cropping and dividing, and anomaly detection-based mobility user recognition [17], [18].

As shown in Fig. 2, the human detection module uses the Mask R-CNN [19] of Detectron2 [20], which can effectively locate humans (pedestrians and mobility users) without additional training. Mask R-CNN is an extension of the bounding box recognition function of Faster R-CNN [21] by adding the ability to predict object masks in parallel. It performed better in instance segmentation, bounding-box-based object detection, and human skeleton key-point detection [19], [20]. The cropping and dividing module eliminates background information, only retains the area obtained from the human detection module, and further divides the detected area into upper and lower parts. The lower part is used to determine whether they are pedestrians or mobility users since the mobility is located in the lower part, which can overcome the limitations of previous anomaly detection studies that were dependent on fixed cameras or only capable of detecting anomalies in static environments [18].

In particular, the anomaly detection-based mobility user recognition module determines whether the user rides personal mobility. This module utilizes the Dynamic Memory-guided Normality for Anomaly Detection (DMNAD) method [17], [18] to differentiate between pedestrians and personal mobility users. DMNAD is a memory-based anomaly detection algorithm that trains only pedestrians and effectively distinguishes them from personal mobility users. The anomaly detection predicts the personal mobility user as abnormal, while the pedestrian is predicted as normal. It is important to note that the DMNAD method trains only normal patterns of general pedestrians, which allows it to effectively distinguish between pedestrians and personal mobility users in dynamic environments. As shown in Fig. 3, there is little difference between the input and output of the pedestrian. However, there is much difference for the personal mobility user. Red areas show the difference between the input and

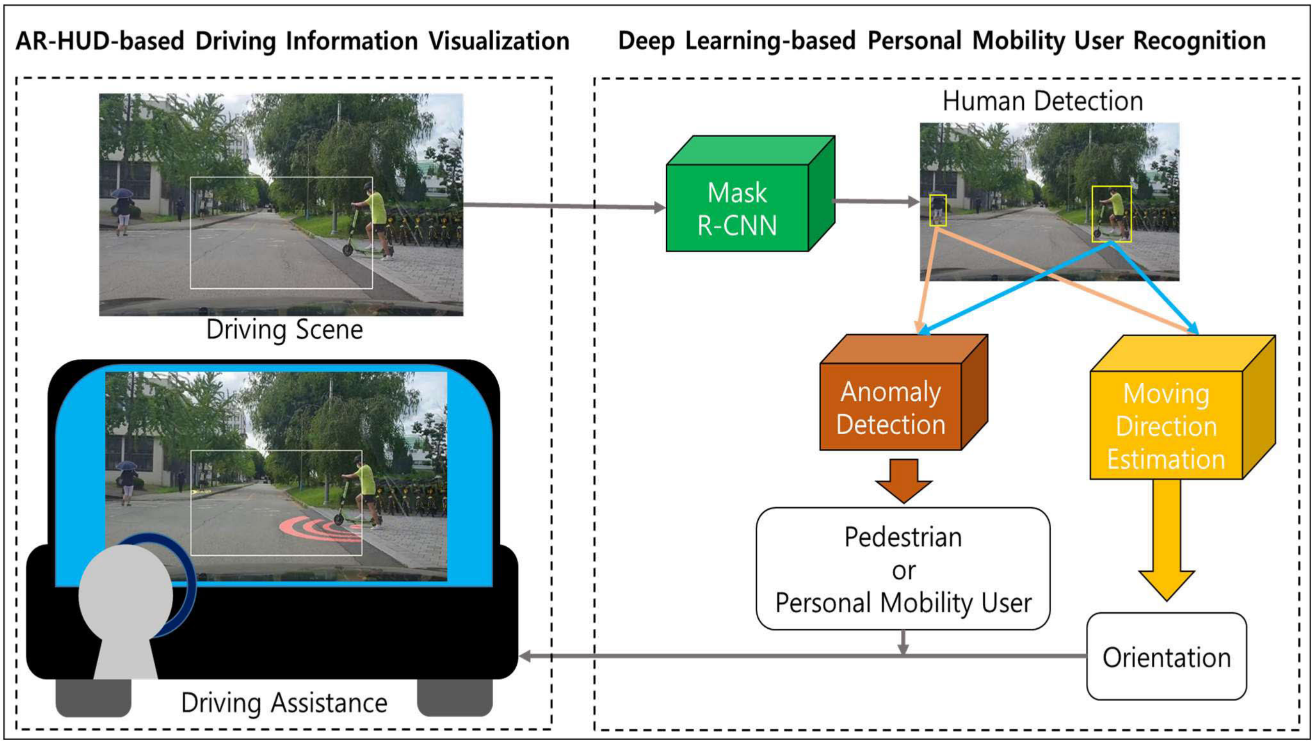

FIGURE 1. Overview of the proposed approach for driving assistance using deep learning and AR.

reconstructed output through the anomaly detection sub-module.

Moving direction or body orientation of pedestrians and mobility users can assist the driver in estimating their next actions. The Monocular Estimation of Body Orientation (MEBOW) [22] is used to estimate pedestrians' and mobility users' moving directions. The MEBOW method, designed for models that aim to estimate body orientation, uses images of human instances from the COCO [23] dataset for its training and testing dataset. This selection of the COCO dataset was made due to its comprehensive nature, which includes a wide range of postures, lighting conditions, occlusions, and background information. As shown in Fig. 4, the deep learning model adopts HRNet [24] as a backbone and ResNet [25] as a head network. Firstly, intermediate feature representations are combined to feed into the head network. Then, the head network estimates 72 orientation bins or directions. Fig. 4 shows an example of estimating the moving direction of the mobility user.

C. AR-HUD-BASED DRIVING INFORMATION VISUALIZATION

It is important to prioritize driving information to overcome the space limitation in the AR-HUD. Chen et al. [14] presented that the priority should be given to visualizing information related to pedestrians. This study also focuses on selectively visualizing pedestrians and personal mobility users on the AR-HUD. To effectively identify the presence of pedestrians in the AR-HUD, radial circles were used, as shown in Fig. 5 (Currano et al. [6]). The location of a pedestrian is represented by yellow radial circles, while red radial circles represent personal mobility users.

Furthermore, the direction of the pedestrian is represented using a yellow arrow. In contrast, the direction of the personal mobility user is indicated with a red arrow, as shown in Fig. 6. We found that the overlap among the radial circles representing the location and the arrows indicating the direction may confuse the driver. For this reason, when both pedestrians and personal mobility users are present at the same time within the AR-HUD, the location is shown using radial circles with red or yellow colors, and information on pedestrian and personal mobility users outside the AR-HUD is only shown as directional arrows along the boundaries of the AR-HUD, as shown in Fig. 6.

The complexity of the display in AR-HUD can be defined based on the different levels of information to be visualized. The information levels are classified as Minimal, Normal, and Complex. At the Minimal level, only the location information of pedestrians and personal mobility users is shown on the AR-HUD. The Normal level expands on the Minimal level by incorporating the moving directions of pedestrians and personal mobility users. Finally, the speed and the fuel information are further augmented in the Complex level. The different levels of driving information are demonstrated in Fig. 7. Fig. 7(a) displays only the location information, Fig. 7(b) includes directional information, and Fig. 7(c) visualizes additional speed and fuel information.

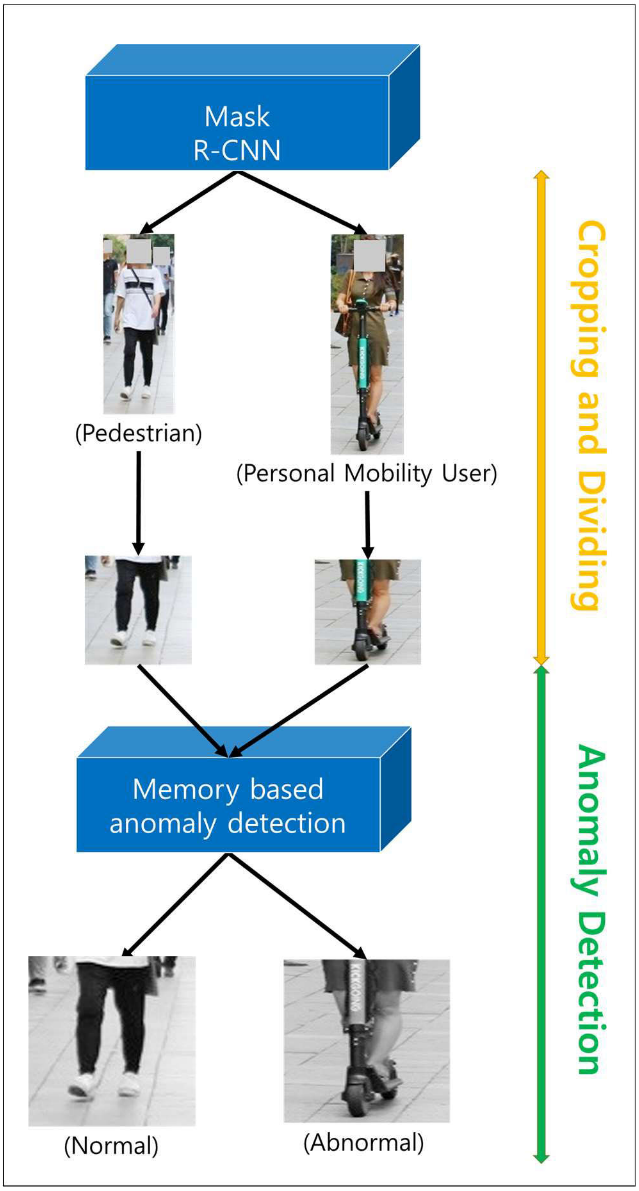

FIGURE 2. Cropping, dividing and anomaly detection for recognizing mobility users.

IV. EXPERIMENT: ONLINE STUDY

This study aims to increase the driver's situational awareness by presenting pedestrians and personal mobility user information in the AR-HUD by combining deep learning-based pedestrian and personal mobility user detection and AR-based visualization. A comprehensive experiment was also conducted to evaluate the usability and situational awareness of the proposed AR-HUD navigation system concerning the location and movement direction of pedestrians and personal mobility users.

Previous research works confirmed that their studies could be effectively evaluated through online simulations with images and videos. For example, Underwood et al. [26] assessed the situational cognitive abilities of novice and skilled drivers for sudden road hazards by observing driving videos. Lu et al. [27] conducted a video-clip study measuring attention, situation awareness, and decision-making in the face of an impending hazard. Inspired by the previous studies [5], [6], [26], [27], the proposed approach was also evaluated through the online study and survey.

To evaluate the proposed approach, participants with driver's licenses and driving experience were recruited. The environment provided in the online study is pre-recorded video scenes on the real road inside and outside the university campus. Unlike previous studies, this study also evaluated information on personal mobility users riding electric kickboards and motorcycles. The results of the online study were used to evaluate the usability and situational cognitive ability. They can provide valuable insights into the effectiveness of the proposed AR-HUD and its potential to improve situational awareness for drivers.

A. EVALUATION METRICS

The System Usability Scale (SUS) [28] and the Situation Awareness Rating Technique (SART) [29], [30] were used to evaluate the usability and situational awareness of driving assistance, respectively. SUS is a widely used metric for assessing the usability of products, including intelligent systems and AR/VR software [28]. The SUS questions are presented in Table 1.

SART is a method used to evaluate an individual's situational awareness, or the degree to which someone accurately understands what is happening in their environment [29], [30]. SART measures situational awareness through a self-reported questionnaire where participants rate their perception and comprehension of their situation. The scores obtained from SART can be used to determine the level of situational awareness and to identify areas for improvement. It consists of ten questions that assess the user's recognition of the demand for their resources, supply of their resources, and understanding of the situation, as shown in Table 2. An evaluation is performed based on participants' survey results and combined to obtain the overall SART score for the system [29]. That is, the ratings of ten questions are then combined in order to calculate a measure of participant SA.

A composite SA score is calculated using the following equation: SA = U – (D – S), where:

U = Understanding
D = Demand
S = Supply

B. BUILDING HYPOTHESES

Prior to conducting the experiment, three hypotheses were established to evaluate the proposed approach. One hypothesis is that the proposed approach can improve the usability of driving assistance by providing locations and moving directions of pedestrians and personal mobility users. The second one is that it can also improve situational awareness while driving. It is important to note that previous studies

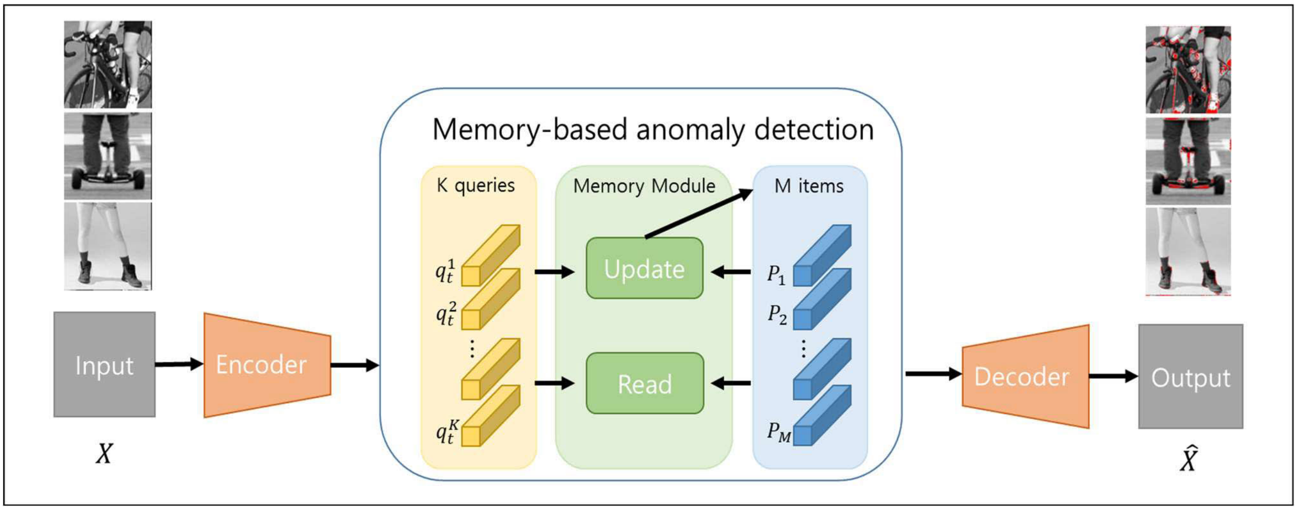

FIGURE 3. Memory-based anomaly detection network used for mobility user recognition [17], [18].

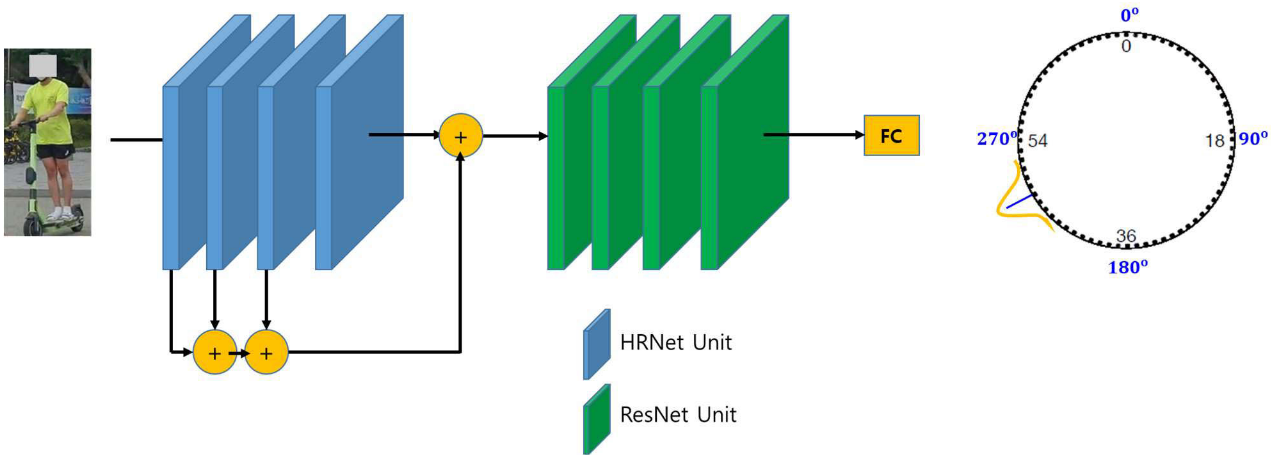

FIGURE 4. Estimation of the mobility user direction using MEBOW [22].

TABLE 1. SUS Questionnaire [28].

No	Questions
1	I think that I would like to use this system frequently.
2	I found the system unnecessarily complex.
3	I thought the system was easy to use.
4	I think that I would need the support of a technical person to be able to use this system.
5	I found the various functions in this system were well integrated.
6	I thought there was too much inconsistency in this system.
7	I would imagine that most people would learn to use this system very quickly.
8	I found the system very cumbersome to use.
9	I felt very confident using the system.
10	I needed to learn a lot of things before I could get going with this system.

have shown that traditional object detection and segmentation techniques often neglected the significance of certain object classes, such as pedestrians, vehicles, and cyclists, in a driving scene [14], [31]. In particular, various types of personal mobility come to the market, so it takes much time and effort to re-train deep learning models. On the other hand, the

TABLE 2. SART questionnaire [29], [30].

Domains	Construct	Definition
Attentional Demand	Instability of situation	Likeliness of situation to change suddenly
	Complexity of situation	Degree of complication of situation
	Variability of situation	Number of variables that require attention
Attentional Supply	Arousal	Degree that one is ready for activity
	Concentration	Degree that one's thoughts are brought to bear on the situation
	Division of attention	Amount of division of attention in the situation
	Spare mental capacity	Amount of mental ability available for new variables
Understanding	Information quantity	Amount of knowledge received and understood
	Information quality	Degree of goodness of value of knowledge communicated
	Familiarity	Degree of acquaintance with situation experience

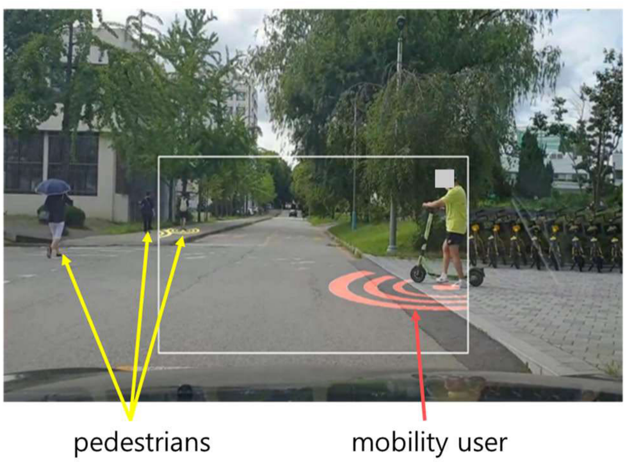

FIGURE 5. Different visualization of pedestrians (yellow radial circles) and personal mobility users (red radial circles).

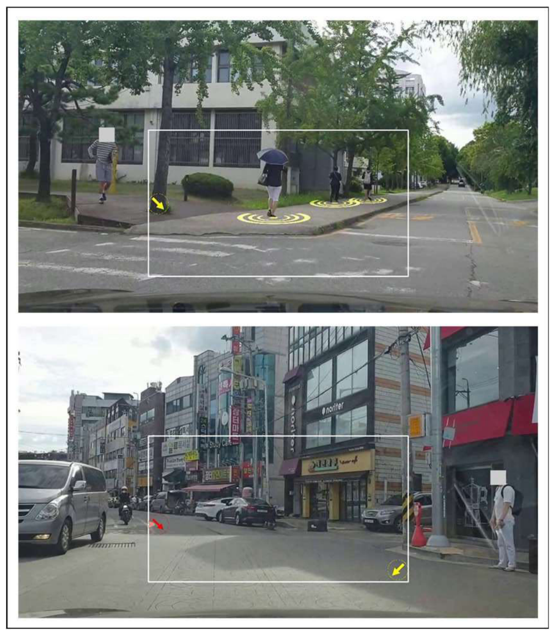

FIGURE 6. Visualization of pedestrian and personal mobility user orientations as directional arrows.

proposed anomaly detection-based method does not require re-training regardless of the different types of mobilities since the proposed approach only train the pedestrian dataset without personal mobilities. The third hypothesis is that adding prioritized information to the HUD does not reduce situational awareness. A previous study has shown that situational awareness decreases as the complexity of the driving situation increases [6]. This is due to the increased amount of information provided, which takes up more space in the HUD and interferes with the driver's cognition. However, this study only adds information on pedestrians and mobility users, ensuring that the HUD space is not significantly influenced, even as the amount of information somewhat increases.

C. ONLINE STUDY PROCEDURE

The online study was initiated with an introduction to the purpose of the study. Prior to the experiment, participants

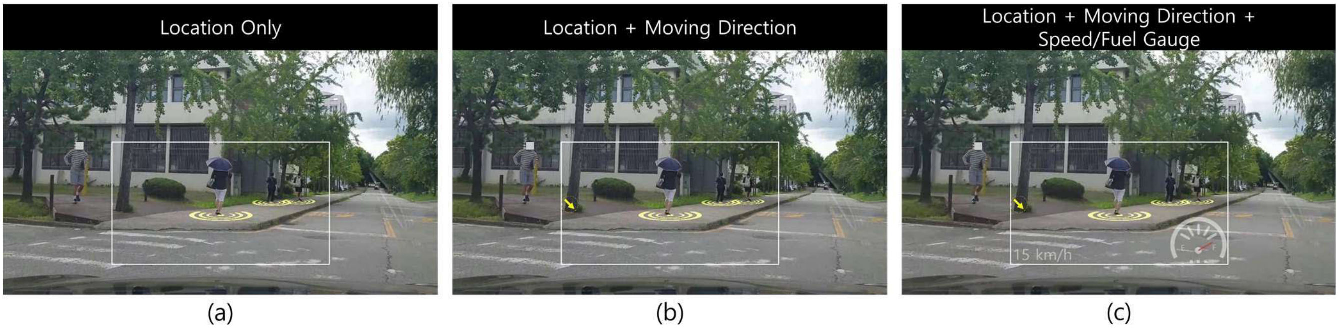

FIGURE 7. The amount of information to be displayed in the AR-HUD.

TABLE 3. Provided information for each system.

	System A: Conventional	System B: Proposed
Provided information	· Speed · Gauge	· Pedestrian and mobility user location · Status of using personal mobility (yellow or red radial circles) · Moving directions

were requested to sign a consent form and provide personal and research-related information. Then, an experimental evaluation was conducted to compare the proposed method (System B) with a conventional HUD system (System A) in Fig. 8 and Table 3. After watching and reviewing several video scenes, participants were requested to complete the SUS and SART surveys for each system, answering 40 questions (10 SUS questions and 10 SART questions for each approach).

An additional evaluation was conducted to evaluate situation awareness (SA) concerning the amount of information displayed in the AR-HUD. A detailed description is shown in Fig. 7 for the visual complexity. A SART survey was conducted for each complexity according to the information amount. In this online experiment, participants answered 20 questions (10 questions were asked for each type). The entire experiment lasted about 15 minutes.

V. EXPERIMENTAL RESULTS

A. PARTICIPANTS

To gather data for the online simulation survey, 87 participants were recruited and completed the online simulation. The experiment was conducted through Google Forms [32]. The demographic information of the participants includes age ranging from 21 to 49 years old (mean age: 29, standard deviation: 7.5) and driving experience ranging from 1 to 29 years (mean driving experience: 6.6, standard deviation: 6.7). Out of the 87 participants, 65 were male (74.71%), and 22 were female (25.29%). In addition, 24 participants (27.59%) mentioned prior experience with HUDs.

B. COMPARATIVE EVALUATION

The qualitative evaluation using the t-test was conducted for the online study results for SUS and SART questionnaires. The t-test results of all 87 participants for the SUS survey showed statistical differences in 5 out of 10 questions, as shown in Fig. 9. These questions indicated better usability of the proposed AR-HUD in the first ($p < 0.05$, to use the system frequently) and fifth ($p < 0.01$, various functions well integrated) questions. On the other hand, for the second ($p < 0.01$, unnecessarily complex), fourth ($p < 0.05$, requires technical help), and tenth ($p < 0.01$, requires a lot of learning) questions, the results indicate that drivers are still unfamiliar with the AR technology and therefore, more experience and training are necessary. The results are reasonable since many participants were unfamiliar with the AR-HUD but showed positive opinions toward the future direction of driving assistance.

Furthermore, we evaluated the usability of the proposed approach between the different levels of driving experience (the novice with less than two-year driving experience and the experienced with more than two years). The statistical analysis showed no significant difference, as shown in Fig. 10. This evaluation shows that most participants have shown similar usability for the proposed approach.

Concerning the experimental results, the proposed AR-HUD system received an overall positive response for future driving assistance. Still, there is a need for further education and improvement in technology acceptance among the users. Nevertheless, we have found that the proposed AR-HUD system can play a crucial role in driving assistance concerning social issues, such as the increasing rate of accidents due to the surge in personal mobility users on the road.

The t-test results of the SART concerning the survey of 82 participants are as follows. The data related to the five participants were excluded since they did not answer specific

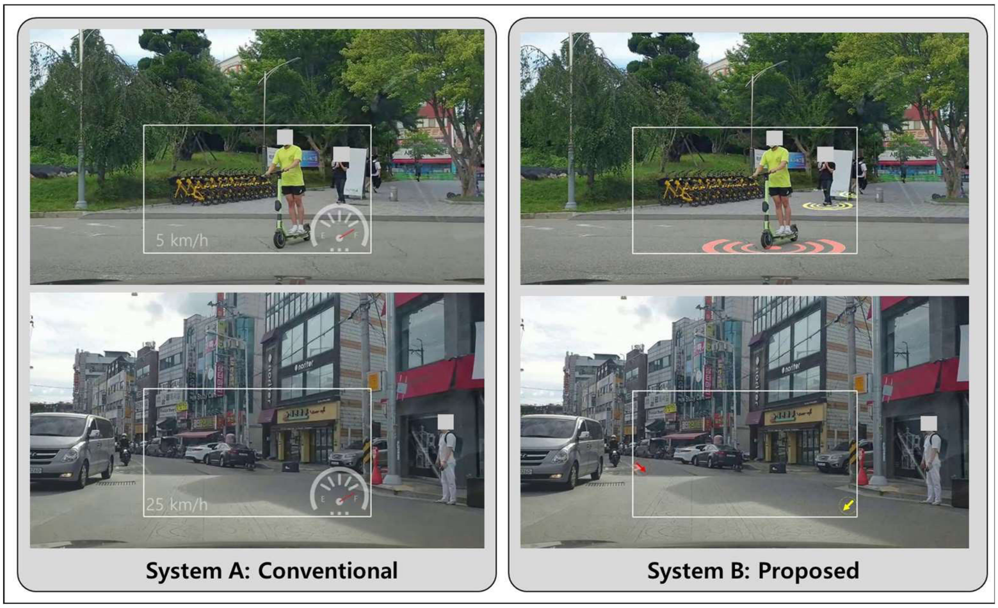

FIGURE 8. Conventional and proposed systems.

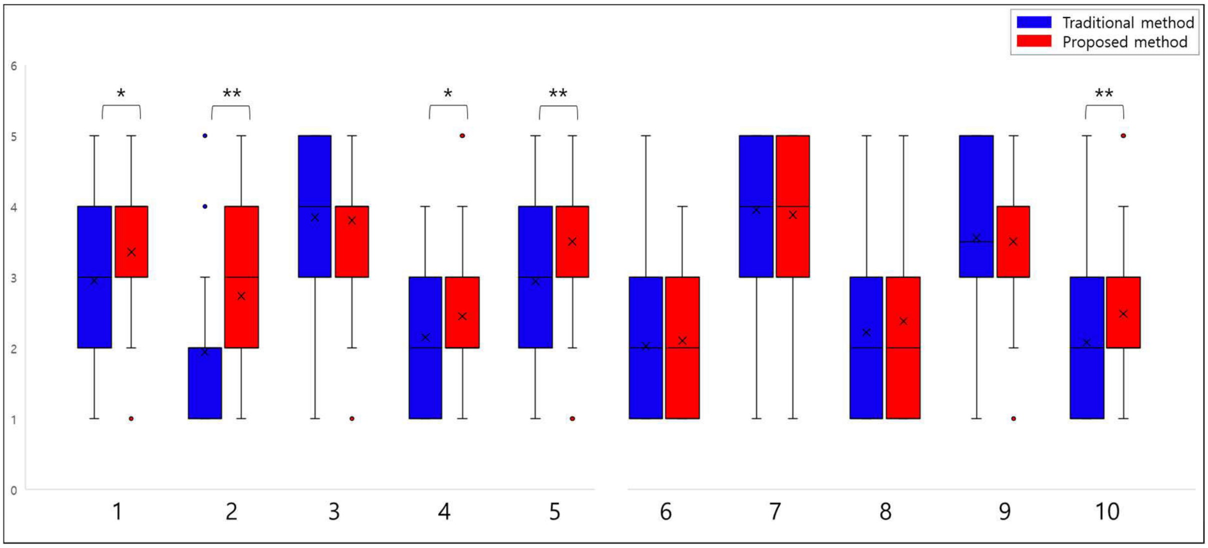

FIGURE 9. Result of evaluating SUS questions (*: $p < 0.05$, **: $p < 0.01$).

questions. Overall, the proposed approach (the composite SA score, $p < 0.05$) showed a higher score concerning the situational awareness of the drivers, as shown in Fig. 11(a). The SART evaluation can be divided into three categories among ten questions (Attentional Demand, Attentional Supply, and Understanding), as shown in Table 2. Among the three categories, a statistical difference was observed in the Understanding category ($p < 0.01$), as shown in Fig. 11(b). The Understanding category composes three questions (amount of information received and understood, quality of communicated knowledge, familiarity with the situation). The statistical result implies that the proposed approach can increase the driver's situational understanding while driving and provide more helpful information.

SART was also evaluated concerning the level of driving experience, similar to the SUS evaluation. As shown in Fig. 12, there was no statistical difference between the novice and the experienced driver.

The visual complexity of the AR-HUD on situation awareness was investigated using an analysis of variance (ANOVA [33]) method. 77 participants (excluding 10 out of 87 participants who did not complete the questionnaire) were evaluated for their situational awareness in three different complexity levels: Minimal, Normal, and Complex. The

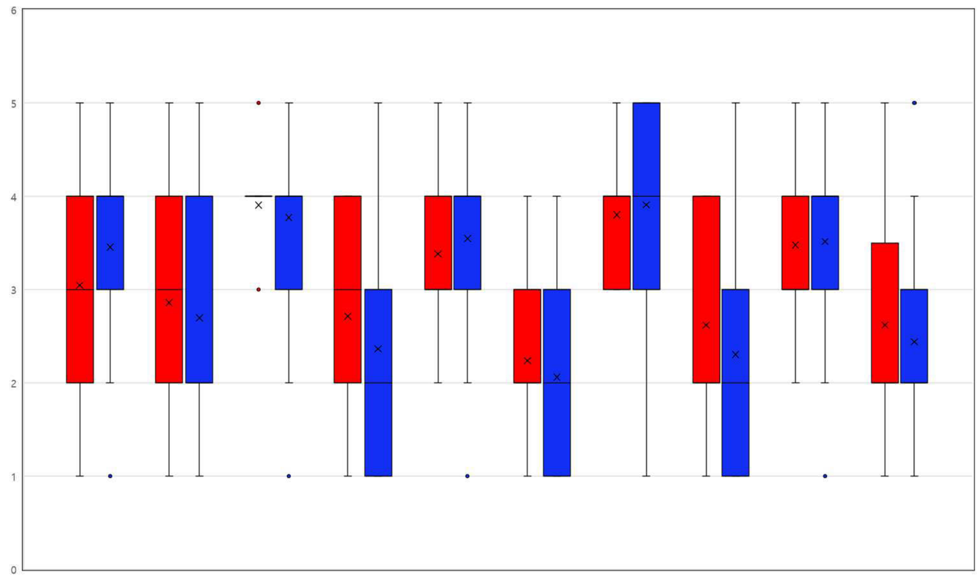

FIGURE 10. Usability evaluation of the proposed approach between the novice and experienced (no statistical difference).

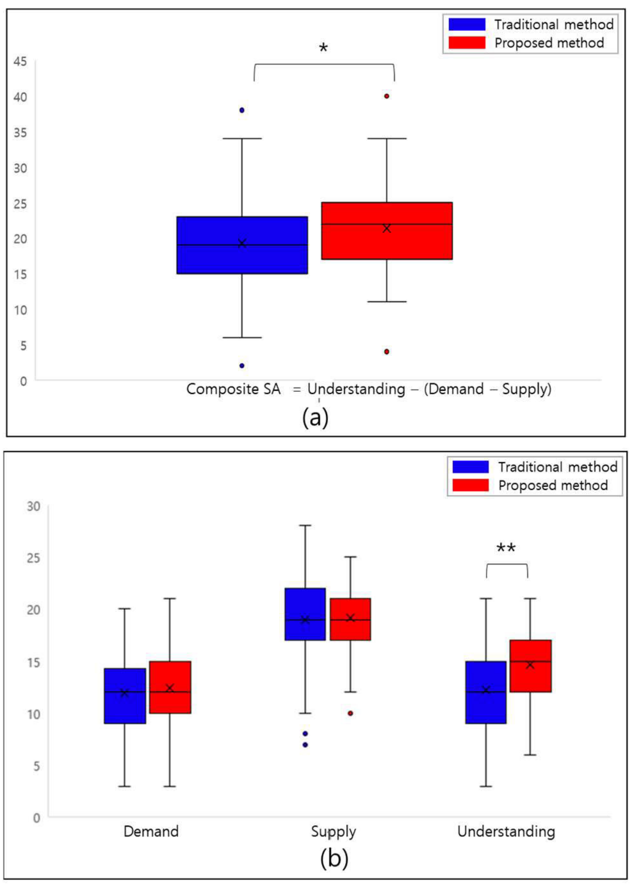

FIGURE 11. SART evaluation: (a) composite SA, (b) domain categories.

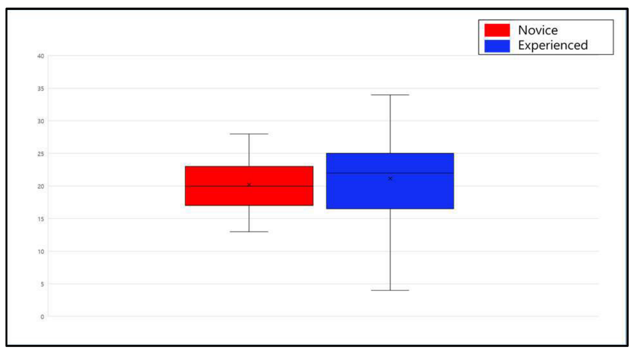

FIGURE 12. SART evaluation between the novice and experienced for the proposed approach (no statistical difference).

information provided in each level is shown in Fig. 7. The participants also watched the pre-recorded scenes corresponding to each level. They completed a survey to evaluate their situational awareness. The correlation between visual complexity and situational awareness was then analyzed. The results indicated no significant difference in situational awareness according to the complexity level, as shown in Fig. 13, which implies that even with an increase in complexity, situational awareness was not lowered. This outcome is attributed to the proposed method, which only adds pedestrian- and mobility user-related information in a limited dislay area. Through this analysis, the AR-HUD might not reduce situational awareness even with increased information when prioritized information is selectively provided.

C. DISCUSSION

After the experiment, the subjective opinions of the participants were also collected. Out of 87 participants, 51 expressed their opinions. Most participants showed positive opinions about the location and moving direction of pedestrians and

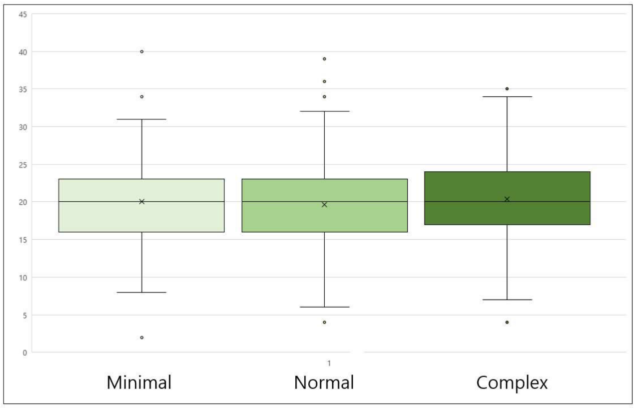

FIGURE 13. SART evaluation for visual complexity.

personal mobility users in the AR-HUD. Several participants mentioned that the system could be useful in anticipating and addressing the risk of accidents since they move quickly. Some participants strongly desired to use the AR-HUD navigation and believed that seeing the pedestrian's location would encourage them to drive slowly. Others also indicated that the information regarding personal mobility on the AR-HUD would be helpful in alerting them to pedestrians they might miss while driving on narrow streets or roads where parked vehicles obstruct their view. The participants also stated that they considered the representation of pedestrian information using AR useful and appreciated the visual representation of the information by checking pedestrians and mobility users with colors.

Negative opinions regarding the system were also mentioned, with the concern that excessive information could hinder their driving abilities. Additionally, comments were made such as, "dynamic objects close to the vehicle are not shown in the provided video," "it is difficult for experienced drivers to perceive the system as useful," "direction information may not be necessary," "yellow and red indicators could be disruptive while driving in crowded areas," and "the user interface (UI) may not be easily adaptable for the old."

Our future research direction will be to solve the negative aspects while maintaining and improving the positive ones.

VI. CONCLUSION

This study evaluated driving assistance by combining deep learning-based pedestrian and personal mobility user recognition and AR-based visualization. The proposed approach showed better situational awareness for driving assistance than the conventional HUD system that usually displays typical information. It was found that the proposed approach can offer more practical support to drivers by providing the locations and moving directions of pedestrians and personal mobility users, thereby enhancing the driver's ability to respond to potentially dangerous situations.

Concerning the experimental results, majority of experimental participants recognized the proposed approach as beneficial and necessary for driving assistance. However, it was also noted that a lack of experience with AR-based HUD systems requires further education and experience to promote its adoption. For future research work, an in-lab experiment with diverse participants in addition to the online study is necessary to conduct a quantitative analysis like measuring response time and accuracy. By conducting quantitative and qualitative analyses, we aim to evaluate more realistic driving situations.

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