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# 자율주행 차량의 보행자 상태 추정 알고리즘 개발

**Development of Pedestrian State Estimation Algorithm on Autonomous Driving**

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서 호 태

# Abstract

# Development of Pedestrian State Estimation Algorithm on Autonomous Driving

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This paper proposes development algorithm that can improve the performance of pedestrian state estimation of autonomous vehicle and verifying performance of developed algorithm. Research on autonomous vehicle technology is now more active than ever, and fully autonomous vehicles are expected to be commercialized in the near future. However, since autonomous driving technology is based on vehicles, it is very important to secure safety

compared to advanced future technologies that are currently being discussed. Especially in the case of urban roads, it is much more difficult to secure the safety of autonomous driving vehicle compare to highway, because traffic factors such as pedestrians, intersections, traffic lights, and shoulder cars are much more complicated compare to highway. In order to fully commercialize an autonomous vehicle, it is essential that autonomous driving is performed on the urban roads, and precise perception of pedestrians is a very important task. In order to fully commercialize. Pedestrians are smaller than the vehicles, inconsistent in the direction of movement, and cannot solve based on communication like V2I in case of signal information.

The vehicle used in this study was HMC IONIQ EV. Sensors mounted on the vehicle include 6 number of IBEO 2-D laser scanners, a vision sensor from Mobileye, and an AVM camera. In case of perceive an obstacle with laser scanner, the position information of the obstacle is accurate and has excellent performance has perceive vehicle or a road facility. However, a post-treatment process is required for classification, and pedestrians is too small to distinguish with other obstacles such as poles or trees. In the case of the vision sensor, h the image processing is excellent in the classification of the object, but, there are big position errors, so it is impossible to estimate the motion of the pedestrian.

In this stud, sensor fusion is used to compensate for the disadvantages of the two sensors. When it is perceived using the sensor configuration of this vehicle, the position of the obstacle perceived by the laser scanner is assumed to be the true value at the corresponding step, since the most accurate data is the laser scanner data. After then, to identify which obstacle is the pedestrian, we selected pedestrian candidates as the nearest laser scanner obstacle to the pedestrian data perceived by the vision sensor. Since the longitudinal error of the vision sensor is considerably larger than the lateral error, the Mahalanobis distance is used instead of Euclidean distance to improve the accuracy of the matching. Since the algorithm is iterated every 0.1 second in this vehicle, the obstacle is estimated to be a pedestrian candidate at every step. If the same obstacle is repeatedly selected as a pedestrian candidate, the obstacle is more likely to be a pedestrian. The reliability information is added to the information of this track to take into information of this track to take into account the number of pedestrian candidates selected. Finally, although the laser scanner data is the most accurate position information that can be perceived in the vehicle, that is different with the actual position of the obstacle, no matter how small. Even if the error is very small, the error can be amplified when the error is used to estimate the speed. Especially, this phenomenon is particularly noticeable when the speed tis small and the

direction changes frequently, such as a pedestrian. To reduce this phenomenon as much as possible, the accuracy of speed estimation is improved by using an EKF.

In this study, algorithm development and simulation were performed using MATLAB/Simulink. Data collection and algorithm verification were performed using real vehicle experiments using autonomous vehicle.

**Keywords**: Autonomous Driving, Obstacle Perception, Pedestrian State Estimation, Sensor Fusion Algorithm, Laser Scanner, Vision Sensor

**Student Number:** 2017-21705

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# Chapter 1

# Introduction

## 1.1. Background and Motivation

Recently, autonomous driving technology has emerged as a new power in all industries including the future automobile industry. With this technology, interest in autonomous driving is also increasing worldwide. Experts predict that fully autonomous driving will occur in the near future as in Fig.1.1.1. Especially, in the self-driving on highway, there has been considerable progress in the autonomous driving and the section where autonomous driving has been successful without driver intervention also expand. In order for autonomous driving to become universal to people after commercialization, it is necessary to be able to autonomously drive from the moment of leaving the home to the arrival at the destination, and this implies that autonomous driving is also important not only on the motorway but also on the urban roads.

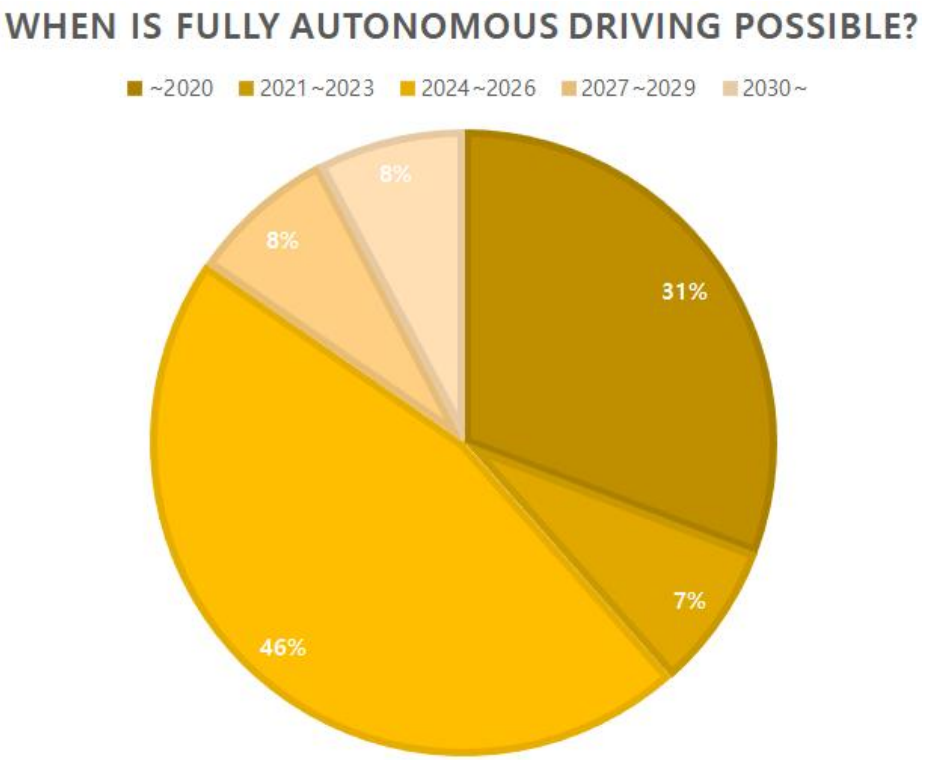


Fig.1.1.1 Time of fully autonomous driving expected by experts

However, autonomous driving on the urban roads has not reached the same level with the autonomous driving on the highway despite its importance. This is because autonomous driving on the urban roads is more difficult than autonomous driving on the highway. In particular, factors such as pedestrians and traffic lights at intersections must be solved for safe autonomous driving in urban roads. In the case of a traffic light, there is a solution using a V2I(Vehicle to Infrastructure) communication system that receives traffic lights signal

information directly. However, in the case of pedestrian recognition, there is only a method of recognizing pedestrian through sensor information.

In this paper, the recognition of pedestrians through the fusion of the laser scanner and the vision sensor is aimed to improve the performance of the pedestrian perception compared to using single sensor. In the case of the 2-D laser scanner and the vision sensor of the vehicle used in this experiment, when the pedestrian perception is performed using only a single sensor, neither of the two cases shows the pedestrian recognition performance at the level to be used for autonomous driving. Therefore, it is inevitable to improve the pedestrian perception performance by using the two sensors together, and the sensor fusion is proceeded through the following process. First, the pedestrians are classified in the vision sensor and then optimize a cost function based on MD(Mahalanobis distance) to match with the data of the laser scanner. Next, the reliability is improved by using the reliability function and tracks is made for managing matching pedestrian data. Finally, EKF(Extended Kalman Filter) was used to improve the accuracy of the estimates. The data used in the development of this algorithm was obtained by using the running of autonomous vehicles, and it was obtained from the roads of Yeongjong Island in Incheon and Seoul National University. In addition, MATLAB was used for the development of algorithms and it was linked with LABVIEW to implement it in autonomous vehicles. By

confirming the execution result of the implemented algorithm, it is confirmed whether it is helpful to improve the cognitive performance of the actual pedestrian.

## 1.2. Thesis Outline

This dissertation is structured in the following manner. Chapter 1 describes the difficulty of self-driving in the urban road, the importance of pedestrian perception in autonomous driving in urban road, and difficulty in pedestrian perception with a single sensor. Part of the sensor configuration of the vehicle used in the research and characteristics of the sensor used to perceive pedestrian proposed in Chapter 2. Chapter 2 also contains the results of experiments to identify sensor characteristics and identify parameters for the algorithm to be proposed in this dissertation. The part of the sensor fusion algorithm and its details is configured in Chapter 3. The details of the algorithm are the method of selecting pedestrian candidates using Mahalanobis distance-based cost function optimization, track management using reliability and state estimation of pedestrian using Extended Kalman Filter. Chapter 3 also covers result of algorithm and vehicle experiments. Chapter 4 concludes with a summary of the contents of this dissertation and the implications of this research.

# Chapter 2

# Sensor configuration and Characteristics

## 2.1. Sensor configuration for perception of autonomous vehicle

The sensor configuration of the vehicle used in this study is shown in Fig. 2.1.1. The laser scanner used in this test is 2-D, 4-layer scanner, with a resolution of about 5'and six mounted around the experimental vehicle. In the case of the used vision sensor, one is mounted at the front and the FOV(Field of View) is ±20. In addition to the sensor, the experimental vehicle has obtained a license to operate the autonomous driving from Korea Automobile Testing & Research Institute and configured with equipment for autonomous driving experiments like Fig 2.1.2.

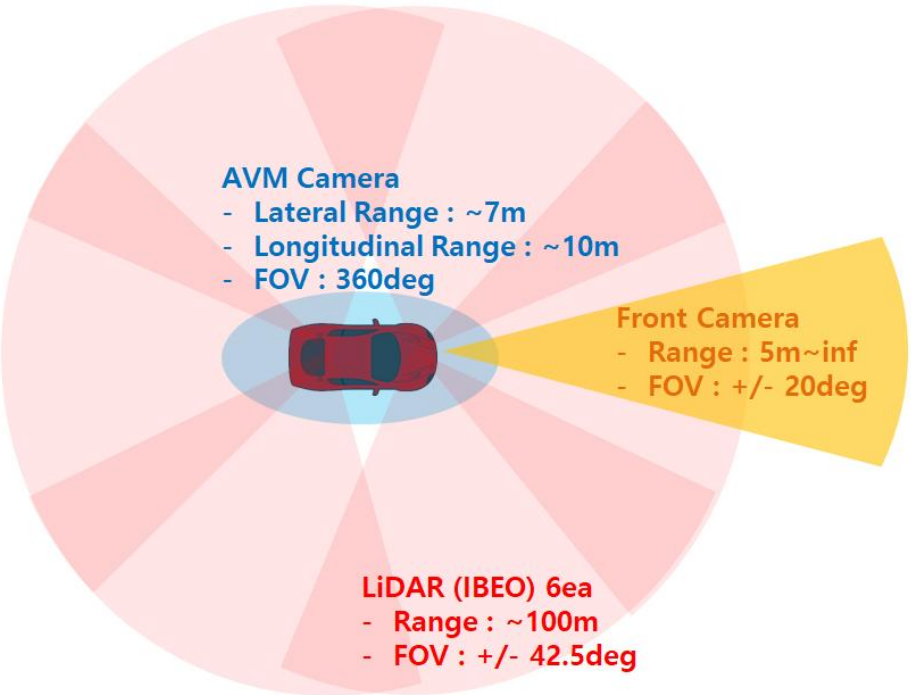


Fig.2.1.1 Sensor configuration and FOV on experimental vehicle

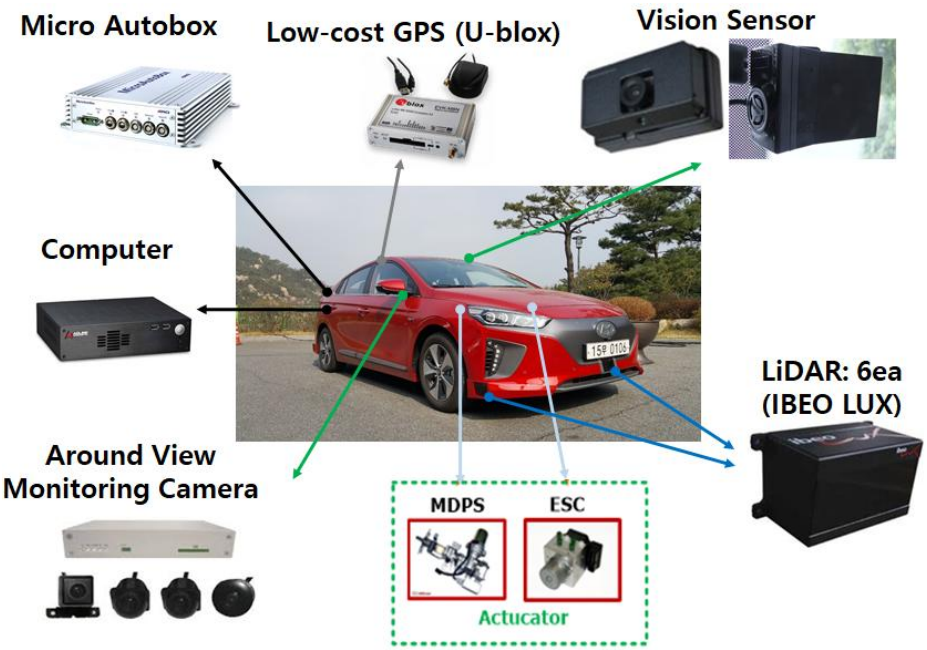


Fig.2.1.2 Experimental vehicle configuration

## 2.2. The characteristic of perception based on laser sensor.

The method of detecting obstacles of laser scanner uses light reflection. Light is less likely to be refracted, and the speed of light is constant for changes in the external environment, so position error is small in object detection. Also, the quantitative analysis of the laser scanner equipment used in this experiment showed that the position error was negligible. It is difficult to confirm the true value of the perception result when the perceptual subject and the object move together, such as driving situation. Especially, in case of pedestrian perception,


Fig.2.2.1 Actual Position of Pedestrian

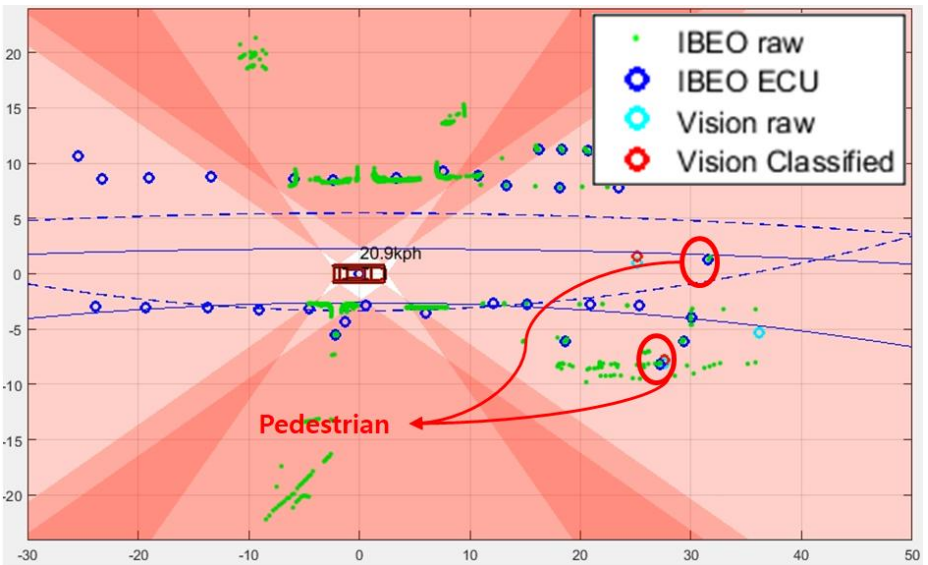


Fig.2.2.2 Pedestrian data from laser scanner versus vision sensor

it is impossible to confirm the true value because it is difficult to equip with high-performance GPS. Considering the low error level of the laser scanner and the difficulty of verifying the true value in the perception field, this paper assumes that the data perceived by the laser scanner is a true value.

For the laser scanner used in this paper, the resolution limit is 0.125 degree and the dimension is 2-D. This means that obstacles with widths of the vehicle are perceived as multiple points and can be post-processed such as clustering and tracking, but pedestrian is perceived as a single point. Because of this phenomenon like Figs 2.2.1 & 2.2.2, the laser scanner cannot distinguish between pedestrians, trees, and poles.

## 2.3. The characteristic of perception based on vision sensor.

For vision sensors, objects can be classified through image processing. This makes it easy to classify pedestrians, which was difficult with laser scanners. As shown in Fig. 2.2.2, it can be confirmed that the pedestrian data is correctly classified. Also, the results of the experiment using the data of real driving in Seoul National University which is urban road environment show that the vision sensor has excellent pedestrian classification ability.

| Test time | Driving Distance | # of pedestrian | # of classification success |
|---|---|---|---|
| 8 min | 3000 m | 66 | 63 |

Table.2.3.1 Successful classifcaition of the pedestrian of the vision sensor

As shown in “Table 1”, this experiment was carried out for 8 minutes on a total length of 3000m, and 66 forward pedestrians occurred, and 63 pedestrians were successfully classified. In the case of three failures, it is also difficult to observe pedestrians by the naked eye as shown in Fig.2.3.1, or when too many pedestrians are standing in a line near the bus stop so sensors cannot perceive all the pedestrians like Fig.2.3.2. These situations does not become a serious problem for autonomous driving. The final failure case is a case where a pedestrian is classified in the vision sensor, even though no pedestrian actually

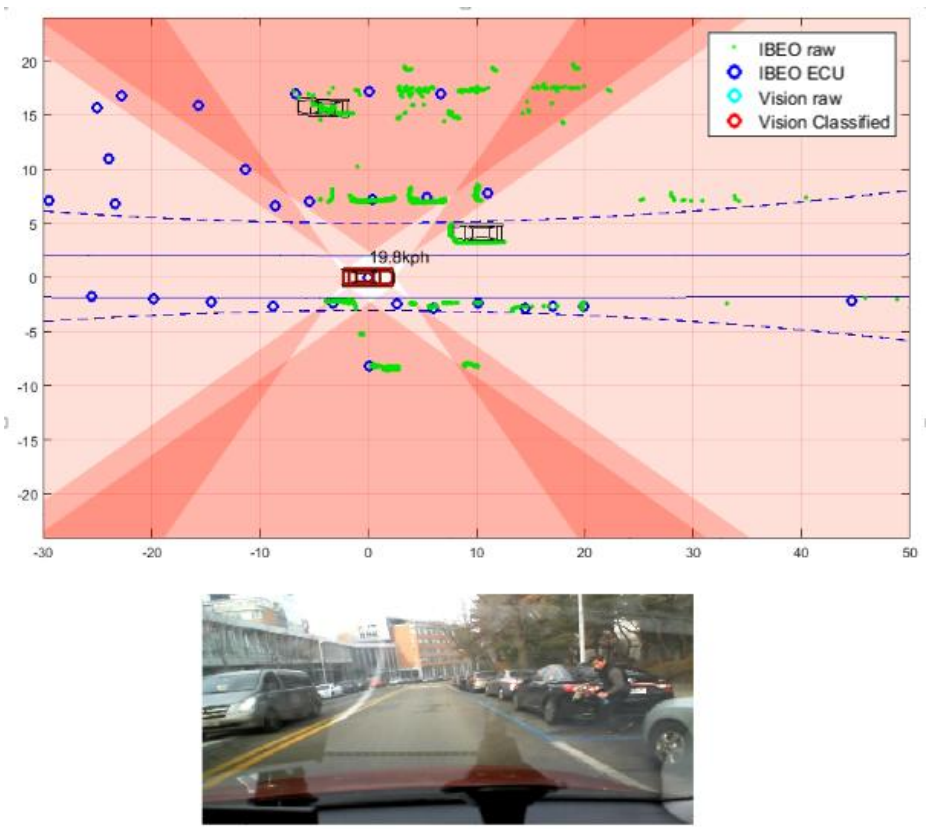


Fig.2.3.1 Classification failure case1 – pedestrian hidden behind car

exist. In this case, it is not bad from the safety point of view, and since the frequency is one out of 66 cases, it does not cause a big problem to the autonomous driving itself. Nonetheless, in this paper we show how to solve the failure case in Chapter 3.4.

As such, the vision sensor shows excellent performance in pedestrian classification, but it is difficult to measure the distance in the image depth direction, that is, the distance to the vehicle traveling direction (longitudinal

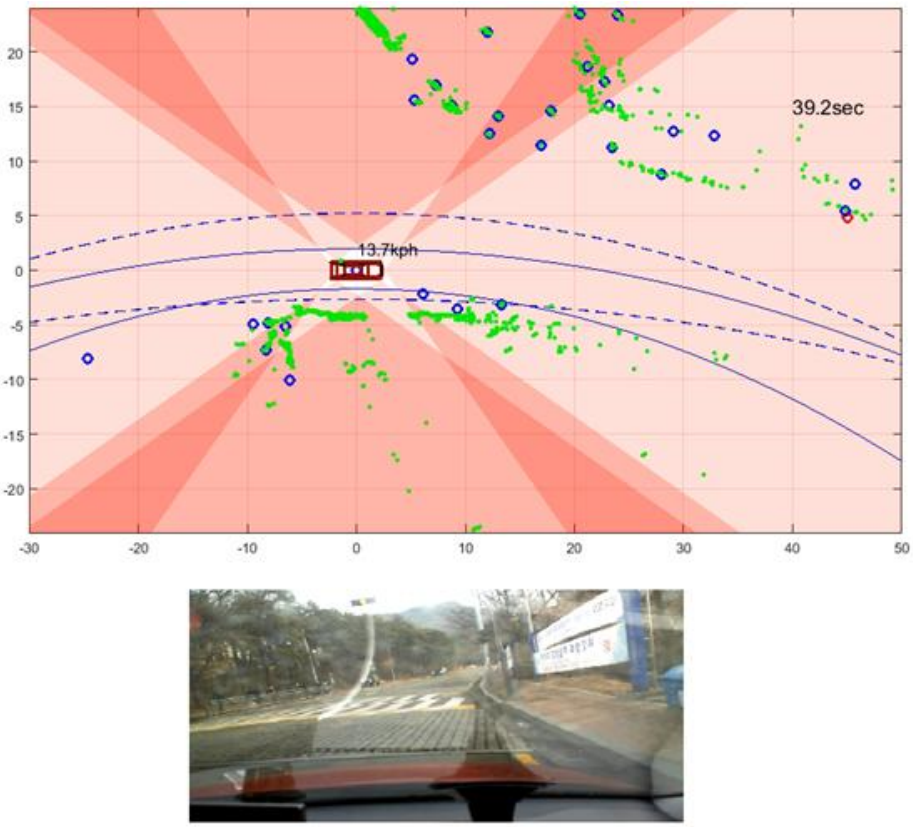


Fig.2.3.2 Classification failure case2 – too many pedestrian

direction) in the case of the vision sensor equipped in front of the vehicle. That is, the longitudinal distance error is large. In the case of the lateral direction errors are generated if the longitudinal position is not accurate, and thus there is a large error as compared with the laser scanner. This is confirmed by the error characteristic of the vision sensor for the pedestrian analyzed by the experiment data obtained from Midan City in Yeongjong Island. Since the analysis of the error characteristics of the vision sensor is an important variable

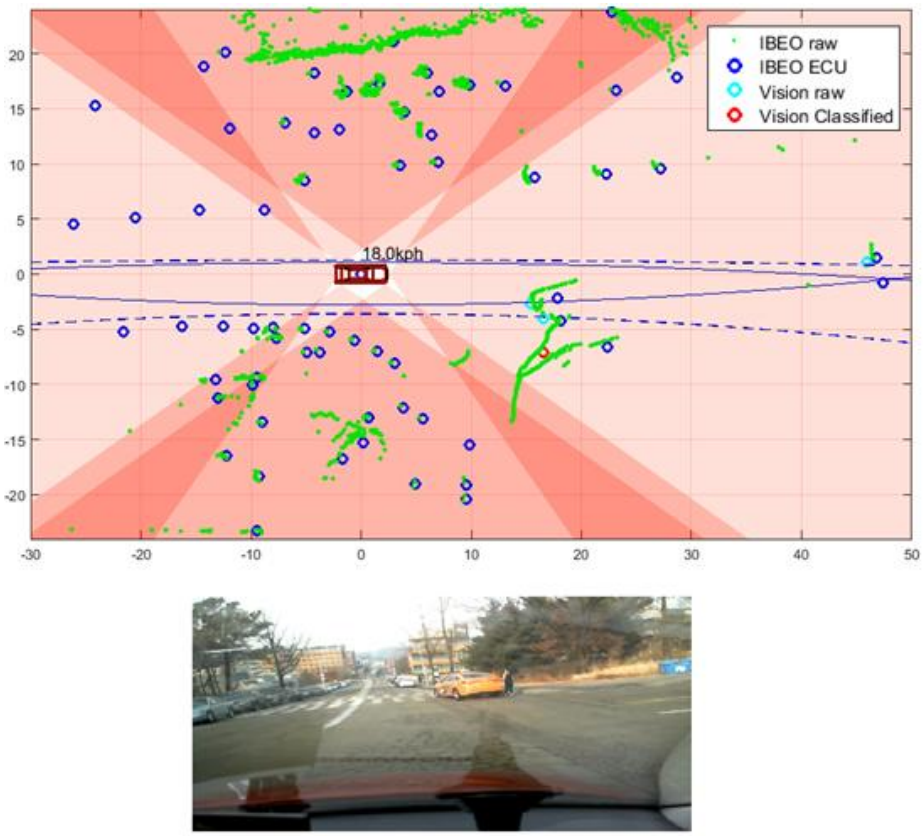


Fig.2.3.3 Classification failure case3 – false perception too many pedestrian

in the optimization process to be introduced in the Chapter 3.3, so detailed descriptions of this experiment will be given in Chapter 3.3.

# Chapter 3

# Fusion of laser scanner and vision sensor

## 3.1. Algorithm Overview

The block diagram of the pedestrian perception algorithm using the fusion of the laser scanner and the vision sensor presented in this paper is shown in Fig. 3.1.1.

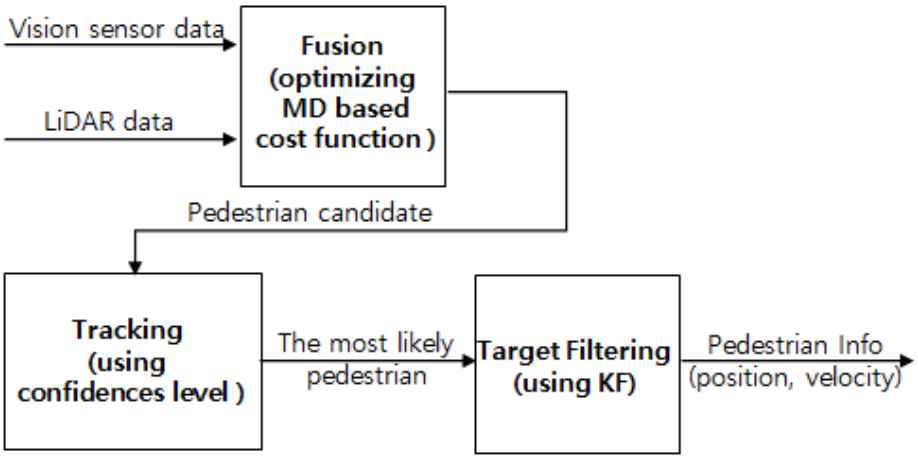


Fig.3.1.1 The algorithm for pedestrian perception by fusion of laser scanner and vison sensor

First, the most appropriate pedestrian candidate among the obstacles detected by the laser scanner is selected based on the position of the pedestrian data detected by the vision sensor. In this step, matching was performed considering the error characteristics of the vision sensor by optimizing the MD-based cost function. Then, the laser scanner obstacle data determined to be most likely to pedestrian at the every iteration by using the method of accumulating the pedestrian candidates selected for each iteration of the algorithm and its reliability in the track. Finally, the algorithm is constructed to derive more precise position and velocity information of the pedestrian by applying EKF using the position information obtained from the sensor fusion and the velocity information obtained from the laser scanner

## 3.2. Selection of pedestrian candidates using MD-based cost function optimization

Assuming that the position of the pedestrian perceived by the laser scanner is correct as mentioned in Chapter 2.2. However, in the case of vision sensor, the longitudinal position error is larger than the lateral error as mentioned in Chapter 2.3. Therefore, like Fig.2.3.3, even if the obstacle is the same distance

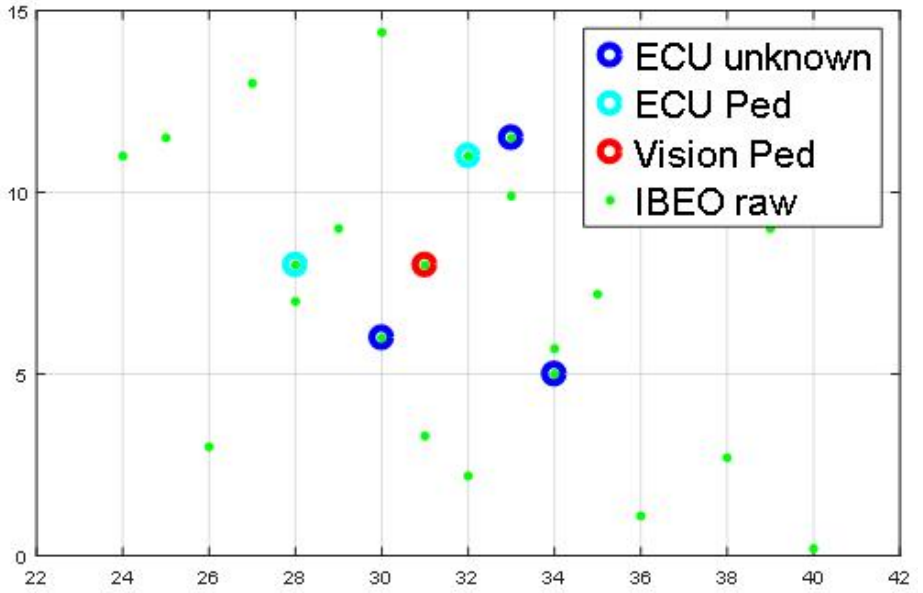


Fig.3.2.1 Issue of matching Laser Scanner & Vision

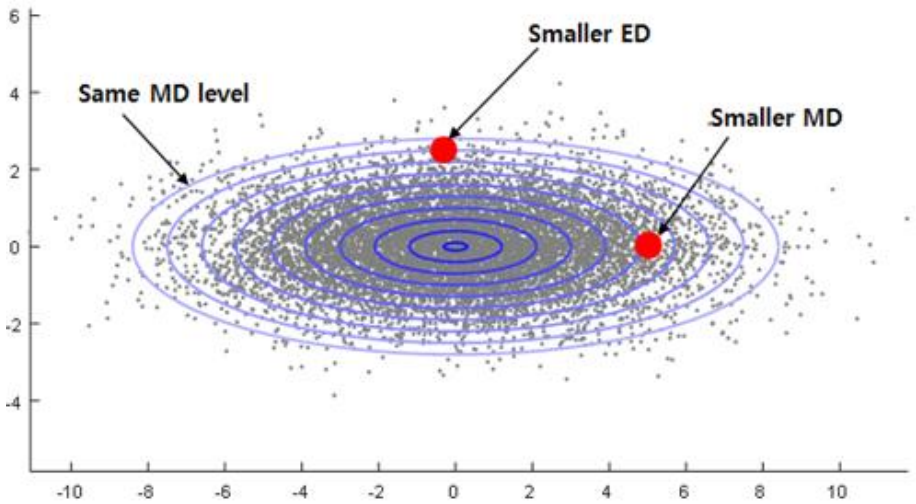


Fig.3.2.2 Comparison of MD & ED

pedestrian detected by the vision sensor, the probability of a pedestrian is not the same if the longitudinal and lateral position of the data are different. Even an obstacle is longitudinally far from the reference obstacle, it could be same obstacle with the reference obstacle since the longitudinal error level of vision sensor is high. On the other hand, even if it is slightly apart in the lateral direction, it is highly likely different obstacle with the reference obstacle because the lateral error level of vision sensor is low. To solve this problem, we used MD(Mahalanobis distance) instead of the commonly used ED(Euclidean distance). In the case of ED, the points on the same circle are the same distance from the center, but in case of MD, like Fig. 8, the points on the same ellipse are the same distance from the center. At this time, the center of the ellipse is

determined by the average of the data and the eccentricity of the ellipse by the variance of the data. In this paper, the average of longitudinal and lateral errors of vision sensor is the center of the ellipse, and the covariance of the longitudinal and lateral errors determine the eccentricity of the ellipse. The laser scanner data that minimizes MD-based cost function is selected as the pedestrian candidates. This process can be expressed as (3.1).

$$X_p = \underset{X_L}{\operatorname{argmin}}\{(X_L - (X_V - \mu_{LV}))^T Q(X_L - (X_V - \mu_{LV}))\} \quad (3.1)$$

$$X = \begin{pmatrix} x \\ y \end{pmatrix} \quad (3.2)$$

$$Q = \begin{pmatrix} Var(\mathrm{x}) & Cov(\mathrm{xy}) \\ Cov(\mathrm{xy}) & Var(\mathrm{y}) \end{pmatrix} \quad (3.3)$$

In (3.1), the subscripts p, L, and V of $X$ indicate respectively the actual pedestrian position, the pedestrian position perceived by the laser scanner, and the pedestrian position perceived by the vision sensor. In (3.2), $X$ is a vector composed of x(the distance of obstacle in the longitudinal direction based on host vehicle) and y(the distance of the obstacle in the lateral direction based on host vehicle). That is, $X_p$, $X_L$, and $X_L$ in (3.1) are the position vector of the obstacle based on the host vehicle. $\mu_{LV}$ in (3.1) means the error average of

obstacles perceived by vision sensor relative to the laser scanner. Q in (3,1) means the error covariance matrix of vision sensor relative to the laser scanner, and its form is the same as (3.3)

It is $\mu_{LV}$ and $Q$ to determine the characteristics of the cost function of MD distance based on (3.1). The cost level contour of the MD is as shown in Fig.3.2.2 where $\mu_{LV}$ determines the center of the ellipse and $Q$ determines the eccentricity of the ellipse. Since the matching through optimization is obtained through (3.1), it is very important to find the error characteristics of the vision sensor in order to improve pedestrian recognition performance. Therefore, in this study, an experiment was conducted to determine the error characteristics of the vision sensor, which will be described in Chapter 3.3.

## 3.3. Selection of error covariance matrix by conducting vehicle experiments

The performance of the MD cost function is ultimately determined by how much the error mean and the error covariance matrix are match the actual value. In this study, we decided $\mu_V$ and Q through analyzing data of the two experiments mentioned in 2.2.

To obtain the data, the experiment was carried out in Midian City, Yengjong Island, Incheon. This experiment was carried out in six scenarios depending on the location of the pedestrian. The six experiments are as follows: each lane except the vehicle traveling path, both sides, and crosswalk scenario, from the four-lane road. The reason for classifying the six scenarios for classifying the

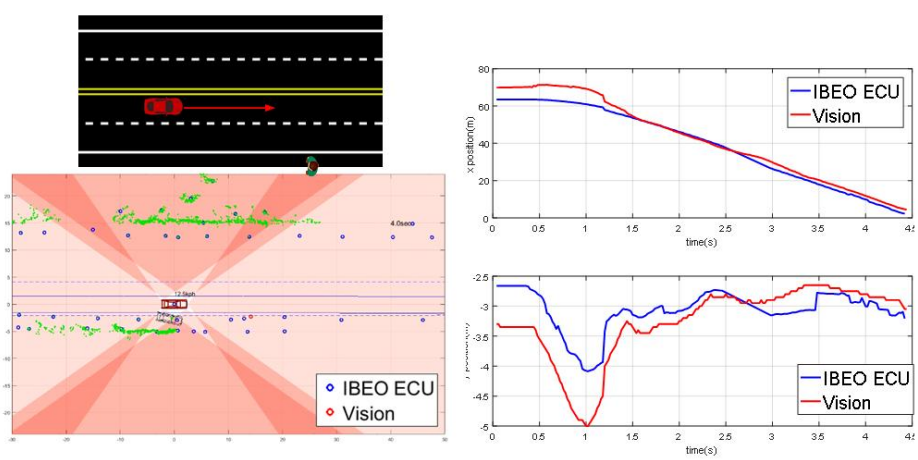


Fig.3.3.1 Scenario 1 – pedestrian on right sidewalk

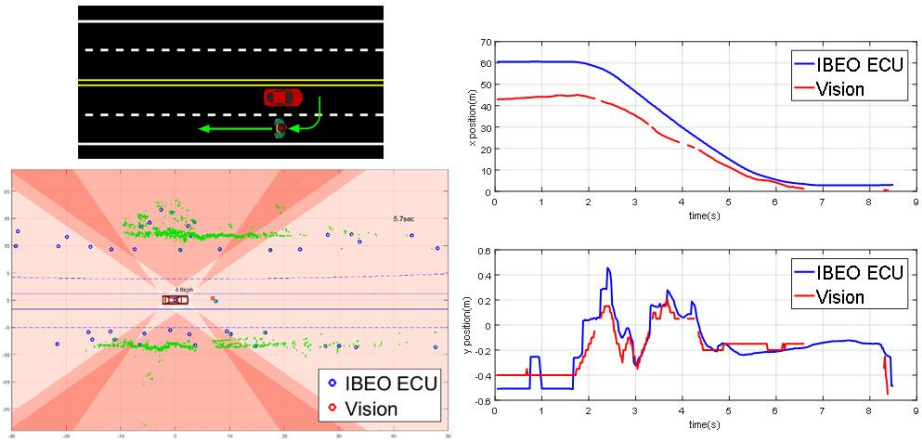


Fig.3.3.2 Scenario 2 – pedestiran on right 2nd lane

six scenarios is to analyze the perception error characteristics of the vision sensor according to the position of the pedestrian.

Figures 3.3.1 through 3.3.6 show the results of experiments for each scenario. In the upper left of the figures, the behavior of the pedestrian in each scenario

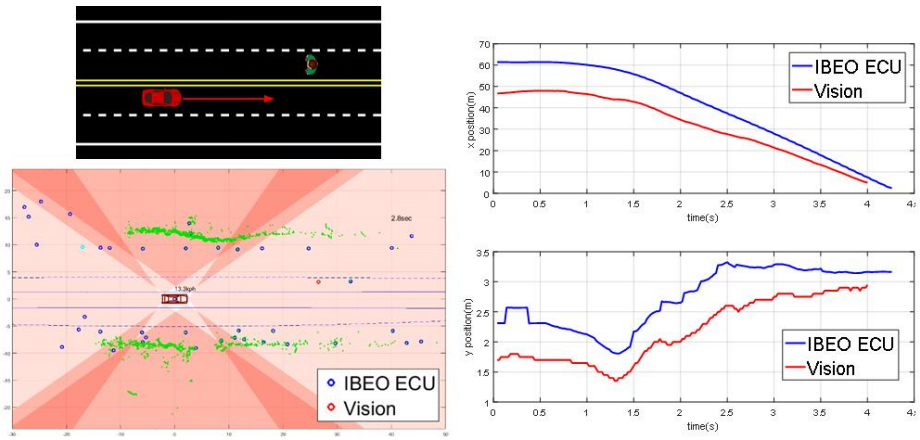


Fig.3.3.3 Scenario 3 – pedestrian on left 1st lane

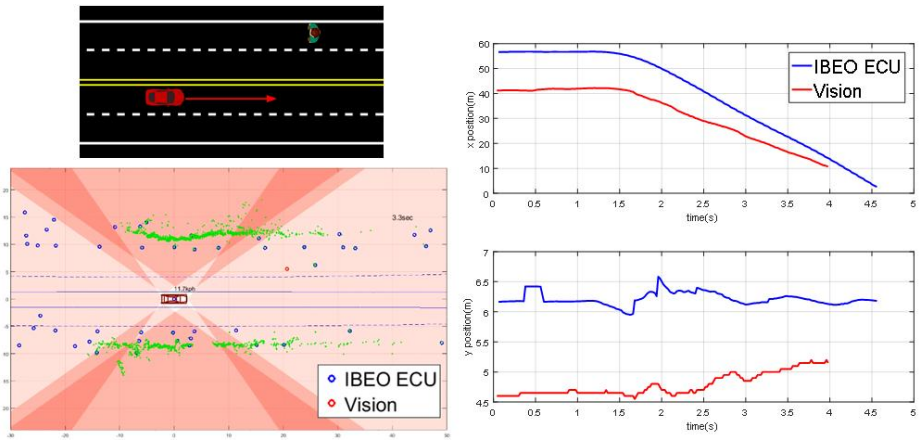


Fig.3.3.4 Scenario 4 – pedestrian on left 2nd lane

is displayed. At this time, the position of the pedestrian perceived by the laser scanner and the vision sensor is displayed as top view on the lower left of the figures. It is the right plot to divide it into the longitudinal position and the lateral position and display it with time.

Through these six experiments, we can see that when the pedestrian is perceived by the vision sensor, the longitudinal position error is larger than the lateral position error. Therefore, it is considered appropriate to use Mahalanobis distance instead of Euclidian distance. In addition, it was found that the further the distance from the vehicle to the pedestrian is, the larger the longitudinal position error becomes. So we can see that as the distance of the pedestrian changes, we have to use different $\mu_V$ and Q. Of course, the position of the pedestrian cannot be precisely known before the algorithm is executed, so

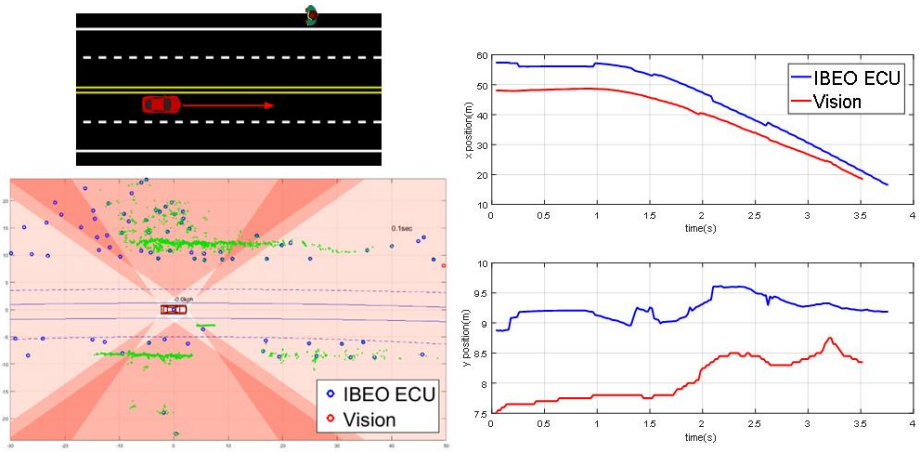


Fig.3.3.5 Scenario 5 – pedestrian on left sidewalk

estimating the position of the pedestrian and $\mu_V$, Q values using the iteration method can be a method for improving the accuracy. However, the amount of change in $\mu_V$ and Q values depending on the distance is not so large as that in the longitudinal direction relative to the lateral position error, so it does not

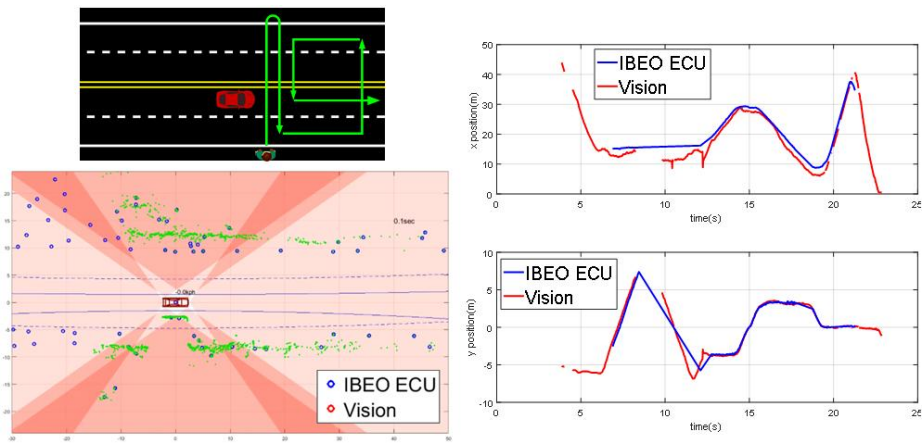


Fig.3.3.6 Scenario 6 – crosswalk and multiple sidewalk

greatly affect the shape of the ellipse in the Mahalanobis distance technique. In addition, since this study ultimately seeks autonomous driving performance through perception of pedestrians, it is advantageous to determine $\mu_V$ and Q values as approximate positions rather than to increase the calculation time of the algorithm by improving the accuracy through iteration.

To get $\mu_V$ and Q, we need to know the error of the vision sensor every time we perceive a pedestrian. True values are required to obtain the error, but as mentioned in Chapter 2.2, it is very unrealistic to obtain the true value of the pedestrian position, and because the accuracy of the positioning of the laser scanner is very high, the pedestrian data perceived by the laser scanner has been selected as the true value. However, since it is very likely that one of the

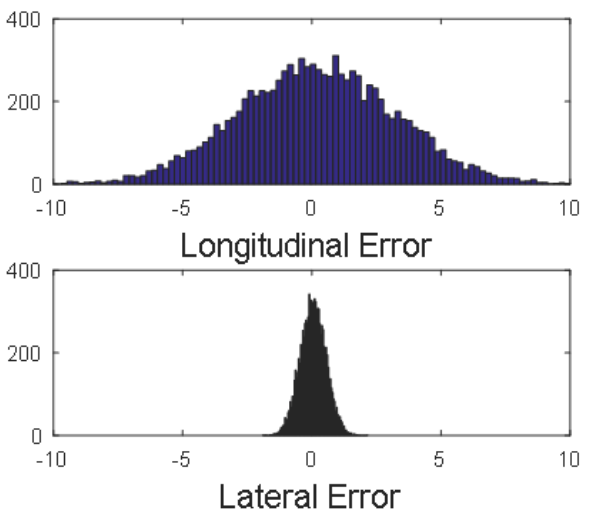


Fig.3.3.7 Error mean & covariance of vision data

obstacles perceived by the laser scanner is a pedestrian, it is difficult to

discriminate by the sensor itself or using the algorithm. Therefore, we tracked every moment which obstacle is pedestrian among obstacles perceived by laser scanner.

In the analysis process, obtaining the position error of the vision sensor data for each step, then calculating error average and error covariance of approximately 4800 data. This is the same as figure 3.3.8. We used these values to perform the matching through the optimization introduced in Chapter 3.3, and got the pedestrian candidate.

## 3.4. Pedestrian track management introducing reliability

If other obstacles of similar size to the pedestrian are close to the real pedestrian, laser scanner obstacle data selected as the pedestrian candidates by the above algorithm may not be a true pedestrian. Even in this case, to accurately estimate actual pedestrians, the concept of reliability was introduced. At each algorithm repetition step, there is one laser scanner obstacle data selected as a pedestrian candidate. Since the laser scanner obstacle data classified as ECU has a track number, the obstacle data selected as a pedestrian candidate at a certain step can be found in the next step. Therefore, laser scanner obstacle data can be manage through tracks and reliability can be tracked. The reliability of the first recognized laser scanner obstacle data is set from 0, and the lower limit of reliability is also set to zero. The laser scanner obstacle data selected as the pedestrian candidate increases the reliability by 2 and if it is not selected as the pedestrian candidate, reduces the reliability by 1. By estimating that the data having the highest reliability value among the laser scanner obstacle data is the pedestrian, it is highly probable to estimate the actual pedestrian among the laser scanner obstacle data.

When there are two or more pedestrians, only the data with the highest reliability cannot be called pedestrians. Therefore, if the number of pedestrians perceived by the vision sensor is n, then n number of data are judged as pedestrians in order of reliability among the laser scanner data.

As can be seen from the experimental results in Section 2.2, the probability of no perceiving the presence of a pedestrian in the vision sensor is very low. However, as shown in Fig. 5, there may be cases where the pedestrian is not perceived by several steps instantaneously in the process of perceiving a single pedestrian. Also, as can be seen in Fig. 1, FOV of the front vision sensor is narrow, so the pedestrian may be moving to blind spot during driving.

## 3.5. Improved performance of state estimation using EKF

The pedestrian tracks selected in 3.3 have position and velocity information. This is an estimate of the laser scanner selected as a pedestrian, and there is no conversation for the velocity information after applying the fusion algorithm. If the same laser scanner obstacle data is selected as a pedestrian during the process of perceiving, the estimation is not necessary. However, if the laser scanner obstacle data selected as a pedestrian changes over time, performance can be improved through estimation using filtering.

The pedestrian motion is a nonlinear differential model because it is a dynamic system based on acceleration, velocity and position. If the system is a nonlinear differentiable model, you can use EKF (Extended Kalman Filter) instead of KF (Kalman Filter). The pedestrian model used the equivalent speed model and the covariance used the error covariance for the vision sensor. The equations of the extended Kalman filter are (3.4) ~ (3.7).

$$\dot{x}(t) = f(x(t), u(t)) + w(t), \quad w(t) \sim \mathrm{N}(0, \mathrm{Q(t)})$$

$$z(t) = h(x(t)) + v(t), \quad \mathrm{v}(t) \sim \mathrm{N}(0, \mathrm{R(t)}) \tag{3.4}$$

$$\hat{\mathrm{x}}(t_0) = E[x(t_0)], \;\; \mathrm{P}(\mathrm{t}_0) = \mathrm{Var}[\mathrm{x}(\mathrm{t}_0)] \tag{3.5}$$

$$\dot{\hat{\mathrm{x}}}(t) = f(\hat{x}(t), u(t)) + K(t)(z(t) - h(\hat{x}(t)))$$

$$\dot{\mathrm{P}}(t) = F(t)P(\mathrm{t}) + \mathrm{P}(\mathrm{t})\,\mathrm{F}(\mathrm{t})^T - K(t)H(\mathrm{t})\,\mathrm{P}(\mathrm{t}) + \mathrm{Q}(\mathrm{t})$$

$$\mathrm{K}(t) = P(t)\,\mathrm{H}(\mathrm{t})^T R(t)^{-1}$$

$$F(t) = \left.\frac{\partial f}{\partial x}\right|_{\hat{x}(t),u(t)}$$

$$\mathrm{H}(t) = \left.\frac{\partial h}{\partial x}\right|_{\hat{x}(t)} \tag{3.6}$$

(3.4) to (3.6) show the Continuous-time extended Kalman filter equation. (3.4) represents the model of the EKF, (3.5) represents the initialization of the EKF, and (3.6) represents the predictive update of the EKF. In this study, the position of a pedestrian was used as the state vector, and the variable acceleration model was used as the dynamic model so the behavior of irregular pedestrians was predicted. The extended Kalman filter is a very well known filter and will not be described in further detail.

The data through the sensor is perceived as the local coordinate system value of the vehicle reference. However, in order to predict the moving of an object, the influence due to the moving of the vehicle must be minimized. This is especially severe if the heading of the vehicle is changing. To do this, we changed the value of the local coordinate system to the global coordinate system

value, applying the filtering logic, and converted it to the value of the local coordinate system. The transformation between the coordinate systems is determined by the Euler rotation transformation matrix and the absolute position of the vehicle itself, as shown in (3.7).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = R \cdot P \cdot Y \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} X_H \\ Y_H \\ Z_H \end{bmatrix} \tag{3.7}$$

x, y, and z indicate the position of the obstacle on the local coordinate system relative to the vehicle, and X, Y, and Z indicate the position of the obstacle on the global coordinate system. Also, $X_H$ ,$Y_H$ , and $Z_H$ indicate the position of the child vehicle in the global coordinate system. R, P, and Y are rotational transformation matrices for roll, pith, and yaw directions, respectively. This can be expressed as (3.8) ~ (3.10).

$$R = \begin{bmatrix} \cos\phi & -\sin\phi & 0 \\ \sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3.8}$$

$$P = \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix} \tag{3.9}$$

$$Y = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\varphi & -\sin\varphi \\ 0 & \sin\varphi & \cos\varphi \end{bmatrix} \tag{3.10}$$

## 3.6. Result of algorithm execution

For the pedestrian perception performance analysis, we applied the algorithm and analyzed the results of the experimental data on the circular path of Seoul National University. As shown in Fig.3.6.1, even when two pedestrians and a pole on the roadside are mixed, pedestrians can be perceived and its speed can also be estimated as shown in Fig.3.6.2.


Fig.3.6.1 Actual Position of Pedestrian

We succeeded in matching the obstacle data of the laser scanner based on the pedestrians perceived by the vision sensor for the data of 30 pedestrians among the 66 pedestrian data obtained from the experiment on the circular path of Seoul National University. However, this does not mean that 30 people out of 66 have succeeded in perceiving pedestrians. Basically, pedestrian perception

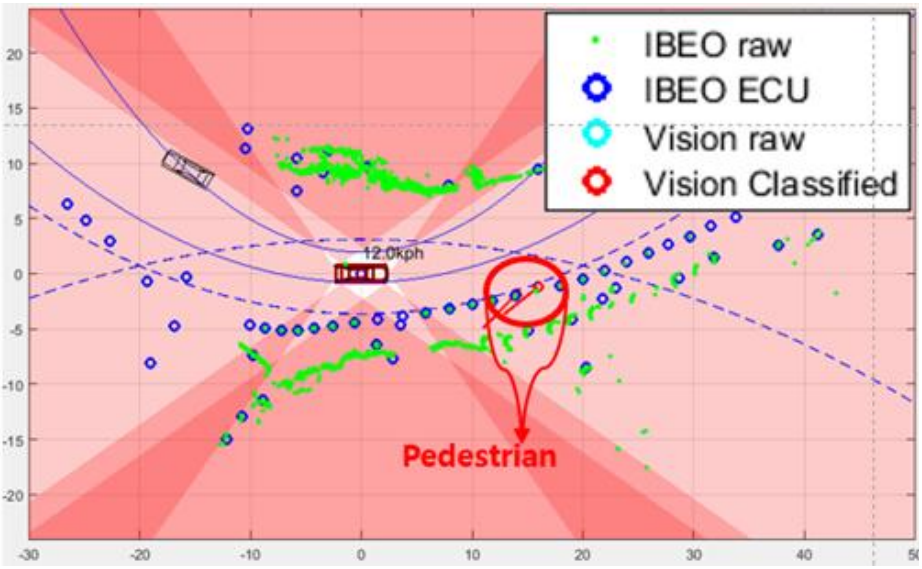


Fig.3.6.2 Pedestrian data after algorithm execution

is possible with the vision sensor, but there is a position error and it is correct to see that 33 of the 66 cases improved this error. Also, as mentioned repeatedly above, it is assumed that the position of the obstacles including the pedestrian perceived by the laser scanner is a true value, since the real value of the pedestrian position cannot be known realistically, so that the position of the matched pedestrians can be accurately perceived. In order to analyze the error of the pedestrian data perceived by the laser scanner, a new experimental method is needed to measure the true value of the pedestrian position in real time.

# Chapter 4

# Conclusion

In this study, we developed algorithm to improve the estimation performance of pedestrian condition by fusion of laser scanner and vision sensor. The algorithm is designed to estimate the pedestrian as much as possible at each stage and it is verified by pedestrian perception data in the real car driving. This will contribute to safe autonomous driving on urban roads.

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# 초 록

## 자율주행 차량의 보행자 상태 추정 알고리즘 개발

본 연구는 자율주행 차량의 보행자 상태 추정 성능을 향상할 수 있는 알고리즘을 개발하고 그 성능을 검증한 것에 관한 내용이다.

차량의 자율주행기술 연구는 현재 그 어느 때보다 활발히 진행되고 있으며, 완전자율주행차량의 상용화도 가까운 미래에 이루어질 전망이다. 하지만 자율주행 기술은 자동차를 기반으로 하고 있기에 현재 화제가 되고 있는 첨단미래기술에 비해 안전성 확보가 매우 중요하다. 특히 보행자, 교차로, 신호, 갓길차량 등의 교통요소가 자동차전용도로에 비해 훨씬 복잡한 도심도로의 경우 자율주행 차량의 안전성 확보는 훨씬 난이도가 높다. 자율주행차량의 완전한 상용화를 위해서는 도심도로에서의 자율주행이 필수적으로 이루어져야 하고, 이 때 보행자를 정확히 인지하는 것은 매우 중요한 과제이다. 보행자는 차량에 비해 크기가 작고, 이동방향에 일관성이 적으며, 신호정보와 같이 V2I 등의 통신기반 해결이 불가능하기 때문이다.

본 연구의 실험에 사용된 차량은 현대자동차 IONIQ EV를 사용하였다. 인지를 위하여 차량에 장착된 센서는 IBEO 사의 2-D 레이저스캐너 6개, 모빌아이사의 비전센서, AVM 카메라 등이 있다. 레이저스캐너로 장애물을 인지할 경우 장애물의 위치정보가 정확하여 차량이나

도로시설물 탐지 등에 우수한 성능을 보이나 장애물들 중 어떤 것이 분류하는 후처리 과정이 필요하며, 보행자의 경우 크기가 작아 가로수, 폴 등과의 구분에 있어 어려움이 있다. 비전센서의 경우 이미지 처리과정을 통하여 물체의 분류에는 뛰어난 성능을 보이나, 위치 오차가 다소 존재할 수 밖에 없고, 이로 인해 보행자의 움직임을 추정하기란 불가능하다.

본 연구에서는 두 센서의 단점을 보완하기 위해 센서융합 기법을 사용하였다. 본 차량의 센서 구성을 이용하여 인지하였을 때, 추정 등의 후처리 과정을 거치지 않은 단계에서 가장 정확한 데이터는 레이저 스캐너 데이터이므로, 레이저 스캐너로 인지된 장애물의 위치를 해당 단계에서의 참값으로 가정하였다. 이 후 장애물들 중 어떤 장애물이 보행자인지 분류하기 위하여, 비전 센서로 인지된 보행자와 가장 가까운 레이저 스캐너 장애물을 보행자 후보로 선정하였다. 이 때 비전센서의 종방향 오차가 횡방향 오차에 비해 상당히 크므로, 유클리드 거리 대신 마할라노비스 거리를 사용하여 매칭의 정확도를 향상시켰다. 본 차량은 0.1초마다 알고리즘이 반복적으로 돌아가므로 매 스텝마다 보행자 후보로 추정되는 장애물이 발생하게 되는데, 동일한 장애물이 반복하여 보행자 후보로 선정되면 해당 장애물은 보행자일 확률이 높다. 장애물이 동일한지를 확인하기 위하여 트랙을 만들어 관리하였고, 이 트랙의 정보에 신뢰도 정보를 추가함으로써 보행자후보로 선정된 횟수 등을 고려하도록 하였다. 마지막으로, 레이저 스캐너 데이터가 차량에서 인지할 수 있는 가장 정확한 위치정보이지만, 장애물의 실제 위치정보와는 아무리 작은 수준이라도 오차가 있다. 작은 위치오차라도 이를 이용해 속도를 추정하게 되면, 특히 보행자처럼 속력이 작고

방향이 자주 변하는 경우에는 오차가 증폭되게 된다. 이러한 현상을 최대한 줄이기 위하여 본 논문에서는 확장 칼만 필터를 사용하여 속도 추정의 정확도를 향상하도록 하였다.

본 연구에서의 알고리즘 개발 및 시뮬레이션은 MATLAB / Simulink를 사용하였으며, 자율주행 차량을 이용한 실차실험으로 데이터 수집 및 알고리즘 검증을 수행하였다.

**주요어:** 자율주행, 장애물 인지, 보행자 상태 추정, 센서 융합 알고리즘, 레이저 스캐너, 비전 센서

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