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Smart Wireless Shoes for Visually Impaired People and EEG Evaluations

Sota Hoshi
Electronic Communication Systems Engineering
National Institute of Technology, Okinawa College
Okinawa, Japan
ac234607@edu.okinawa-ct.ac.jp

Kazuki Aishima
Information and Communication Systems Engineerring
National Institute of Technology, Okinawa College
Okinawa, Japan
ic201201@edu.okinawa-ct.ac.jp

Satto Shinzato
Information and Communication Systems Engineerring
National Institute of Technology, Okinawa College
Okinawa, Japan
ic201223@edu.okinawa-ct.ac.jp

Ryoga Washizawa
Information and Communication Systems Engineerring
National Institute of Technology, Okinawa College
Okinawa, Japan
ic201243@edu.okinawa-ct.ac.jp

Yusuke Shinzato
Information and Communication Systems Engineerring
National Institute of Technology, Okinawa College
Okinawa, Japan
ic201224@edu.okinawa-ct.ac.jp

Katsuya Nakahira
Information and Communication Systems Engineerring
National Institute of Technology, Okinawa College
Okinawa, Japan
nakahira@okinawa-ct.ac.jp

***Abstract*—In recent years, much research has been conducted on automatic operation control of automobiles and mobile devices, and these studies assume that the mobile device is equipped with a camera and range-finding sensors. In contrast, this research targets mobile devices for the visually impaired and refers to elemental technologies to realize smart wireless systems in which sensing data is acquired on the infrastructure equipment side and shared by each mobile device using wireless technology. In addition, the performance of the devices was evaluated using EEG.**

***Keywords*—wireless communications, smart wireless technology , EEG sensor**

I. Introduction

Automated driving systems have reached Level 3, and 70 million cars, delivery robots, and other vehicles (hereafter referred to as mobile units) are expected to be produced in 2030. Currently, however, a single mobile vehicle is equipped with many expensive sensors, such as cameras and range-finding sensors.

We estimate that the entire mobile unit will be equipped with 3.5 billion sensors, which is 50 times more than the total number of mobile units. Sensing data is often common, such as images and point clouds.

Therefore, we believe that sharing sensing data among individual mobile units is the key to increasing production efficiency. In other words, it is necessary to develop a new smart wireless control technology that aims at efficient use of sensing data by acquiring sensing data at the infrastructure facility side and sharing it with each mobile unit using wireless.

Smart wireless control technology is shown in Fig. 1. By equipping the infrastructure side, such as traffic lights and streetlight cameras on the left side of Fig. 1, with cameras and area measurement sensors, we are aiming for a future in which sensing data can be shared with automobiles, delivery robots, drones, and other public transportation vehicles on the right side of Fig. 1 via high-speed wireless communications. In this study, the mobile device will be limited to shoes for the visually impaired and smart wireless will be considered.

II. Development of Shoes for the Visually Impaired Who Are Mobile

In this study, we evaluated the elemental technologies to realize smart wireless and EEG-based devices for the mobile device as a shoe for the visually impaired.

A. Overall view of shoes

Fig. 2 shows an image of shoes for the visually impaired. The AI determines areas where the visually impaired can safely move around, and the shoe-type device clearly communicates this information using a Braille block mechanism on the sole of the foot. The shoes consist of an elevating Braille mechanism, a camera, a foot-push generator, a vibration element, and an image-detecting AI. Images acquired from the camera are used to detect safety zones using semantic segmentation. If the user is able to walk, the system pushes up the guidance block built into the right foot, shown on the right in Fig. 2, and pushes up the warning block if the user is unable to walk or is paused. In addition, if there is an obstacle, traffic light, or car in front of the wearer, a vibration element is used to convey information to the shoe wearer. To enable continuous use of the shoes, a foot-push power generation mechanism is provided.

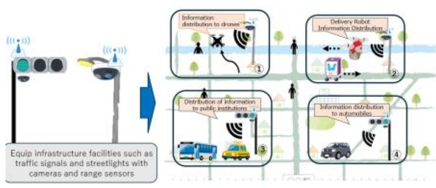

Fig. 1. Example of information distribution by sensors mounted on the infrastructure side

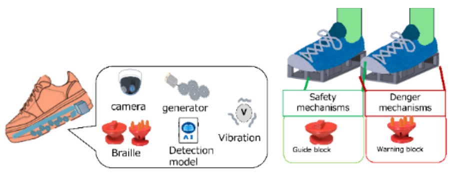

Fig. 2. System Overview

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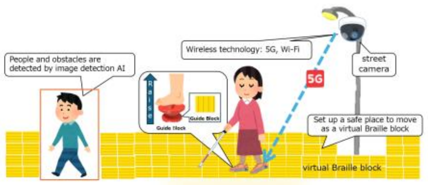

Fig. 3. Gait control combining camera video and GPS for smart wireless shoes

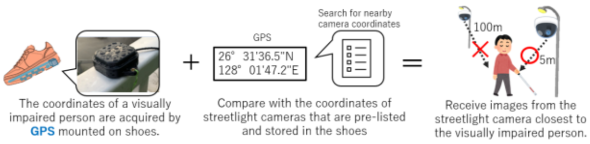

Fig. 4. Flow of selection method of streetlight cameras by GPS

Fig. 5. Self-estimation with GPS and image detection AI(left) Detection walkable areas and determination of walkability by AI(right)

III. Methodology of Smart Wireless for Shoes

A. *Overall of smart wireless shoes*

The overall image of smart wireless shoes for the visually impaired is shown in Fig. 3.A microcontroller installed in the shoes worn by the visually impaired person in the center of Fig. 3 transmits camera images from the streetlight camera installed on the road on the right side of Fig. 3 to the microcontroller via medium-range wireless communications such as 5G and Wi-Fi. While the AI grasps the surrounding situation, it detects the safe walking area as the yellow virtual Braille block area in Fig. 3 based on the GPS coordinates mounted on the shoes[1].The Braille block mechanism, which imitates Braille on the shoes in the center of Fig. 3, transmits information from the feet to support free walking for the visually impaired.

B. *Development of a streetlight camera selection method*

In order to assist the visually impaired in walking safely when they move, we are considering a system that selects the one camera that shows the visually impaired person in the highest resolution from the images of streetlight cameras and other fixed surveillance cameras to determine the safety of the visually impaired person. The coordinates of the visually impaired person (hereinafter referred to as "self-coordinates") are acquired by the GPS shown in Fig. 4 (left), which can detect the coordinates of the visually impaired person with an accuracy of several centimeters. The image of the streetlight camera closest to the self-coordinates is received.

TABLE I. Comparison of detection rates between Method 1 and Method 2(left) and detection rates for each camera in Method 2(right)

	Detection rate (%)
Method 1	93.88
Method 2	93.15

	Detection rate (%)
Camera1	85.60
Camera2	96.52
Camera3	96.56
Camera4	94.97

C. *Self-estimation from camera image*

In self-estimation, the visually impaired person himself is identified from multiple persons in the camera image . First, the GPS-coordinates of the four corners of the camera image shown in Fig. 5 left are measured in advance. Next, the image-coordinates of all pixels are calculated from the GPS-coordinates of the four corners using equations (1) and (2). Next, the image-coordinates closest to the self-coordinates are identified. At the same time, all persons in the camera image are detected by the image detection AI. Finally, the person whose image-coordinates is closest to the self-coordinates is identified as the visually impaired person himself.

$$Z_X = \frac{(Dx - Ax)}{1280} \times 640 + Ax \qquad (1)$$

$$Z_Y = \frac{(Dy - Ay)}{720} \times 360 + Ay \qquad (2)$$

D. *Establish a method for identifying walkable areas*

Semantic segmentation is used to extract the sidewalk and hallway areas in the camera image shown in Fig. 5 right. Next, the inner 90% of the extracted area is identified as the safe area. If the safe region is the 1 meter radius around the visually impaired person wearing a walking aid device in the upper left corner of Fig. 5 right, then the visually impaired person is considered to be able to walk [2].

IV. Validation of the Streetlight Camera Selection Method

A. *Verification Method*

Randomly moving objects are placed in a square area of 170 cm on each side. The moving object is selected at random from front, back, right rotation, and left rotation, and the AI detects the moving object using either the method in which a single web camera continuously captures images or the method in which a web camera is placed in the four corners of the square area and the camera is switched to detect each of the four divided areas, and the detection rate of the moving object is compared. Moving objects are detected by object detection using Yolov8[3].

B. *Verification Results*

A Table 1 left shows the detection rate for each of the following two methods. Method 1 uses a single web camera and method2 uses four web cameras in four corners of a square area and switching the camera to detect each of the four divided. The results shows that the detection rate of Method 2, which uses four cameras and switches the camera to detect each segmented area, is 0.73 points lower than that of Method 1.

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Fig. 6. Overview of EEG Measurement System and Electrode Arrangement Diagra

C. Considerations and Discussions

As a reason for the better detection rate for Method 1 than for Method 2, we considered the high possibility that only one of the four cameras was degraded in the camera image. In fact, when we reviewed the video, we found one camera with degraded and blurred images, even though the same web camera was used. To verify the discussion, the video acquired with Method 2 was divided into each camera image, and the detection rates are shown in Table 1 right. The results show that only Camera 1 had a decrease in detection rate due to video degradation. However, given the high detection rate of the other normal cameras, assuming that Camera 1 was operating normally, and comparing the average of the three normally operating cameras and the detection rate of Method 1, we can predict that Method 2 is the method with the higher detection rate by 2.13 points.

V. Detection of Resting State Using EEG

There is no method to quantitatively measure whether people feel a sense of security when using the developed shoes for people with disabilities. Therefore, in this study, the magnitude of the resting state is quantitatively measured by comparing the ratio of alpha waves, which are an indicator of the resting state, and beta waves, which are an indicator of the aroused state, in the brain waves using the EEG measuring device shown in Fig. 6 left. Before evaluating the results with the developed shoes for the visually impaired, we will verify the results by comparing the walking of a normal person and a visually impaired person in order to examine the line that clearly distinguishes between the anxious state and the resting state.

A. Overview of the EEG measurement system

The overall system for EEG measurement and data collection, where electrodes are attached to the headgear created by a 3D printer to perform EEG measurement with the OpenBCI board, and data is transmitted to a PC using Bluetooth communication. The electrodes are shown in Fig. 6 right. 10-20 method is used to attach the electrodes to $O2$, $F4$, and $C4$. The frequencies of α wave for $O2$ and β wave for $F4$ are easy to obtain. $C4$ is located midway between $O2$ and F4. α waves indicate the relaxed state, while β waves indicate the aroused state. (The 10-20 method measures the nasal root, occipital tubercle, and right and left anterior auricular points, respectively, and obtains vertex (Cz) from the midpoint of each. The electrodes are placed in 10, 20, 20, 20, 20, 20, and 10% divisions between the nasal root and occipital tubercle, and between the left and right anterior auricular points.)

B. Establishment of device safety evaluation using alpha and beta waves

Establish a method for device safety evaluation. For waveforms obtained from the brain, perform a spectrum analysis of α and β waves using Equations (3), (4), and (5) to identify α and β waves. The α/β ratio is then obtained and compared using equation (6).

TABLE II. Comparison of Detection Rates for Each Camera in Method 2

	Case (1)	Case (2)
α 波	0.0033326	0.0024481
β 波	1.2397E-9	1.6047E-9
α/β 比	2688212.3	1525512.2

$$x(n) = \sum_{k=0}^{\frac{N}{2}} \left(a_k \cos\left(\frac{2\pi}{N}kn\right) + b_k \sin\left(\frac{2\pi}{N}kn\right)\right) \quad (3)$$

$$X(k) = X_R(k) + jX_I(k) \quad (4)$$

$$P(f) = |X(f)|^2 = X(f) \cdot X(f) \quad (5)$$

$$\frac{\alpha}{\beta} = \frac{P_\alpha}{P_\beta} \quad (6)$$

C. Verification Method

To compare the EEG of a normal person and a visually impaired person walking, EEG measurements are made for 10 seconds with a sampling rate of 200 under the situation of walking with eyes open and walking with meditated eyes.

D. Verification Results

Table 2 shows the spectrum of α and β waves and the α/β ratio for the two Cases (1) and (2), respectively. This is because in Case (1), the subjects can walk only with visual information, whereas in Case (2), they need to rely only on information such as feel and sound, which increases their concentration compared to Case (1). In other words, based on the respective EEGs of normal and visually impaired subjects when they walk, it is predicted that the α/β ratio will be higher in the resting state and lower in the aroused state (concentrated and anxious state).

E. Conclusion

Targeting mobile devices for the visually impaired, we proposed a method to realize a smart wireless system in which sensing data is acquired on the infrastructure equipment side and shared by each mobile device using wireless. We then verified the high detection rate in the streetlight camera selection method and were able to predict that 96.1% detection was possible. Finally, we were able to predict that the α/β ratio would be higher in the resting state and lower in the awake state (focused and anxious) based on the respective brain waves of a normal person and a visually impaired person walking using an electroencephalogram (EEG) measuring device.

Acknowledgment

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