An Artificial Intelligence Edge Computing-Based Assistive System for Visually Impaired Pedestrian Safety at Zebra Crossings

Wan-Jung Chang, *Member, IEEE*, Liang-Bi Chen, *Senior Member, IEEE*, Cheng-You Sie, and Ching-Hsiang Yang

***Abstract*—This article proposes a wearable assistive system based on artificial intelligence (AI) edge computing techniques to help visually impaired consumers safely use marked crosswalks, or zebra crossings. The proposed wearable assistive system consists of a pair of smart sunglasses, a waist-mounted intelligent device, and an intelligent walking cane (stick). A deep learning technique is adopted for zebra crossing image recognition in real time. Visually impaired consumers need to wear the proposed smart sunglasses and waist-mounted intelligent device and hold the proposed intelligent walking cane when they approach a zebra crossing. When a visually impaired pedestrian reaches a zebra crossing, they will immediately receive a message about the current situation at the crossing and the traffic light signal. Experimental results show that the accuracy of real-time zebra crossing recognition of the proposed system can reach up to 90%.**

***Index Terms*—Artificial intelligence of the Internet of Things (AIoT), smart glasses, visually impaired, walking cane, pedestrian walking safety, wearable assistive devices, zebra crossing.**

I. INTRODUCTION

RECENTLY, the World Health Organization (WHO) published its newest global statistical dataset [1] on October 8, 2019. These data indicated that at least 2.2 billion people are visually impaired or blind. Moreover, the majority of these visually impaired people are over the age of 50.

Clearly, visually impaired people might face a certain level of inconvenience in their daily lives. Hence, it is difficult for visually impaired pedestrians to walk alone in strange and complex zones or regions. At present, visually impaired pedestrians have used guide dogs [3] and white walking canes (sticks) [4] to help guide them and improve their walking safety when they go out independently.

After training, guide dogs can help visually impaired individuals efficiently avoid ground obstacles and provide directional guidance, but the cost of training guide dogs is extremely high. On average, each guide dog requires approximately 18 months of training, with costs ranging from $25,000 to $42,000 U.S. dollars. Additionally, each guide dog can only serve a visually impaired individual for 8 to 10 years, so guide dogs have problems related to the short supply, high cost, and limited life cycle.

Alternatively, white walking canes are inexpensive and lightweight; moreover, they can be used to effectively detect ground obstacles below the knees of visually impaired individuals. Currently, most visually impaired individuals use white walking canes to improve their walking safety. However, in complex outdoor environments, many individuals still experience the following three common dangerous walking situations [5]–[10].

Aerial and Suspended Obstacle Collision A survey by Manduchi and Kurniawan [5] indicated that, on average, 15% of visually impaired people hit an aerial or suspended obstacle every month. Forty percent of visually impaired people fall each year because of hitting an aerial or suspended obstacle; additionally, 95% of visually impaired people collide with obstacles while walking along a road. In this regard, a white walking cane can only detect ground obstacles or steps below the knee.

Therefore, visually impaired individuals cannot sense aerial and suspended obstacles [6] in front of them when walking (such as half-open iron rolling doors, tree branches, and signs), which may result in the individual being struck by the object, potentially causing serious injury.

2) High Fall Risk A statistical report by Legood *et al.* [7] noted that the probability of falling for visually impaired people is 1.7 times that for ordinary people, and the probability of falling immediately after standing up is 1.9 times that for the average person. When a visually impaired individual walks alone and falls, they may feel less confident and helpless when walking alone in the future, and serious injury may occur due to not getting timely assistance.

Crossing Intersections and Possibly Colliding With Vehicles According to a survey [8] of usability studies from 218

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visually impaired consumers in Taiwan, 35.3% of visually impaired consumers said that they were unable to determine whether they were using a marked crosswalk (zebra crossing) while crossing the road, and 61% said that voice traffic signs are lacking. The above results suggest that when visually impaired pedestrians use intersections, they are often exposed to a high risk of being struck by vehicles because they cannot determine the current status of the intersection.

To overcome the first two abovementioned issues, we designed and implemented an intelligent assistive system [9], [10] composed of a pair of smart glasses, an intelligent walking stick, a mobile device app, and an online cloud-based management platform for visually impaired consumers to provide functionalities that improve outdoor walking safety, including detection and notification functions related to falling and detection and avoidance functions for aerial and suspended obstacles in front of the user.

Based on our previously developed assistive system [9], [10], this article proposes an artificial intelligence (AI) edge computing-based [11] wearable assistive system that adds zebra crossing recognition and traffic sign reminders to assist visually impaired consumers in safely using zebra crossings. Please note that this article focuses on introducing and discussing the design and implementation of the assistive system for the safe use of zebra crossings. The other related functionalities (such as obstacle collision avoidance and fall detection with notification) of the proposed assistive system will not be introduced in this article, but the introductions to the other related functionalities can be found in our previous work [9], [10].

The remainder of this article is organized as follows. The related works are reviewed and discussed in Section II. The proposed assistive system is introduced in Section III. A prototype of the proposed assistive system and related experiments are provided in Section IV. Finally, Section V concludes this work.

II. Related Works

In recent years, there have been some related works [12]–[24] on assisting visually impaired individuals in safe walking. Islam *et al.* [12] reviewed the existing schemes and developing trends of walking assistive systems for visually impaired consumers.

For indoor navigation, Bai *et al.* [13], [14] proposed a set of schemes for visually impaired consumers that involved wearing smart glasses in indoor environments. The proposed smart glasses used a depth-detection camera and an ultrasonic sensor to sense the indoor environment. A depth-based wayfinding algorithm was used, which was combined with augmented reality (AR) glasses to enhance the visual processing ability of the visually impaired consumers. For blind visually impaired consumers, the indoor distance, orientation and navigation functions were sensed by ultrasonic sensors, and notifications were sent by headphones regarding the avoidance of obstacles.

Advani *et al.* [15] developed a smart glasses/gloves-based multitask grocery assistive system for visually impaired consumers that was capable of product recognition, person detection, and food recognition. This assistive system was focused on grocery shopping applications. Moreover, the developed assistive system can be adopted in multiple contexts.

Lee *et al.* [16] designed a smart glasses-based system for indoor positioning and navigation that can be used by visually impaired consumers. To determine positions in a room, a homemade QR code label is attached to the indoor environment. The location information in the QR code tag is transmitted to the mobile device via Wi-Fi. Hence, a visually impaired consumer can know the current location by voice playback. If there is an obstacle in front of the visually impaired person, information will be sent to the mobile device by the ultrasonic sensor installed above the smart glasses; vibrations are used to help the visually impaired consumer safely avoid the obstacle.

However, the walking safety issues that pose the highest risk to visually impaired consumers are related to outdoor activities. The outdoor behavior of visually impaired consumers is relatively difficult to control. Hence, there are more risk factors (such as crossing roads and construction sites and interacting with pedestrians and vehicles) that must be considered in outdoor environments than in indoor environments. Ramadhan [17] presented a wearable assistive navigation system for outdoor use composed of a microcontroller (MCU) board, some sensor devices, a mobile phone communication device, a GPS module, and a solar cell panel. The assistive system adopted a set of sensors to track the path of the user and alert the user to obstacles in front of them; sounds and a buzzer worn on the wrist were used to alert the user.

Elmannai and Elleithy [18] proposed an intelligent framework system that integrated sensor-based and computer vision-based technologies. The fusion of these sensor data and the application of computer vision technology can be used to detect multiple objects and improve the accuracy of collision avoidance. An obstacle avoidance algorithm based on image information and fuzzy. logic was proposed to provide accurate information and assist visually impaired consumers in avoiding obstacles by using fuzzy logic. The system was deployed and tested, and it achieved 98% accuracy in object detection and 100% accuracy in collision avoidance in actual real-time scenarios.

Lapyko *et al.* [24] presented a cloud-based assistive navigation system for outdoor use that consisted of a GPS receiver, a smartphone, and a cloud-based service platform. This system provided three scenarios for visually impaired consumers when they were walking outdoors. In the first scenario, visually impaired consumers are approaching a zebra crossing; the smartphone lets them know when a zebra crossing is within 5 meters. In the second scenario, visually impaired consumers can use the gesture function to control the smartphone for bench recognition. If a bench is detected within 10 meters, information is sent to the smartphone. The third scenario involves assisting visually impaired persons in detecting the status of traffic signals. Visually impaired consumers can determine the current state of a traffic signal by using their smartphones, and whether there is enough time for a user to pass through the intersection is also predicted.

Table I summarizes a comparison among existing assistive systems and the proposed assistive system. Most of the related

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TABLE I
A COMPARISON AMONG EXISTING ASSISTIVE SYSTEMS AND THE PROPOSED ASSISTIVE SYSTEM

Work	Sensors Adopted	Detection Devices	Indoor/Outdoor	Goals	Special Features
Bai *et al*. [13], [14]	Depth-detection camera and ultrasonic sensor	AR-based smart glasses	Indoor	Navigation with the avoidance of obstacles	1) The indoor distance, orientation and navigation functions can be sensed. 2) Notifications are sent by headphones regarding the avoidance of obstacles. 3) A depth-based wayfinding algorithm was used, which was combined with augmented reality (AR) glasses to enhance the visual processing ability of visually impaired consumers.
Advani *et al.* [15]	Temporal sensor, vibration motors, and camera	Smart glasses and gloves	Indoor	Product recognition, person detection, and food recognition in grocery shopping market	1) Focused on grocery shopping applications. 2) The assistive system can be adopted in multiple contexts.
Lee *et al.* [16]	Microcamera and ultrasonic transducer	Smart glasses	Indoor	Positioning and navigation. The visually impaired consumers can know various information, including location and nearby obstacles.	A specific custom visual maker is designed to obtain various location and indoor environmental information.
Elmannai & Elleithy [18]	2 camera modules, gyro sensor module, PIR motion detection module, GPS module, and compass module	Experimental development board	Indoor/Outdoor	Multi-object detection for avoiding obstacles in front	1) Sensors and computer vision techniques are integrated. 2) An obstacle avoidance scheme is developed based on fuzzy theory with image depth information.
Chang *et al.* [9], [10]	IR transceiver module, vibration motor, 6-axis (gyro + accelerometer) motion tracking sensor module, GPS module, and LPWAN module	Smart glasses and intelligent walking stick	Outdoor	Fall event detection and front aerial obstacle avoidance.	1) Two fall recognition schemes are fused to ensure real fall event occurrence. 2) LPWAN is adopted to send an urgent notification to family members or caregivers.
Lapyko *et al.* [24]	GPS module and real-time kinematic	Smartphone	Outdoor	Street navigation	1) A cloud-based outdoor assistive system 2) When visually impaired consumers are approaching a zebra crossing, related information (such as traffic light status) will be provided.
Proposed Assistive System	Image (camera) sensor module, time-of-flight (ToF) laser-ranging module, vibration motor, 6-axis (gyro + accelerometer) motion tracking sensor module, GPS module, and LPWAN module	Smart glasses, intelligent walking cane, and intelligent waist-mounted device	Outdoor	To assist impaired pedestrian walking safety at zebra crossings	1) We keep the special features and functions from our previous work [9], [10], including fall detection, front aerial obstacle avoidance, and LPWAN-based urgent notification. 2) A deep learning technique is adopted for zebra crossing image recognition in real time. 3) When a visually impaired pedestrian reaches a zebra crossing, they will immediately receive a related message about the current situation at the crossing and the traffic light signal.

works used a GPS for outdoor positioning, but the GPS positioning error was as high as 20-30 meters, which obviously is not practical in real applications involving zebra crossings. Therefore, to overcome this problem, in this article, we propose a wearable assistive system based on deep learning, AI and edge computing techniques to help visually impaired consumers safely use zebra crossings.

III. THE PROPOSED ASSISTIVE SYSTEM

A. Design Concept

The proposed AI edge computing-based assistive system aims to automatically recognize zebra crossings and improve the outdoor walking safety of visually impaired pedestrians at intersections. Fig. 1 shows the proposed assistive system, which consists of an intelligent waist-mounted device (see Fig. 1(a)), an intelligent walking cane (see Fig. 1(b)), and a pair of smart sunglasses (see Fig. 1(c)) to assist visually impaired pedestrians in walking at intersections when they deviate from zebra crossings.

Hence, to provide a visually impaired pedestrian with the ability to recognize whether they have deviated from a zebra crossing, we adopt a popular and powerful commercial development board with a built-in GPU-based embedded system as an AI edge computing execution core. With this board, deep learning-based real-time zebra crossing image recognition can be performed in conjunction with the proposed intelligent waist-mounted device.

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(a) (b) (c)

Fig. 1. The proposed assistive system. (a) Intelligent waist-mounted device. (b) Intelligent walking cane. (c) Smart sunglasses.

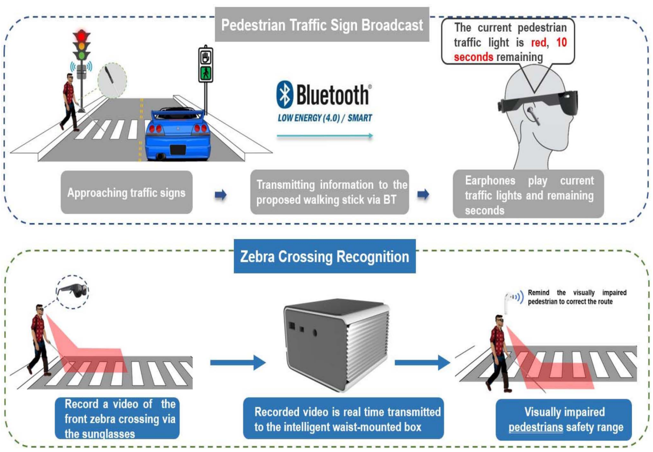

Fig. 2. Application scenarios for the proposed assistive system.

Possible application scenarios of the proposed AI edge computing-based assistive system are shown in Fig. 2. When a visually impaired pedestrian is approaching a traffic signal (also known as an accessible pedestrian signal (APS)) at an intersection, the proposed intelligent walking cane can receive the current pedestrian traffic signal information and transmit it to the proposed intelligent waist-mounted device.

Moreover, the proposed intelligent waist-mounted device provides a visually impaired voice guidance service through earphones via Bluetooth (BT) wireless communication. In addition, a video of the zebra crossing is recorded via the front camera (image) module of the proposed smart sunglasses, and the video is transmitted in real time to the proposed intelligent waist-mounted device.

A zebra crossing in front of a pedestrian can be recognized in real time to determine whether the pedestrian deviates from the crossing when walking through the intersection. Hence, the probability of collisions between the visually impaired pedestrian and vehicles can be reduced. As a result, the proposed AI edge computing-based assistive system can effectively improve the walking safety of visually impaired consumers.

B. Integration With Intelligent Accessible Pedestrian Signals (iAPSs)

APSs [25] are assistive devices via which relevant information can be communicated about walk and do not walk intervals at signalized intersections in a nonvisual form to visually impaired pedestrians. Recently, intelligent accessible pedestrian signal (iAPS) mechanisms [26], [27] have been developed and installed in many regions. Generally, an iAPS mechanism is built based on low-energy (BLE) beacon-based protocols that use BT technology [28]. An iAPS mechanism can be interconnected to BLE devices (such as the proposed intelligent walking cane) that can broadcast a universally unique identifier (UUID) to nearby mobile or wearable devices via the BLE beacon-based protocol.

Fig. 3. An example of the three key values of each beacon (UUID, major, and minor).

The proposed intelligent walking cane of the proposed assistive system can be connected to an iAPS mechanism that was developed in Taiwan. This iAPS mechanism has been installed in many regions in Taiwan and consists of an APS, sound micropositioners, beacon equipment, and a mobile device app.

Each beacon has three key values, UUID, major, and minor values, as shown in Fig. 3. In this work, we can use the UUID identification code specified in the program to determine whether a voice announcement system device for pedestrian signals can be used to avoid interference from other BT devices. Then, we use the minor value generated by the beacon signal to determine if the traffic signal is red or green and the number of seconds until the traffic signal changes.

We use the minor value to assess the status of the traffic signal and the number of seconds until the signal changes. The minor value received by BT is hexadecimal and is converted into a decimal value. We divide the signal status into two states. The system considers a 512 base a red light and a 256 base a green light. Moreover, the number of seconds remaining in the traffic signal is given by increasing these base values. Thus, the proposed intelligent walking cane can analyze the signal to determine the current state of an intersection traffic signal and the remaining time before the signal changes.

Therefore, a visually impaired pedestrian can receive the current iAPS information via the BT wireless earphones to determine the current traffic light signal state and remaining time before the signal changes. Thus, the system enhances the confidence of visually impaired pedestrians crossing the road and reduces the collision risks that may be encountered when crossing intersections.

C. Zebra Crossing Recognition

The proposed AI edge computing-based assistive system aims to automatically recognize zebra crossings and improve the outdoor walking safety of visually impaired pedestrians at intersections. In such cases, large amounts of data need to be processed at a reasonable cost with limited memory and computing power. The architecture of an inception-based deep learning module [29] is simpler than that of other high-performance neural network (NN) architectures.

Hence, an inception-based deep learning module is adopted in the zebra crossing recognition process for the proposed assistive system. The main task of the inception-based deep learning module is to receive the compressed images in anchor boxes and use them to predict the possible object types (zebra crossings). As a result, the prediction and recognition

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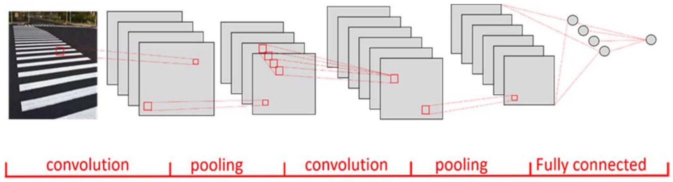

Fig. 4. Convolutional blocks are spatially reused to build the network.

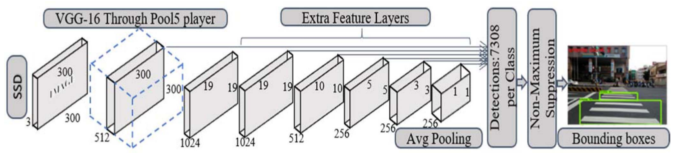

Fig. 5. Architecture of the SSD_Inception_v2 module.

results are output as a picture, and complete recognition is completed.

As shown in Fig. 4, the main design concept of the inception-based network architecture involves finding the optimal local sparse structure in a convolutional visual network. Hence, this structure needs to be covered and predicted by the available dense components, and convolutional building blocks are spatially reused to establish networks.

In this article, we use the SSD_Inception_v2 module, which is an open-source combined deep learning module, as shown in Fig. 5. First, an image of a zebra crossing is input into the first module, the single-shot multibox detector (SSD) [30], which is a convolutional neural network (CNN)-based object detection tool. The SSD uses a convolutional layer to predict the symbolism of multiple boxes and the offset of each box to determine the object category of each box simultaneously.

Next, the features of the zebra crossing image are extracted through the VGG-16 CNN module [31], and six different feature maps are used to detect targets of different scales. By using the average pooling layer, the input zebra crossing image is divided into several rectangular areas, and the average value is output for each subarea. Finally, the training object is subjected to non-maximum suppression based on bounding boxes to identify possible zebra crossings.

After the convolutional layers of different sizes are predicted, the relativity of multiple convolutional layers and the offset of each convolutional layer are determined. Large convolution maps can detect small objects, and small convolution maps are better at detecting large objects.

Each new feature layer can use a series of convolutional kernels to generate fixed-size prediction results. For a feature layer of size m×n with p channels, the convolutional kernel used has a 3×3×p structure. The resulting detection result is then a score for the attribution category or the positional offset from the preset bounding box. At each m×n feature map location, using the above 3×3 core will produce an output value. The position offset value of the detected bounding box is the relative distance between the output preset bounding box position and the position of the feature map at this point.

After the detector is generated, many detection frames that meet the basic sample requirements will be generated, but there are also many samples that do not meet the basic sample requirements; these negative samples far outnumber the positive samples, which can cause an imbalance between the negative and positive samples, thus making convergence difficult during training. Therefore, we first sort the corresponding basic samples from the negative samples at each object position and select the best samples according to the credibility of the basic samples to ensure that the ratio of final negative samples to positive samples is 3:1. This ratio promotes rapid optimization and stable training.

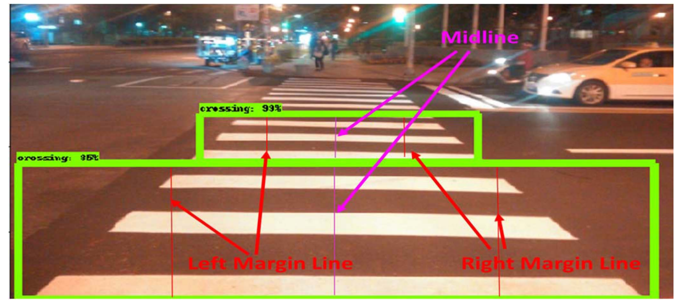

Fig. 6. An example of detecting zebra crossing walking deviations and providing subsequent warnings.

Moreover, to increase the number of training samples and improve the accuracy of recognition, data augmentation [32] is performed such that each training image is randomly selected as follows. The original image is used to sample a patch, and the sampling of the minimum object is based on values of 0.1, 0.3, 0.5, and 0.7. A patch for random sampling involves an original image size ratio in the range of [0.1, 1] and an aspect ratio between 0.5 and 2. When the center of the base sample is in the sampled patch, the overlapping part of the patch is retained. After these sampling steps, each sampled patch is adjusted to a fixed size and flipped randomly with a probability of 0.5.

D. Detection of Zebra Crossing Walking Deviations and Subsequent Warnings

When zebra crossings are recognized at road intersections, we can perform real-time detection of zebra crossing walking deviations and provide subsequent warnings, as shown in Fig. 6. The green blocks are recognized as zebra crossing objects in front of a pedestrian. Furthermore, we divide the left and right quarters of the green blocks to obtain the left margin line and right margin line, respectively. The midline is the center estimated by the proposed smart sunglasses. The midline and margin lines can assist in detecting walking deviations. Moreover, if a margin line overlaps with the zebra crossing margin, a walking deviation warning will be transmitted to the earphones to tell the visually impaired pedestrian to correct their route.

IV. Prototype Demonstration and Experiments

A. Prototype Demonstration

Fig. 7 shows a photograph of a prototype of the proposed assistive system. The proposed assistive system includes a pair of smart sunglasses, an intelligent walking cane, an intelligent

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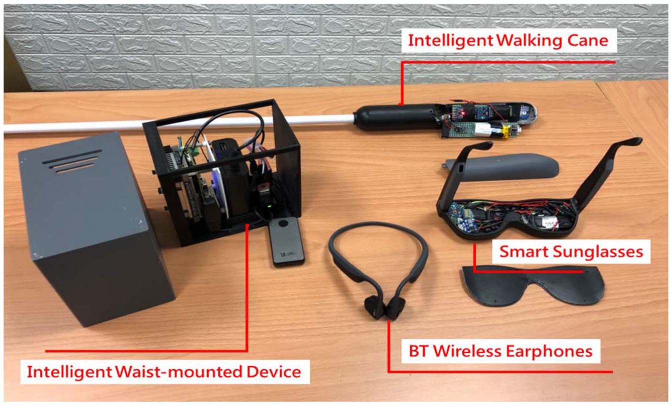

Fig. 7. Photograph of a prototype of the proposed assistive system.

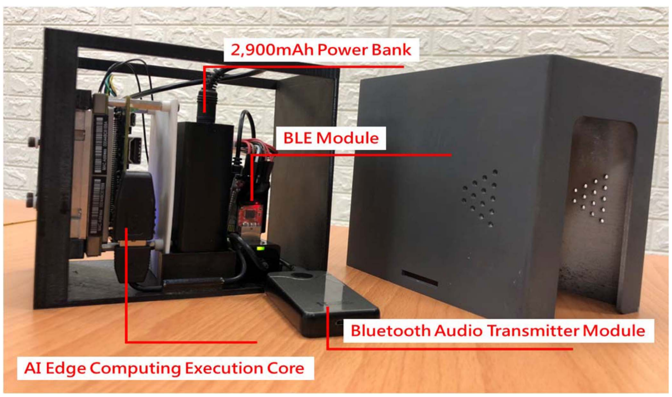

Fig. 8. Photograph of the prototype of the proposed intelligent waist-mounted device.

TABLE II
SPECIFICATIONS OF THE AI EDGE COMPUTING EXECUTION CORE

Name	Specifications
CPU	Dual-core 64-bit CPU, operated at 2.26 GHz Quad-core 64-bit CPU, operated at 1.9 GHz
GPU	256-core Pascal architecture 8 GB GDDR5X RAM with 10 Gbps operated at 1,733 MHz
RAM	8 GB 128-bit LPDDR4
SSD	512 MB PCIe
Power	7.5 W

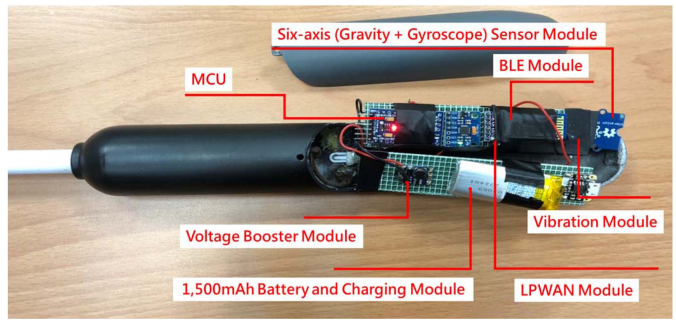

Fig. 9. Photograph of the prototype of the proposed intelligent walking cane.

waist-mounted device, and BT wireless earphones and is capable of assisting in crossing intersections, detecting falls and sending fall notifications, and detecting and avoiding front aerial and suspended obstacles.

Figs. 8 to 10 show photographs of the prototype implementation of the proposed intelligent waist-mounted device, the proposed intelligent walking cane, and the proposed smart sunglasses, respectively. Fig. 8 shows the architecture of the proposed intelligent waist-mounted device. This device consists of an edge computing execution core, a 2,900 mAh power bank, a BLE module, and a BT audio transmitter module. A popular commercial development board with a powerful built-in GPU-based embedded system is adopted as the AI edge computing execution core; notably, real-time zebra crossing image recognition can be performed by the proposed intelligent waist-mounted device in conjunction with this board. The specifications of the adopted AI edge computing execution core are shown in Table II.

Fig. 9 shows a photograph of the architecture of the proposed intelligent walking cane, which integrates a BLE module, a low-power wide-area network (LPWAN) communication module, a GPS module, a six-axis (gravity + gyroscope) sensor module, a vibration motor module, a voltage booster module, an MCU module, a 1,500 mAh battery and a battery charging module. The BLE module is responsible for communication with the proposed smart sunglasses. The LPWAN module uploads the GPS position and fall messages to the cloud-based online information platform [9], [10].

Fig. 10 shows a photograph of the architecture of the proposed smart sunglasses, which integrate an image (camera) module, a time-of-flight (ToF) laser-ranging module, a BLE module, a six-axis (gravity + gyroscope) sensor module, an MCU module, a 1,500 mAh battery and a battery charging module. The BLE module is responsible for communication with the proposed intelligent walking cane. The image (camera) sensor module, ToF laser-ranging module, and six-axis sensor module are mounted on the proposed smart sunglasses to record real-time video and aid in fall/suspended obstacle detection.

Hence, when visually impaired consumers cross an intersection, the intelligent waist-mounted device can receive the current pedestrian traffic signal information from the iAPS, and a voice guidance service is provided through the BT wireless earphones. This system can assist visually impaired consumers in determining whether they are deviating from the zebra crossing when walking in an intersection to reduce the chance of collisions between pedestrians and vehicles. Hence, the proposed assistive system can improve the walking safety of visually impaired consumers.

B. Experiments

We prepared zebra crossing photo data for deep learning training and testing. The photo dataset included 1,150 images with a size of 640×480. There were 750 scenes during the day, 200 views at night, and 200 pictures of slippery ground, as shown in Fig. 11.

Several possible suitable candidate modules for object detection with deep learning are selected based on

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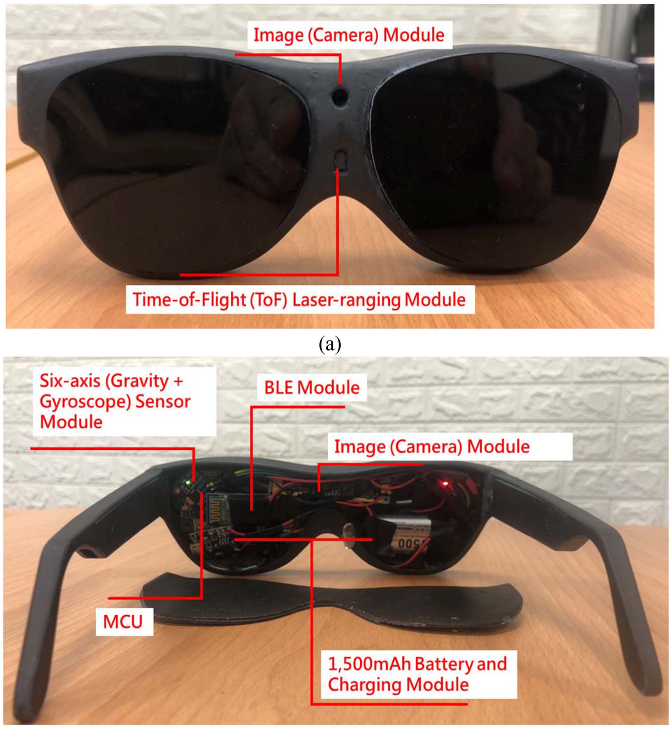
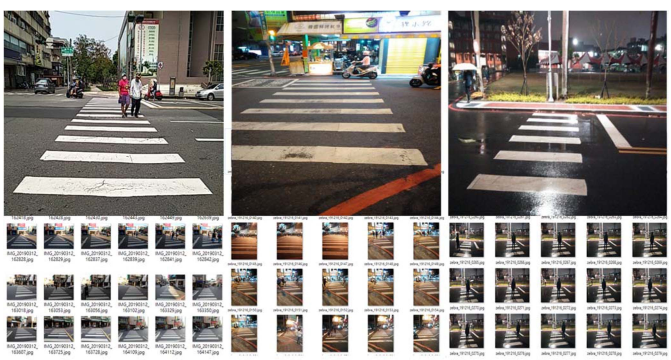


(a)

(b)

Fig. 10. Photographs of the prototype of the proposed smart sunglasses. (a) Front. (b) Rear.



(a) (b) (c)

Fig. 11. Training and test datasets. (a) During the day. (b) Night. (c) Slippery ground.

TABLE III
SEVERAL POSSIBLE CANDIDATE OBJECT DETECTION DEEP LEARNING MODULES FOR THE COCO DATASET BASED ON SPEED AND ACCURACY [33]

Module Name	Execution speed (ms)	COCO dataset mAP
ssd_mobilenet_v1_coco	30	21
ssd_inception_v2_coco	42	24
ssd_resnet50_fpn_coco	76	35
faster_RCNN_inception_v2_coco	58	28
faster_RCNN_resnet50_coco	89	30

TABLE IV
SPECIFICATIONS OF THE DEEP LEARNING TRAINING SERVER

Name	Specifications
CPU	6-core 64-bit CPU 12 threads operated at 3,500 MHz
GPU	Pascal architecture 8 GB GDDR5X RAM with 10 Gbps operated at 1,733 MHz
RAM	16 GB × 4
SSD	512 GB PCIe
HDD	1 TB; 7,200 RPM

TABLE V
RESOURCES USED IN THE ANALYSIS OF THE CANDIDATE OBJECT DETECTION DEEP LEARNING MODULES

	RAM	CPU	GPU
ssd_mobilenet_v1	4,741 MB	57%	99%
ssd_inception_v2	4,905 MB	55%	99%
ssd_resnet50_fpn	5,650 MB	22%	99%
faster_RCNN_inception_v2	5,281 MB	36%	99%
faster_RCNN_resnet50	5,747 MB	36%	99%

TABLE VI
EXPERIMENTAL RESULTS FOR ZEBRA CROSSING OBJECT DETECTION

Tested module	Accuracy (%)	Average detection time (s)
ssd_mobilenet_v1	83.1	0.052
ssd_inception_v2	92.2	0.075
ssd_resnet50_fpn	90.1	0.52
faster_RCNN_inception_v2	92.4	0.59
faster_RCNN_resnet50	90.5	1.66

the coco dataset based on speed and mean average precision (mAP) [33], as shown in Table III. Then, it is necessary to convert the image and the JavaScript object notation (JSON) [34] file that frames the zebra crossing in a record file for the deep learning framework to accelerate the processing of the packaged binary file in the deep learning training module. We use a popular open-source API to adjust the parameters of the deep learning training module as an adjusted configuration file. The adjusted configuration file is used for training over 150,000 steps on the deep learning training server, and the training time is approximately 48 hours. The specifications of the deep learning training sever are shown in Table IV. Table V shows the resources used in the analysis of the candidate object detection deep learning modules. Table VI shows the experimental results for zebra crossing object detection. The mAP and average detection time obtained in this experiment show that the SSD_Inception_v2 module is the most suitable for real-time zebra crossing detection.

Fig. 12 shows experiments in which zebra crossing recognition was successfully performed in three different situations (during the day, at night, and for slippery ground) in real time. Finally, the proposed assistive system was also successfully tested for zebra crossing recognition, walking deviation detection and warning provision on a road in Tainan, Taiwan. Fig. 13 shows a visually impaired pedestrian using the proposed assistive system to walk across a zebra crossing.

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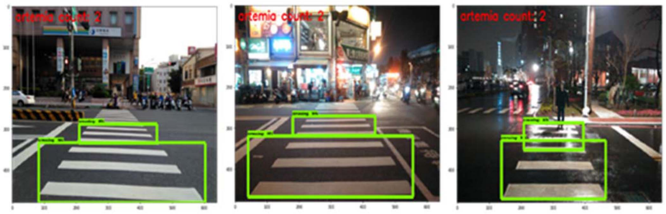

(a) (b) (c)

Fig. 12. Zebra crossing recognition results. (a) During the day. (b) Night. (c) Slippery ground.

Fig. 13. Photograph of a real application test case on a road in Tainan, Taiwan.

V. Conclusion

In this article, an AI edge computing-based wearable assistive system is proposed that is composed of a pair of smart sunglasses, a waist-mounted intelligent device, and an intelligent walking cane (stick) for assisting visually impaired pedestrians when using zebra crossings. An AI edge computing-based deep learning technique is adopted to recognize zebra crossings at an intersection from the front view. Experimental results showed that the recognition rate can reach 90%. By using the proposed assistive system, when a visually impaired consumer crosses a zebra crossing, they immediately receive a message about their current walking pattern and the traffic signal. As a result, the goal of improving walking safety when crossing intersections can be achieved by adopting the proposed AI edge computing-based wearable assistive system.

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