Vehicle Driver Interaction using EMG Signal Analysis

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Abstract

In this paper, we present an EMG signal analysis and classification technique for hand gesture recognition specialized for autonomous vehicle environments. In addition, we propose a new user interface method that considers the bio signals received from wearable devices and the characteristics of self-driving cars. EMG is an electrical property produced to command the contraction and relaxation of muscle tissue. The medical surface EMG sensor mounted on the MYO armband used in the experiment transmits EMG signals and sensor information wirelessly from the arm to the terminal via Bluetooth. The EMG-based interaction system proposed in this paper processes the collected EMG signals to classify hand gestures and interacts with the autonomous driving system. Gestures for control transfer are classified in a double threshold method through EMG signal analysis and used as a more efficient interface by applying a separate low pass filter. This EMG-vehicle interaction system was developed to enable control of an autonomous vehicle through a system capable of controlling an autonomous vehicle. In addition, we introduce constraints and methods using vehicle state information to reduce gesture recognition errors that may occur in situations unintended by the driver.

Keywords
EMG sensor, wearable devices, EMG-vehicle interaction, autonomous vehicle and Data Augmentation.

1. Introduction
1.1 Purpose of the Study
With the recent increase in self-driving cars, human error, which is the biggest cause of traffic accidents, can be greatly reduced, reducing the accident rate. On the other hand, drivers who will use self-driving cars expect to have a new experience in the vehicle space as the operation for driving is greatly reduced.

The development of high-speed mobile communication can be fully utilized as V2X communication, and a car connected to a computer network can provide more infotainment technology to drivers and passengers. Connected Car, which provides various information services by receiving various accident information, road conditions and parking space information through the Internet, is a technology with high utilization as a road safety and driving assistance device. The spread and development of such wireless mobile high-speed communication can greatly change the existing infotainment system that occupants can experience in a vehicle.

According to the classification and definition of autonomous driving systems by the Society of Automotive Engineers (SAE), an association of automotive engineers, autonomous vehicle technology can be divided into five levels. Currently, vehicles that consumers can purchase are driving assistance systems corresponding to the second level of the autonomous driving system. Level 3 of the autonomous driving system defines that autonomous driving is possible under the condition that the system responds when the driver is asked to drive. Therefore, the driver and the autonomous driving system must cooperate to drive, and in this situation, the transfer of the driving control right between the driver and the autonomous driving system inevitably occurs. However, the interface between the vehicle and the driver through the existing method has a problem of intuition when the driver transfers the control right to the autonomous driving system. According to research by NHTSA (National Highway Traffic Safety Administration, 2000), from controlling secondary equipment used while driving (radio, navigation, interior light, etc.) etc.) can decrease the driver's concentration and increase the risk of an accident (Ranney et al. 2000). When the transition from the autonomous driving system (auto-pilot) to the driver is required, the autonomous driving system requests the driver in advance within the driving range or secures control time for safe braking of the vehicle at all times. Vehicle control is possible in the section. On the other hand, in a situation where the driving control right is transferred from the driver to the autonomous driving system, the existing method of using external buttons or sensors causes carelessness and makes it difficult to secure safety in driving. In this paper, we present a more intuitive and novel gesture recognition concept and method using EMG for safe transfer of driving control.

1.2 Analysis Methods using EMG

The academic world has continued research in various ways to analyze and utilize EMG signals. One of them is a method using Wavelet Transform. Reaz et al. (2006), Wavelet Transform is an appropriate method for analyzing signals of irregular waves such as EMG. Fang et al. 1997 developed a technique to classify signals estimated as SMU (Single Motor Unit) signals from EMG signals measured on the surface using Wavelet Transform. The SMU signal referred to in this research paper refers to the EMG signal generated from a single unit of muscle fiber. In addition, EMG signal analysis methods using various artificial intelligence have been studied. Putnam et al. (1993) experimented with moving a slider in a GUI environment through an artificial neural network using EMG signals. In addition, GUI elements such as the Pull Down menu or List Box of the Windows computing environment were intuitively controlled through this. Del et al. (1994) expressed the degree of contraction and relaxation of the desired muscle through Fuzzy c-menas (FCM) after finding feature points through Fourier analysis. In particular, in this study, noise, not EMG signals generated from muscle contraction and relaxation, was separately classified.

1.3 Vehicle-Driver Interface

1.3.1 Operation and Safety of the Infotainment System

Similar to wearable devices, high-performance computing systems are being used in the recent automotive industry to develop more fancy infotainment due to low-power design and miniaturization of components. A high-level infotainment system requires a more complex and systematic operation than the existing in-vehicle audio system. However, secondary manipulation while driving greatly increases the risk of a traffic accident because it distracts the driver's gaze and attention. According to traffic accident statistics, it can be seen that the accident rate increased after DMB became available to receive terrestrial digital broadcasting in vehicles.

1.3.2 Vehicle-Human Interface Trends and Prospects

Recently, the IT industry has been scrambling to spread the vehicle platform as shown in Figure 1. Recently, vehicle platforms created by IT companies include Apple's Carplay, Google's Android Auto, and Microsoft's Windows Embedded Automotive. In the case of Microsoft, it has been widely used as an infotainment platform using Windows CE. Recently, with the spread of smartphones, it is evolving into a connected car that is connected to a vehicle platform and network. The evolution of the in-vehicle infotainment system has had a great impact on the driver-vehicle interface (Chris 2014) (Google 2014) (Tua 2016) (Wminer 2015)

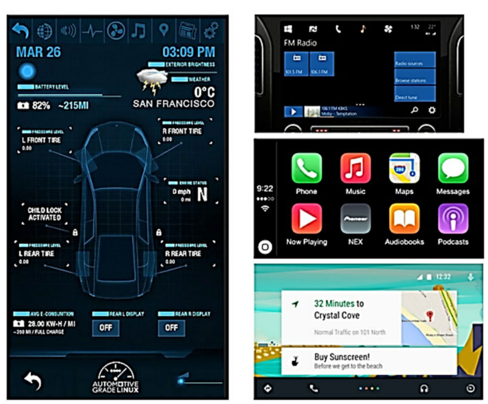


Figure 1. Various in-vehicle infotainment systems

Operation through a touch interface is also increasing in a vehicle infotainment system developed according to the concept of a smartphone developed based on a touch screen. BMW, which used to focus on the jog dial and button type for operational stability while driving, is also providing a touch-based interface to recently released high-end vehicle models and an interface that controls the infotainment system through vision-based hand gesture recognition. According to a study by BMW and the University of Munich, gesture-based interfaces in vehicles show superior results to other methods for driver's gaze dispersion (Pickering 2005). Jæger et al. (2008) studied the difference in driver's gaze dispersion when a tactile button-type interface, touch interface, and gesture interface were used to control secondary equipment in a vehicle, and as a result, gestures caused the least gaze dispersion. concluded to occur. The gesture interface they used was designed to be perceived only in a specific space inside the vehicle, so the driver was slightly distracted to check the perceived space.

1.3.3 Wearable Devices, Drivers and V2X

There are also cases in which vehicle driver carelessness has occurred due to the appearance of wearable devices. Google Glass, a wearable computer, is worn on glasses, has sensors such as GPS, camera, and microphone, and carries out user commands through voice. Through the data of these sensors and internet connection, functions such as LBS service or augmented reality are supported. However, it was judged that this type of wearable computer caused the driver's visual inattention, and 8 states in the United States tried to legally restrict the use of Google Glass while driving, but all were rejected (Gershowitz 2014). As a wearable device, the most common released product is a smart watch. Smartwatches are rapidly expanding their market and are being launched with sensors that can recognize more and more biometric information (Rawassizadeh et al. 2015). In addition, Microsoft and IAV are developing an ADAS system that warns drivers of vehicles driving around intersections by exchanging location information of pedestrians with wearables and smartphones through the network through the development of V2X technology. (IAV 2016).

1.3.4 Various Interfaces Through the Steering Wheel

As the infotainment system of a vehicle develops, the steering wheel interface designed not to interfere with the driver's driving has also evolved. Most recently produced vehicles have a button-type interface mounted on a steering wheel to enable operation of various devices while driving. Through this, secondary control such as navigation, radio, and mobile phone installed in the vehicle, as well as ADAS technologies such as ACC (Adaptive Cruise Control) and OBC (On Board Computer) control are possible. Recently, a button-type input method has been further developed to utilize a touch interface or gesture. Gesture Recognition Steering helps you control the vehicle according to the situation by using various gestures with your thumb. This human-friendly interface is not only more intuitive than the existing button method, but also enables many types of functions to be performed (Continental 2016).

Volvo unveiled a method using paddle shifts as an interface for self-driving cars on highways to be released in the future. The vehicle is a self-driving car at SAE level 4, and is equipped with a new interface that presses and holds the paddle shift on both sides to transition between autonomous driving mode and driver driving mode. In addition, even if autonomous driving is not possible, the driver can safely stop the car on the shoulder of the road or in a temporary parking space, unless the control of the vehicle is transferred to the driver.

In the case of a button attached to the steering wheel or a touch type interface, quick input is possible when the driver's hand is holding the steering wheel. However, if the autonomous vehicle's system is controlling the steering wheel, it is difficult to use the buttons on the rotating steering wheel in this situation because the driver is not concentrating on driving.

1.3.5 Vision-based Gesture Recognition

Gesture recognition solutions through vision are more common than gesture recognition through EMG. Representative sensor devices include Kinect, Leap Motion, and HoloLens. The Kinect is a device originally created to capture the player's motion on the gaming platform, the Xbox. However, it has an RGBD sensor (equipment that measures RGB images and depth D) with relatively good performance compared to its low price, so this equipment is used in many studies. This equipment measures the depth of an object by projecting a special pattern of infrared rays and analyzing the pattern through an infrared image sensor (Albitar 2007). LeapMotion is a device that tracks the user's hand in a three-dimensional structure using a patternless infrared light source and a high-speed image camera that shoots at 200 Hz (Weichert et al. 2013). Unlike Kinect, since it was developed for hand gesture recognition, it operates at a relatively short distance, but has high resolution and accuracy. However, since both devices are vision-based hand tracking systems using infrared rays, they show accurate reliability only indoors. Therefore, there are several problems in using it in a vehicle environment. First, these vision-based devices are difficult to use during daytime driving because of the infrared rays that shine into the vehicle's interior. Since the inside of a vehicle creates various environments depending on the direction of the vehicle and direct sunlight, there are many environmental vulnerabilities in recognizing gestures with vision-based equipment. Second, due to the spatial characteristics of the interior of the vehicle, the area that the vision-based sensor can recognize is limited. Therefore, in the case of recognizing through a vision sensor, gesture recognition is usually only possible in a specific area inside the vehicle, making it less accessible as an interface.

2. Body

2.1 System Configuration

2.1.1 Autonomous Vehicle System

For the experiment of this study, each autonomous driving system module installed in the autonomous vehicle is connected through the ROS (Robot Operating System) framework as shown in Figure 2, and each state information is synchronized and exchanged. The vehicle is equipped with modules that can control the vehicle and determine the driving path and state of the vehicle, and autonomous driving is possible through cooperation between these software modules. The EMG gesture recognition module for transferring the control right between the driver state recognition system and the autonomous driving system creates a separate TCP connection to exchange driver state result information and gesture recognition result information through the TCP server.

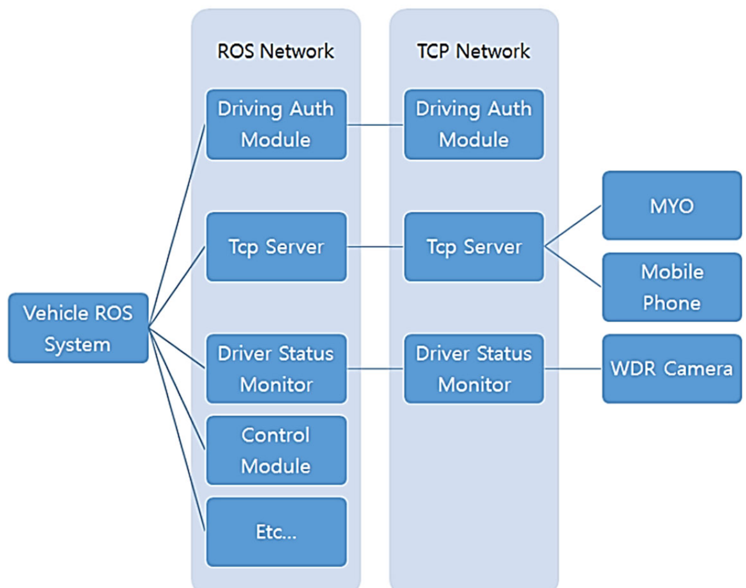


Figure 2. System configuration diagram of the self-driving car used in the experiment

The TCP server analyzes the data collected through ROS and first checks whether it falls within the range of constraints by the current vehicle information, and according to the result, the recognized gesture command is delivered to the driving control right transfer system or ignored. In addition, through other smart phone applications or smart watches connected through TCP, the driver or a passenger can be warned. The self-driving car used in the experiment is equipped with various sensors as shown in Figure 3 to enable complete self-driving, and performs self-driving functions through an industrial computer system operating at 24V. Vehicles are generally built on SUV models released to consumers (Park et al. 2015).

Figure 3. Sensor configuration diagram of the self-driving car used in the experiment

2.1.2 Driver Condition Recognition System

The autonomous driving system vehicle used in the experiment is equipped with a driver condition recognition system that checks the driver's condition. The driver condition recognition system uses a combination of an infrared light source, a band-pass filter that passes only light of a specific amplitude, and a wide dynamic range camera sensor to show robust detection results even in dynamic vehicle interior conditions as shown in Figure 4. The driver state recognition system finds the user's face and detects parts of the face, such as eyes, pupils, nose and mouth, and detects where the driver is looking and whether his or her eyes are closed to determine the overall driver's condition. In particular, when determining gaze dispersion, a three-dimensional model is created using feature points such as the corners of the eyes, the tail of the mouth, and the nose of the driver to estimate the head posture. The estimated result compensates for the detected pupil position so that the degree of driver's gaze dispersion can be more accurately identified. The driver state recognition system scores the information identified in this way based on the frame counter and divides the level into points for drowsiness and distraction. If it is determined that the driver's condition confirmed through vision is at the stage of an inability to drive, the system recommends the driver to change to autonomous driving mode.

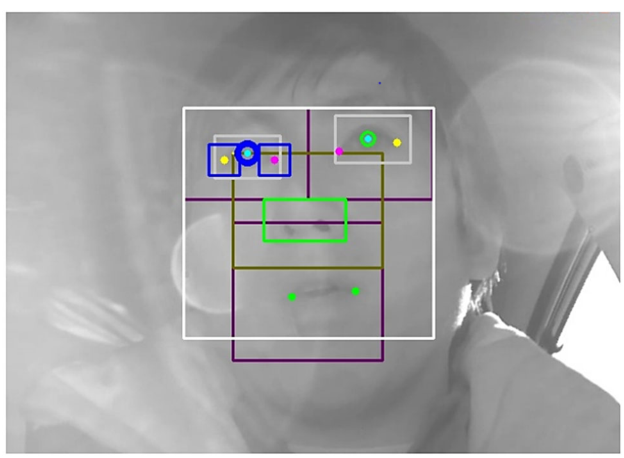


Figure 4. Driver Condition Recognition System Results

An incapacitating situation refers to a situation in which a driver is dozing off while driving or distracted while performing other activities. In this paper, we analyzed the degree of distraction of the driver when the driver changes control of the self-driving car through the information on the gaze dispersion detected by this system.

2.2 EMG Gesture Recognition in Vehicle

2.2.1 EMG-based Gesture Recognition

In order to analyze EMG signals, a utility that can separately collect EMG signals was created. All developed utilities are made using C# and Win-dowsForm, run on Windows operating system and require .NET framework. A total of 16 EMG signals from up to 2 Myo armbands and 8 EMG sensors on both arms are recorded in real time and displayed in graphs. OxyPlot, an open source graph library for drawing graphs, was used. In addition, at the same time, images can be saved together through a PC camera connected to the PC. Using the utility developed in this way, it was possible to collect EMG signals from 10 drivers while driving an experimental self-driving vehicle at a driving test site several times. Based on the EMG signals collected in this way, it was possible to find an appropriate classification method and a method of using the signals through analysis and experimentation. The EMG recognition system developed through this study receives 8-byte EMG signal values from the Myo armband through low power Bluetooth communication. One byte represents one sensor value and can be expressed as a signed integer. And this armband samples the sensor value at a rate of 200Hz and sends it to you. When looking at the sampled EMG signal, it takes the form of irregular vibration. To deal with this, first, samples recently received from each EMG sensor are collected and a standard deviation as shown in Equation (2.1) is obtained. The standard deviation value obtained in this way becomes the most basic data for distinguishing gestures. In the formula, Et means the collected n EMG sensor values, and the deviation of the xth sensor obtained in this way is defined as Emgx. The average value μ used to obtain the standard deviation was replaced with 0.

$$Emg_x = \sqrt{\frac{\sum_{t=1}^{n}(E_t - \mu)^2}{n}} \quad (\mu = 0) \tag{2.1}$$

In the system developed in this paper, each gesture was classified by applying the DoubleThreshold as shown in Equation (2.2) below to the 8 Emgxs calculated in this way. However, for a more flexible recognition rate, the calculated 8 EMGx values are normalized before applying the Double Threshold algorithm. The normalized value reduces erroneous recognition due to the difference in the degree of force applied when performing a gesture. If the calculated value stays within the set minimum and maximum threshold values, the corresponding gesture is identified. However, when a gesture is performed, the analyzed value is not always maintained and often vibrates, so an additional filter is applied to implement accurate and stable interface input.

$$Act(x) = \begin{cases} 1 & th_{low} \leq Emg_x \leq th_{max} \\ 0 & th_{low} < Emg_x \text{ or } Emg_x > th_{max} \end{cases} \tag{2.2}$$

Since the separated driver's gesture result is a result that occurs at a speed of 200Hz, the problem of chattering of the result value had to be solved. To this end, an additional time-based LowPass filter was applied to more clearly distinguish the results. When the number of gestures detected by the system exceeds a set number of times for a certain period of time, it is recognized as a performed gesture and an event is generated.

3. Experiments and Analysis

3.1 Experiment Environment

Experiments were conducted using various systems according to the experimental location. In the case of the indoor experiment, the experiment was conducted on a desktop computer without considering the vehicle environment. The pure gesture recognition experiment, which does not require connection with the vehicle system, was conducted indoors. When conducting an experiment similar to the vehicle environment or in connection with an actual test vehicle, the experiment was conducted using two mobile computer systems depending on the situation.

Myo, which measures EMG signals from the driver's arm, is a wearable device that uses a low-power, low-clock ARM series CPU, and a communication module that transmits and receives EMG signals and control signals also uses Bluetooth LowEnergy technology.

If an experiment using an actual test vehicle is necessary, the experiment was conducted on two driving test tracks according to the driving speed. The gaze dispersion that appears during low-speed driving has different characteristics, so it was tested separately. When testing rotation at low speed and intersection, the experiment was conducted at the vehicle-road linkage test intersection of the Intelligent Automobile Parts Promotion Agency. The road is configured like the road of a real-life city intersection. It consists of a section where straight driving is possible and a section where rotation is possible at high speed. In case the vehicle has to drive at a speed of 60 km/h or higher due to the test procedure, the experiment was conducted in the high-speed driving circuit.

3.2 Experimental Procedures and Methods

The experiment was largely divided into two parts (gesture recognition through EMG, scenario performance data collection and analysis during low-speed driving). First, for gesture recognition, four types of gestures were analyzed in advance and the recognition rate was tested when performing them. When measuring the recognition rate for gesture recognition, the experiment was conducted only with the result of DoubleThreshold without applying the LowPass filter. First, four types of gestures were performed five times each to record the EMG signals in advance, and then the EMG signals were analyzed using the method presented in this paper to set critical regions for each cell. The four motions consist of opening the hand, clenching a fist, and bending the wrist to the left and right as shown in Figure 5.

Figure 5. Four types of gestures used in the experiment

These four types of gestures are the same as those of the classifier provided by default in Myo. All detections were classified using 25 samples corresponding to 250 ms. In order to determine the ground truth on the collected data, the recorded images were visually compared, and the beginning and end of each gesture were recorded separately. Second, a scenario-based test was conducted while driving at low speed. When the driver's condition recognition system recognizes the driver's closed eyes and recommends switching to autonomous driving mode, the process of transitioning the vehicle to autonomous driving mode using gestures through electromyography was recorded and experimented with by recording data. Using a vehicle equipped with an autonomous driving system, driving and experiments were conducted in the straight section and intersection section of the ITS test driving route of the Intelligent Automobile Parts Promotion Agency. In the simple transition experiment, the driver touched the mobile phone or operated the navigation system in the autonomous driving mode, and the transition was performed 2 to 3 times according to the system recommendation. In addition, the driver was instructed to make a P-turn using the intersection of the ITS test driving route to find out whether an unintended transfer of control occurred by instructing the driver to turn left or right at the intersection, and it was confirmed by video that there was no misrecognition during the complex operation. Third, while driving at 60Km/h or more on a high-speed road, instruct the experimenter to generate control transfer of the self-driving car at any time by using gestures through EMG or by using general buttons, and at the same time measure the frequency of gaze dispersion and the transition time did Vehicle information, inertial navigation system information, and driver status recognition information were collected while rotating the high-speed main circuit of the Intelligent Automobile Parts Promotion Agency using a vehicle equipped with an actual experimental autonomous driving system. In order to test control full-duplex gaze dispersion, data were collected by repeatedly transferring control while driving at 60 km/h and 80 km/h. In addition, when a lane warning occurs after inducing lane departure while driving at high speed, the driver transfers the control right to the driver and then collects data on the behavior of returning to the lane.

3.3 Gesture Recognition Experimental Results and Analysis

To observe the recognition rate of the gesture recognition system, four types of gestures were performed 5 times each and EMG signals were recorded and charted as shown in Figure 6.

Ground marked with a + character indicates the beginning and end of the gesture confirmed by the video, and Detected marked with a × symbol is the result of the gesture recognized through EMG.

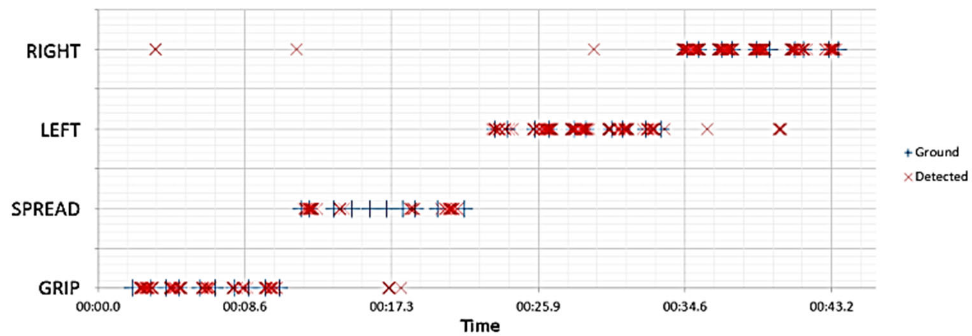
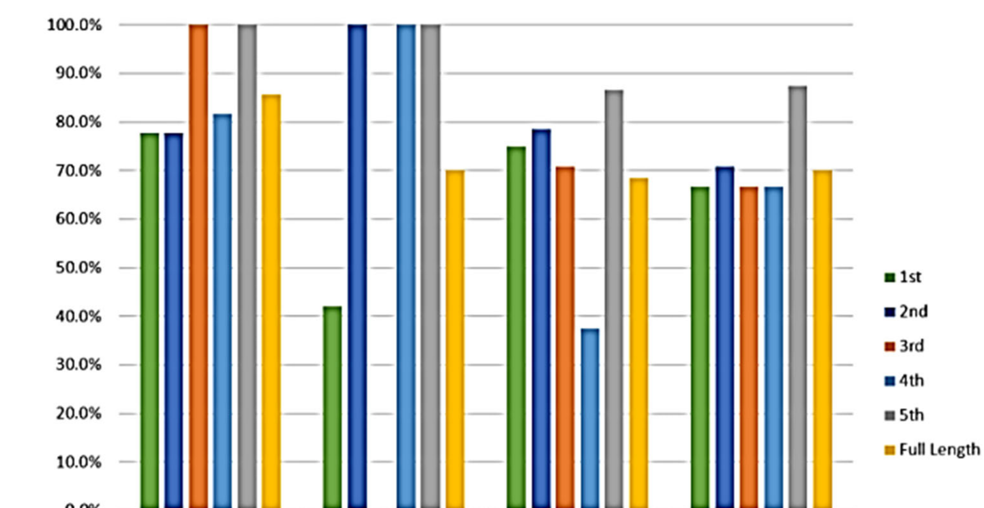


Figure 6. Graph showing clipped areas and detected gestures

GRIP is the action of clenching a fist, SPREAD is the action of opening the palm, and LEFT and RIGHT are the actions of bending the wrist to the left and right, respectively. In the case of spread on the chart, the false recognition rate and misrecognition were relatively high. In particular, it was incorrectly recognized as GRIP around 00:17.3 seconds, but 5 detection results appeared, and 14 results were displayed on average in the correctly recognized results. In the case of the spread motion, it is judged that it shows the most complex EMG pattern as can be compared in the figure.

The false-positive ratio for the actually measured overall recognition rate is about 27.31%, but this figure becomes meaningless when a low pass filter based on time is used. Since most of the false detections are confirmed to be near the ground truth area, this seems to be due to the synchronization between the image and the EMG signal and the characteristics of the gesture, which are difficult to distinguish with the naked eye. Figure 7 is a graph showing the reliability measured for each interval.



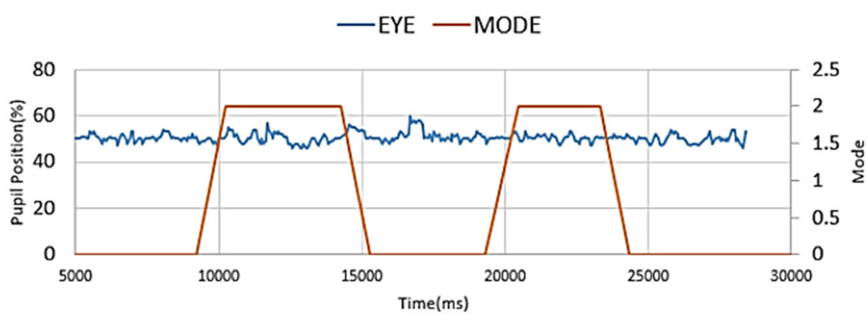
	GRIP	SPREAD	LEFT	RIGHT
1st	77.8%	42.1%	75.0%	66.7%
2nd	77.8%	100.0%	78.6%	71.0%
3rd	100.0%	0.0%	71.0%	66.7%
4th	81.8%	100.0%	37.5%	66.7%
5th	100.0%	100.0%	86.7%	87.5%
Full Length	85.7%	70.0%	68.4%	70.1%

Figure 7. Confidence chart for each gesture

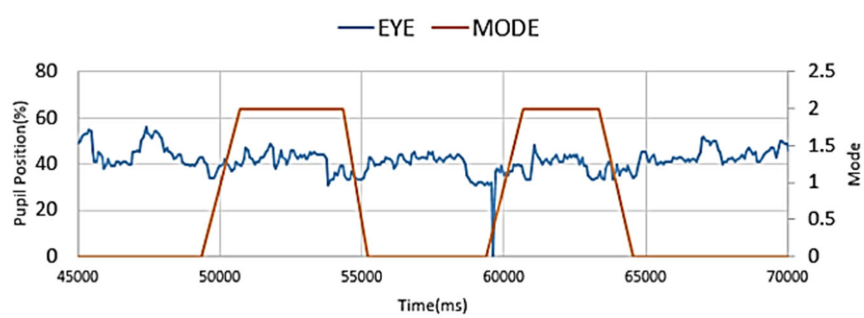
Reliability was calculated with a margin of about ± 1 second in each area, and all false detections outside ± 1 second were ignored. Looking at the graph, it can be seen that the recognition rate is relatively low in the SPREAD action compared to other gestures. In particular, the third attempt out of a total of five attempts did not detect any results at all. The start and end of the gesture measured with the naked eye in this part have an interval of about 1 second. One of the causes of misrecognition in this section is that a sufficient number of samples were not used because the gesture was repeatedly made for too fast a time. However, misrecognition calculated using the entire range did not fall significantly compared to other LEFT and RIGHT gestures.

3.4 Low-speed driving test results and analysis

While driving, the pupil position information was extracted from the driver state recognition system while randomly moving between the autonomous driving mode and the driver driving mode, and a comparative analysis was conducted. The pupil location was recorded by converting the location of the pupil away from the outer corner of the right eye into a percentage. In the graph of Figure 8, EYE represents the location information of the pupil, and MODE represents the control transfer information transmitted to the vehicle. The control right transition information of the vehicle is displayed as 2 in the autonomous driving mode and 0 in the driver driving mode. Looking at the graph in Figure 8(b), it was confirmed that the driver's pupil moved a lot when the button was used. On the other hand, in Fig. 8(a), it was confirmed that there was no large pupil movement even in the section where control transition occurred. Therefore, the control transfer of an autonomous vehicle using EMG reduces driver's distraction, enabling safer driving.



(a) Use of electromyography



(b) using the button

Figure 8. Data collected when performing control transfer during low-speed driving

It can be seen that the pupil position information dropped to -1 around 59,000 ms on the graph of Figure 8(b). This is marked as -1 because it did not detect the pupil. In addition, it can be confirmed that the pupil moves to a large extent at around 48,000 ms and around 58,000 ms. It is determined that the driver moved the pupil to recognize the position of the button.

4. Conclusion

In this paper, a method for an intuitive user interface for safe and efficient driving mode conversion in an autonomous driving environment is presented. Recently, in order to find a specific button typical of the autonomous driving mode switching method, a new switching method was implemented and tested using an EMG-based wearable device as a method to reduce the risk of gaze dispersion that occurs while driving. Through experiments, it was confirmed that the operation using gestures, which is the method presented in this paper, relatively reduces driver's distraction compared to the existing button operation method, and enables switching of driving modes while stably maintaining vehicle steering. In particular, the proper setting of the number of sampling of EMG sensor values for recognizing gestures and the low-pass filter that rectifies them prevented most unintended commands, preventing the recognition rate from deteriorating due to errors. In addition, additional vehicle information was used to limit the control transfer conditions, and it was confirmed that this allows the driver to more safely switch the vehicle from manual driving mode to autonomous driving mode. In addition, by determining the amount of force given to the driver's arm and the position of the arm through the EMG, it is possible to determine whether the driver's current condition is a state in which he can manually drive a vehicle or not. This can be used to safely move the vehicle to the shoulder of the road or other safe areas in preparation for a situation in which the driver cannot accept the system's mode change request when the system requests a transition to the manual driving mode.

In this paper, a new type of user interface is provided, and as a comparison target, the button operation, which is a general mode switching method, was selected as a standard in consideration of one of the vehicle peripheral devices or the installed infotainment environment among the autonomous driving mode switching methods, and the experiment was conducted. . In order to secure more reliability of the proposed gesture-based method, it is necessary to compare the lack of information sharing that is not provided by car companies and to compare with more various wearable devices or buttons and interfaces mounted on vehicles and vehicle models. In addition, it is judged that more quantitative and qualitative evaluations that individual drivers can experience and feel are additionally needed in the future through more diverse driving environments and many experimental groups. Based on this, future research will attempt EMG analysis through Recurrent Neural Network, which will show good performance in analyzing time-sequential data as it is likely to be a method that can more closely judge the recognition rate and situation. This is expected to be able to implement more abstract and complex gestures, and it is judged that higher flexibility for the proposed gesture method can be secured by applying it to an autonomous driving system.

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