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Performance Analysis of Sensor Fusion Models for Brake Pedal in a Brake-by-Wire System

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***Abstract*—This paper focuses on analyzing the performance of sensor fusion models for a brake pedal in electromechanical braking (EMB) systems. To properly control a brake, a signal obtained from a pedal is important and must be stable. Sensor fusion models can be used to make the pedal signal more stable and resilient against the abnormalities. In this work, a pedal sensor and a pedal effort sensor are exploited for the sensor fusion to control the brake. Then, we analyze the performance of each fusion model (e.g., average method, moving average method, median filter, iterative filter, and Marzullo's algorithm) in various fault scenarios. We propose the hybrid method using multiple models to have the better resiliency and to detect the faulty sensor as well. For the practical experiments, we employ the real measurement data set obtained from a vehicle at different speeds. Then, its fused result is validated using EMB system test bench to confirm how the fused result influences on the motor of the brake.**

***Keywords*— electromechanical braking system; fault; fault detection; sensor fusion;**

I. Introduction

With the increasing demand for the driving safety, many technologies, such as antilock braking systems (ABS), electronic stability programs (EPS) and traction control systems (TCS), have been developed by many researchers and companies. Eventually, the trend of the development in the brake technology will progress towards "brake-by-wire" and this technology in a brake will be considered as an essential element for hybrid vehicles and electric vehicles as well [1], [2]. In general, "brake-by-wire" system could be categorized into two implementations: electrohydraulic braking (EHB) systems and electromechanical braking (EMB) systems.

In case of the EHB system, the current hydraulic brake fluid is still used for the braking system. It generates the hydraulic pressure for each wheel in accordance with the signal obtained from a brake pedal. However, using the hydraulic fluid brings disadvantages, such as the lack of longevity of hydraulic components, the need for additional devices, and the leakage of hydraulic oil. In contrast, the EMB system uses the electronic signal instead of the pressure of the fluid in order to convert its value to clamping force which controls a motor for each wheel. The advantages of using EMB system are the more accurate control of the braking force and the faster response using fast motor dynamics. Recently, EMB system has been developed by the well-known companies, such as Continental and Bosch [3], [4]. Since failures of the brake-by-wire system might cause a serious traffic accident, making the brake system fault tolerant is essential in terms of driver's safety. Fault detection and diagnosis, and more accurate control should be supported in the robust brake-by-wire systems. For recent works, Schwarz *et al.* have developed the method to estimate the clamping force of the disk brake [5], [6]. Hoseinnezhad *et al.* have studied on an accurate and robust method to estimate the position and speed of actuators using the resolver signal of a motor, and the automatic calibration of resolver parameters that are changed according to the temperature, pad wear, and aging has been developed [7], [8]. In addition, a hardware redundancy is employed in a brake-by-wire system to ensure fault-tolerant for the safety [9], [10] and the sensor fusion method for brake-by-wire has been developed by [11]. While most researches are mainly focused on the motor and actuator parts, the improvement of the safety by exploiting sensors redundancy for the brake pedal is also needed. In EMB systems, a pedal is equipped with sensors indicating the level of the brake force demanded by a driver. With the redundant information from multiple sensors and fusion techniques, the EBM system can be more fault tolerant and have the safer performance as well.

In order to have the resiliency to the bake-by-wire system for the safety of a driver, we investigate the sensor fusion models and conduct experiments with real measurement data and EMB test bench to confirm that the fusion model is well suitable for the bake-by-wire system. In this paper, based on the result of the sensor fusion performance, we propose the hybrid method using multiple models to have the better resiliency and to detect the faulty sensor as well.

To do this, Section II describes the brief explanation of EMB systems and a sensor fusion model. Then, in Section III, each sensor fusion model is elaborated to explain how it works. In Section IV, the case study shows the system architecture and the evaluation performance for sensor fusion models. Moreover, the hybrid method is introduced. Then, this paper is concluded with future works in Section V.

II. EMB System and Sensor Fusion Model

In this section, the basic idea of EMB systems and sensor fusion techniques are discussed for the better understand. With the hardware redundancy, the sensor fusion method can be used for a brake pedal in EMB systems. Sensor fusion techniques make the brake pedal more resilient against abnormalities.

A. Electromechanical Brake (EMB) Systems

EMB systems are already on the recent market for the electric park brake (EPB) and many companies have tried to develop EMB systems.

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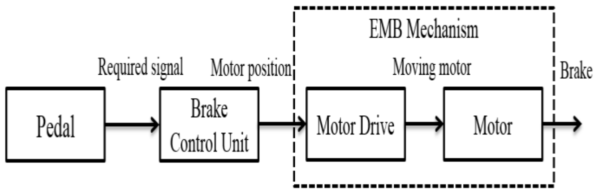


Fig. 1 General architecture of EMB systems.

The EMB system consists of a motor, a reduction gear, and a screw gear. It is basically similar to the existing brake systems except for using the hydraulic pressure. In Fig. 1, it shows the general architecture of EMB systems. A driver gives an electrical signal to a brake control unit (BCU) using sensors (e.g., pedal sensor). The required braking force is calculated in the BCU from the electrical signal. The calculated braking force is converted into the motor position and is transmitted to the motor driver to rotate the motor.

The motor position generates a clamping force between the pad and the disk, which offers the braking torque. In addition, the information (i.e., the electrical signal) of the percentage for the pedal position is broadcasted through controller area network (CAN) bus. Therefore, if the sensor signal is faulty, the control of braking is not stable, which could make the system in a catastrophic situation.

B. Sensor Fusion Techniques

In general, malicious attacks, severe faults, and external noise are considered as factors making the system unreliable. To address these factors, many researchers in various areas have studied on the effective sensor fusion method with multiple sensors [12], [13]. One important consideration is the sensor model to improve the accuracy of the value measured by a sensor since the resilient system suffered from unexpected conditions such as attacks, faults, environmental uncertainty is related to how well the system responds or adapts to those. In general, there are two main classes of sensor models: probabilistic and abstract [14]. In the case of the former, it uses pre-designed noise distributions (e.g., Gaussian) and provides the estimated value by calculating with the distributions. On the other hand, in the later, it could be based on the intervals that are determined by each sensor's measurement and the error bound, which doesn't assume any effect of the noise distribution. Therefore, it doesn't rely on the assumption compared to the probabilistic models. In this paper, we focus on the sensor fusion techniques that don't require system dynamics (i.e., estimate a value only using sensor measurements).

III. Sensor Fusion Model

In this section, we consider the system that has multiple sensors measuring the same physical value (e.g., the velocity measured by an encoder, IMU, and GPS), and describe how each sensor fusion model works. Among the sensor fusion methods, five models (naïve average model, moving average model, Marzullo model, median model, and iterative mode) are selected for this work. These all models estimate the optimal value by measurement date obtained from multiple sensor and don't require a system model (i.e., system dynamics).

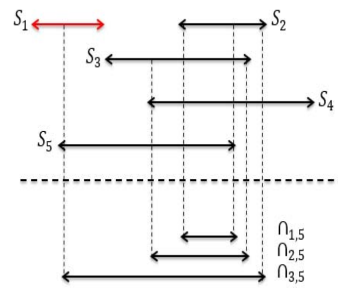


Fig. 2 Example of Interval-based fusion process.

A. Naïve Averaging Model

A naïve averaging model is the most general method to merge multiple values. Let s_i denote the i-th sensor among multiple sensors n and V_i the measurement value obtained from sensor s_i . Then $\hat{v}$ represents the estimated value, which is written as below.

$$\hat{v}_t = \frac{v_1+v_2+v_3 \cdots v_n}{n}, \quad (1)$$

where n is the number of sensors. If we assume that there is a malicious sensor s_k, who sends a different measurement, the estimated value $\hat{v}$ is significantly influenced by the malicious value. It is because that the range of the malicious sensor s_k is unlimited (i.e., $v_k \in (-\infty, \infty)$). Therefore, the naïve averaging method is not well fault-tolerant.

B. Moving Average Model

A moving average is used to analyze data by generating the series of averages of different subsets over time. The type of this method can be classified into three types: simple, cumulative, and weighted forms. With a series of numbers and a fixed subset size, the first element of moving average is calculated by taking the average of the initial fixed subset. Then, the subset is shifted forward to calculate the next element. Herein, the subset excludes the first number and includes the next number of the subset. This process is repeated over the entire data series. In general, the moving average is used with time series data to smooth out short-term fluctuations and find long-term trends. The simple moving average can be expressed as below.

$$\hat{v}_t = \frac{v_t+v_{t-1}+\cdots+v_{t-(n-1)}}{n}, \quad (2)$$

where $\hat{v}_t$ is the time series and represents the output, and n is the number of sensors in a given subset. v_t is the latest value and it is updated every time the subset is shifted forward. After calculating the first value, a new value comes into the sum. At that time, the oldest value is excluded. Using this method, the transient fault could be alleviated. It is because the estimated value is calculated with the time series of measured values.

C. Marzullo's Filter

Marzullo has proposed an interval based fault tolerant fusion method [15]. Each sensor makes its interval $[v_i - \epsilon, v_i + \epsilon]$ that is determined by the measurement value v_i and the error bound ϵ. For example, if the measured value is 7 and the error bound is 2, the internal can be represented as [5, 9]. Here, the error bound

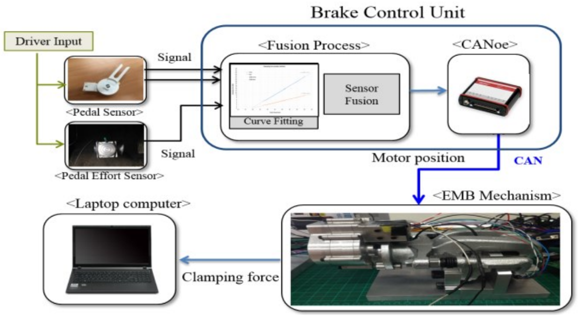


Fig. 3 EMB mechanism and the system architecture.

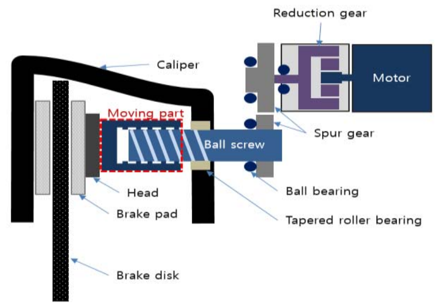


Fig. 4 Diagram of EMB mechanism.

can be obtained from the specification that a manufacturer provides. If the manufacturer doesn't provide it, the error bound can be calculated by the scheme [14]. Fig. 2 shows the example of interval based fusion process. The red interval represents the malicious measurement. The fused result is different according to $\cap_{f,n}$, where *f* is the number of faults and *n* is the total number of sensors. As shown in the Fig. 2, when the number of faults increases, the result interval becomes larger, where the length indicates the accuracy of the fused result

D. Median Filter

Median filtering is a nonlinear digital filtering and it is often used to remove noise/abnormalities (e.g., faults and attacks). The key idea of this filter is to use the median value among neighbors. For instance, let's consider the system that has several sensors $s_{i=1\cdots,n}$. We denote $X = \{x_1, \cdots, x_n\}$ the set of measured values from the sensors and $\hat{v}_t$ the estimated value (i.e., output). The equation for the median filter is expressed as below. With this method, the faulty value (even extreme value) can be removed.

$$\hat{v}_t = \begin{bmatrix} x_m, \ \ when\, n\, is\, odd\ \ and\ \ m = \left(\dfrac{n+1}{2}\right) \\ \dfrac{1}{2}(x_m + x_{m+1}), when\, n\, is\, even\, and\, m = \left(\dfrac{n}{2}\right) \end{bmatrix} \tag{3}$$

E. Iterative Filtering

Iterative filtering is one of the methods using the weighted average. By iterating the weight averaging calculation, the measured values are converged on one output. This method can be used for the secure data aggregation technique for wireless sensor networks in the presence of collusion attacks in [16]. Let's consider a system with multiple sensors $s_{i=1\cdots,n}$. Then, we also assume that the system works on one block of the measurement where each block comprises of the measured value at T consecutive instants. Therefore, a block of the measurement is represented as a matrix $X = \{x_i : i = 1, \cdots, n\}$ where $x_i = \{x_i^t : t = 1, \cdots, T\}$ is a sequence of readings obtained from sensor S_i.The gathered values are iteratively and simultaneously computed with a sequence of weights $w = \{w_1, w_2, \cdots, w_n\}$ which reflects the trusty measurements. The iterative process starts with the equal weight to all sensors (i.e., the initial weight = 1 to each sensor).

$$\hat{v}^{l+1} = \frac{X \cdot w^l}{\sum_{i=1}^{n} w_i^l} \tag{4}$$

where $\hat{v}$ is the estimated value and *l* is represented as the round of iteration ($l \geq 0$). From the second round, each sensor has the different weight that is calculated based on the distance from each sensor to the previous value calculated using weight averaging. This process is iteratively performed until the value is converged. The method to obtain the weight is explained in [15].

IV. Case Study

In this section, we introduce the experiment environment and compare each sensor fusion model in three fault scenarios: *1)a zero fault, 2)a biased fault, 3)a random fault*, by conducting a real-world case study using the real measurement data obtained from a vehicle and the EMB system bench. Besides, the issue of measuring the different physical variables between the pedal sensor and the pedal effort sensor is addressed through the curve fitting process.

A. System Description

Fig. 3 shows the system architecture used for this work. When a driver pushes a brake pedal (i.e., driver's input), three signals are obtained from a pedal sensor and a pedal effort sensor as shown in the figure. The pedal sensor provides two signals, which indicates a level of a pedal position and both signals show the same measurement (i.e., the redundancy). In the case of the pedal effort sensor, it gives one signal that is considered as the pressure force from a driver.

Since two sensors measure the different physical variables: *the level of the pedal position and the level of the pressure force*, the function based on the relationship between the pedal position and the pressure force is needed (i.e., curve fitting problem). Therefore, the signal of the pressure force is converted into the position of the pedal using the curve fitting function. Then, the sensor fusion process is performed using several sensor fusion models described in Section III.

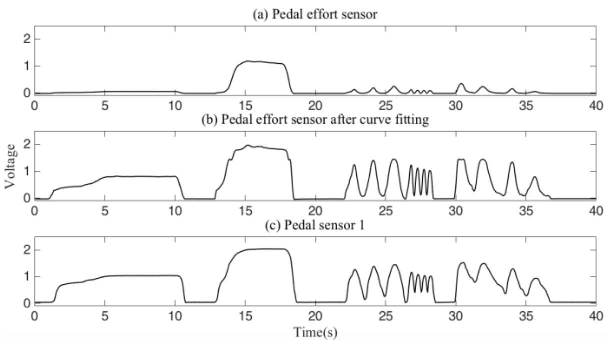


Fig. 5 Relationship between a pedal and a pedal effort sensor.

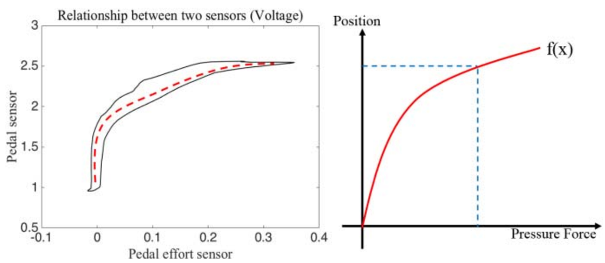


Fig. 6 Example plot of position against pressure force.

The fused result is broadcasted to main ECUs and BCUs through CAN bus using CANoe to control a motor of the EMB bench. This EMB bench shows how the fused results influence on a motor, a disk, and a pad in a brake system by measuring the clamping force measured by a load cell sensor. If the clamping force is higher than the normal state, it results in the sudden braking. In contrast, lower clamping force causes the long braking distance.

As shown in the diagram of the bench in Fig. 4, the EMB mechanism consists of several components, such as the reduction gear, the spur gear, the ball bearing and so on. The reduction gear decreases the revolution speed of a motor to increase the enough torque for the movement of the motor. The spur gear is used to transfer the power to the under gear. By moving the ball screw forward/backward, the head pushes the brake pads to grab the brake disk. The detailed specifications for each component, such as the name of the model and the gear ratio are summarized in Table I.

TABLE I. SPECIFICATIONS FOR EMB COMPONENTS

Component Name	Specification (Manufacturer)
Motor	EC-4Pole 30 model (Maxon)
Reduction Gear	Planetary Gearhead GP 32 HP model 86:1 Ratio
Spur Gear	Hand Crafted Gear model 1:1 Ratio
Ball Screw	Single cylinder nuts model (BLIS) Diameter : 32mm, Lead 5mm
Bearing	NSK 6800 model (NSK)

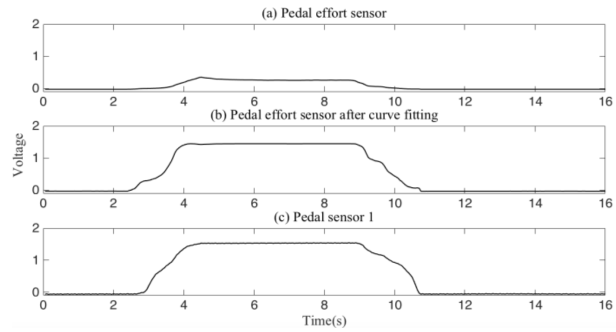


Fig. 7 Further evaluation of the curve fitting process.

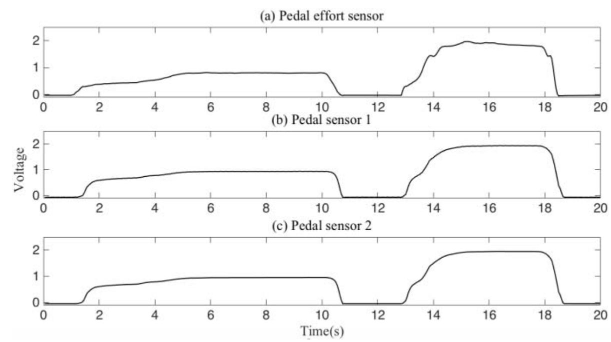


Fig. 8 Three sensor signals.

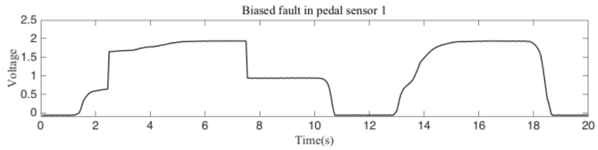
B. Curve Fitting Process

As mentioned in the previous subsection, the pedal sensor measures the level of the pedal position and the pedal effort sensor provides the measurement of the pressure force when a driver pushes a pedal. Fig. 5 represents the difference between the pedal sensor and the pedal effort sensor. As shown in Fig 5(a) and (c), when a driver slightly presses a pedal (after 20 seconds), the difference between two sensors is obvious. It is because each sensor measures difference physical variables. Therefore, the process to convert the pressure force measured from the pedal effort sensor into the level of the pedal position is needed. Therefore, we address this issue using the curve fitting method.

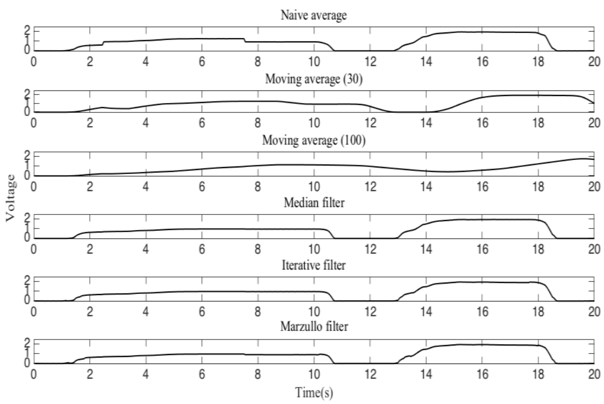
The first thing to do this process is to find the relationship between two sensors. The left figure in Fig.6 shows the relationship between the pedal effort and the pedal sensor. Based on the relationship, the virtual curve that indicates the relationship of two sensors is determined. The right figure shows the example plot of the process, where x axis represents the pressure force and the y axis is the position of a pedal. Using the curve fitting process, the physical value of the pressure force is converted to the level of the position. Herein, the polynomial and the parameters used for this process are expressed as below.

$$\mathrm{f}(\mathrm{x}) = p1x^5 + p2x^4 + p3x^3 + p4x^2 + p5x + p6 \quad (5)$$

where the function is the fifth-order equation and parameters *p1, p2, p3, p4, p5* and *p6* are 23.53, -79, 97.81, -55.27, 13.5 and 0.2217 respectively.

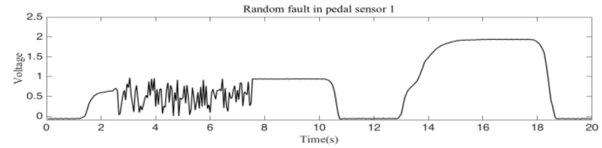


(a)

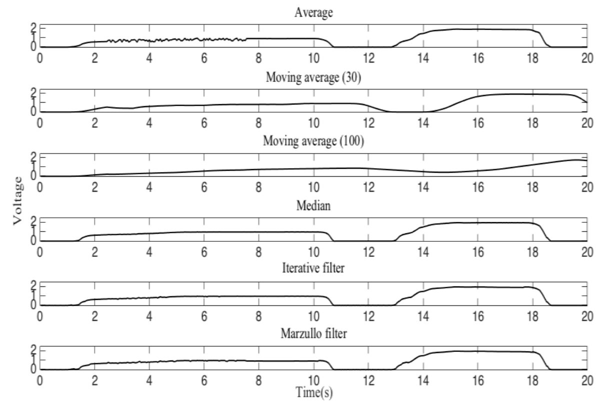


(b)

Fig. 9 Result of sensor fusion in zero value fault.



(a)



(b)

Fig. 10 Result of sensor fusion in random value fault.

Fig. 5(b) shows the result of the curve fitting process. In this figure, we can see that after curve fitting process, the signal of the pedal effort sensor has a more similar pattern to the signal of the pedal sensor. Therefore, the sensor fusion can be performed. To provide a more thorough result, another data is employed for the curve fitting process using the same function. As shown in Fig. 7, the result shows that the obtained curve fitting function is properly working well for other real measurement data sets as well.

C. . Performance Evaluation: Sensor fusion

In this section, we evaluate the performance of each fusion model to find the well-suited fusion technique for the EMB system. Five models described in Section III are used for the experiments with several fault scenarios. Fig. 8 shows each signal of sensors for the sensor fusion. Fig 8(a) is the pedal effort sensor value after the curve fitting and other two figures represent the value of the pedal sensor. Each sensor value is sampled with 20Hz. We first conduct the experiment of the sensor fusion without faults (i.e., normal operation). It is found that all of the sensor fusion methods show the similar results in the normal operation. To evaluate the performance of each model in the fault situation, we consider three fault scenarios.

- One of three signals provides the zero value
- One of three signals provides the biased value
- One of three signals provides the random value

Herein, we also assume that among three signals, only one of three signals provides faulty measurement. The first experiment is the scenario of the zero value fault. Among three signals, one of pedal signals (i.e., pedal sensor 1) provides zero value. In this fault scenario, it is shown that the average method is slightly influenced by the fault unlike other methods. For the more evaluation, the biased value (magnitude: 1) is inserted (from time 2.5s to 7.5s) in the pedal sensor 1 as shown in Fig. 9. The magnitude of the fault is decided to be roughly as large as the size of the half of the maximum value of sensors. The result shows that only average method is significantly influenced the biased value. Other methods remove the effect of the fault. Herein, it is confirmed again that the average method is not well fault-tolerant.

Lastly, we evaluate the fusion models with the random fault (i.e., uniformed distribution, magnitude: 1). In the Fig. 10, the result shows that the random fault influences on the signal more than other faults. However, except for the average method, all of other models significantly reduce the effect of the random fault. In the case of the average method, it shows the unstable fused values in the time where the fault is present. Table II summarizes the result of the performance of each method, which is analyzed using the Root Mean Square Error (RMSE). The RMSE value represents the difference between the fused results with faults and the fused results without any faults (i.e., normal operation). Therefore, the smaller value indicates the less effect of the faults. Each table shows different fault scenarios for both sensors.

To summary, the effect of the random fault is more influential than other fault types. In all fault scenarios, the average method is obviously not resilient against faults. It leads the system to the unstable and malfunctioning state, which could cause the catastrophic accidents. In the case of the moving average, it shows the better resiliency against the faults than the average method. However, it is still influenced by faults. In addition, the moving average method has the better performance if the window size increases. The iterative filter is resilient in all fault scenarios, but when the malicious value is too extreme, it takes time to converge the optimal value.

TABLE II. VALUE OF RMSE FOR EACH METHOD

(a) RMSE value in case of the pedal effort sensor failure

Method (window size)	Root Mean Square Error (RMSE)		
	Zero Fault	Biased Fault	Random Fault
Naïve Average	0.1149	0.1676	0.0643
Moving Average (30)	0.1095	0.1591	0.0377
Moving Average (100)	0.0931	0.1374	0.0257
Median Filter	0.0031	0.0072	0.0028
Iterative Filter	0.0215	0.0192	0.012
Marzullo Filter	0.0236	0.0298	0.0241

(b) RMSE value in case of the pedal sensor failure

Method (window size)	Root Mean Square Error (RMSE)		
	Zero Fault	Biased Fault	Random Fault
Naïve Average	0.1420	0.1771	0.0740
Moving Average (30)	0.1107	0.1915	0.0454
Moving Average (100)	0.0862	0.1699	0.0450
Median Filter	0.0092	0.0087	0.0074
Iterative Filter	0.0521	0.0314	0.0271
Marzullo Filter	0.0788	0.0433	0.0609

Lastly, the median method and Marzullo filter show the similar performance. Unlike other methods, these two methods remove the extreme value using its own scheme (i.e., the median value and the overlapped interval). Besides, compared to median filter, Marzullo filter can identify which sensor has the malicious faults [16], but this method needs the additional information (i.e., error bound) or the preprocessing process [14] to obtain the error bound for determining intervals. Based on the result of the sensor fusion, the median and Marzullo model are selected for the hybrid sensor fusion in order to have the better resiliency and to detect the faulty sensor as well.

D. Hybrid method using Median and Marzullo model

In the result of the performance evaluation for sensor fusion models, it is found that the median filtering has the better performance than other models. However, even though the effect of the faults is discarded using sensor fusion models, it is also important to note the faults happen in the system for the potential dangers. Among the fusion models used in the work, Marzullo's algorithm is able to detect faults present in the system. Marzullo model uses the intervals to check whether the faulty sensor exists in the system or not. If there is the interval which is not overlapped with any other intervals, this interval is considered as the faulty measurement. Therefore, by using the median filter and Marzullo's algorithm, we can benefit from both then. Fig. 11 shows the architecture of the hybrid method using the median and Marzullo model. From the multiple sensors measuring the same physical value, the measured values are used as the input for both models. In the hybrid method, the median model generates its own sensor fusion value and the Marzullo's model runs parallel with the median filter to determine whether the fault exists in the system or not.

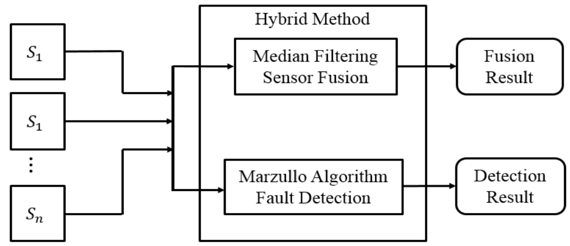


Fig 11. Architecture of Hybrid method.

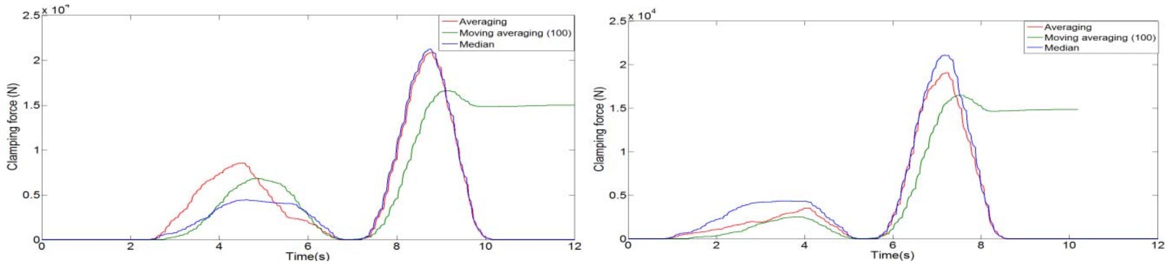
E. Motor control using CANoe

CANoe is the simulator to make virtual ECUs and broadcasts messages on CAN bus. With this simulator, VN1630 [17] device is used in order to control the motor of the EBM system bench in our work. As briefly described in subsection A, the fused signal is converted into the percentage that indicates the position of the pedal. For instance, when a driver fully steps on a brake pedal, the percentage indicates 100%. We first make the virtual ECU to use CAPL function in CANoe, which is our developed program to read the fused result file and make the CAN message based on the fused result. When constructing the message, the information of CAN ID and the transmission period are required. In our work, the CAN ID is set as 0Xf1 and the message is broadcasted with the 10 ms period for the EMB system bench. The constructed virtual ECU is connected to the main ECU (i.e., hardware) to control the motor via VN1630 device. In accordance with the message, the motor moves and the load cell sensor measures the pressure between the disk and pads, which is called the clamping force.

F. Performance Evaluation: Clamping force

Based on the results of subjection C, the evaluation for the clamping force is conducted to see how the malicious fused results influence on the motor using the EMB bench. The EMB bench used in this work is for the front wheel of a vehicle. For this experiment, we only choose the three of fusion models (i.e.., naïve average, moving average, and median filter). It is because that the naïve average and the median shows the worst and best performance among others and the moving average has the delay that other methods do not have.

Fig. 12 shows the result of experiments. Each line represents the clamping force measured by the load cell sensor and the different color indicates each method of the fusion model. The measured clamping force represents the pressure to grip the disk by pads. In the case of the naïve average, it is found that due to the biased signal, the clamping force suddenly increases between 2 s to 6 s. In contrast, the random fault causes the clamping force to decrease (1s to 5s) unlike the biased attack. Since the motor repeatedly moves forward and backward with the fast speed, the motor can't generate the enough clamping force. The result of moving average shows that even though it reduces the effect of the biased faults, the clamping force in the random fault is lower than even the naïve averaging method. In addition, moving average makes the delay because the output value is calculated



(a) Biased fault scenario

(b) Random fault scenario.

Fig 12. Result of measuring clamping force using EMB test bench.

using the average of values in a given window size. Therefore, if the window size is too large, it can't directly reflect the intention of a driver, which couldn't be well suited for the brake system. Lastly, the median filter almost removes the effect of the biased and random faults and shows the most similar result to the normal operation.

V. Conclusion

In this paper, in order to design the sensor fusion model having the better resiliency and the capability to detect faulty sensors for the brake pedal in EMB system, we analyze the performance of several sensor fusion models. The fault tolerant model in the brake system is imperative for the safety of a driver. The system uses the pedal and the pedal effort sensor to measure the intention of a driver. However, since both sensors measure the different physical value, the process to convert into the same value is needed, which is called the curve fitting. After the process of curve fitting, the sensor fusion is performed in several faults scenarios. In the result, the naïve average method shows that it is significantly influenced by all of faults compared to other methods. The moving average reduces the effect of faults, but since this method uses the average of values in a given window size as output, it causes the delay and can't directly reflect the intent of a driver. This delay could cause to increase the braking distance, which might not be well suited for the braking system. Based on the result of the sensor fusion, we propose the hybrid sensor fusion method using both the median and the Marzullo model to benefit from both. The proposed method provides the stable estimated value and detects the faulty sensor as well under the fault situation.

For a more practical evaluation, with the results of the sensor fusion, we conduct the experiment using EMB bench to know how the fused result influences on the motor. The result shows that the median has the most similar clamping force to the normal compared to others. Also, it is found that the biased fault causes to increase the clamping force while the random fault results in decreasing the clamping force. The inappropriate clamping force causes in the sudden braking or the long braking distance. For our future work, we plan to model the EMB bench and develop the model based fault diagnosis system. Therefore, even though the faults occur in the system, the system can detect the fault and reconfigure the system to accommodate the faults.

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