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Tactile Paving Detection by Dynamic Thresholding Based on HSV Space Analysis for Developing a Walking Support System

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ABSTRACT In this research, we present a system that enables independent walking in individuals with visual impairment by recognizing tactile paving. The system warns the user about dangers posed by deviations from the walking path or possible collisions. Therefore, the tactile paving itself and obstacles on it must be detected. This paper discusses problems related to detecting tactile paving. To address these problems, a new camera-based method is introduced, which detects tactile paving automatically. The method relies on a dynamic threshold approach in the HSV color space, making the image processing more robust against varying lighting conditions, environments, and differences in color. Such an approach is not possible using the methods based on fixed thresholds reported in the literature. The results of our experiments confirm that high rates of tactile paving detection were achieved under various conditions.

INDEX TERMS Image processing, human support, color detection, computer vision, healthcare systems.

I. INTRODUCTION

According to World Health Organization statistics (World Health Organization, 2019), as of 2019, there are 2.2 billion people around the world who have some form of visual impairment or blindness [1]. In addition, the number of elderly people worldwide is increasing (Fig. 1).

Moreover, a study by Anglia Ruskin University found that the number of individuals with visual impairment worldwide will increase threefold over the next 30 years due to population aging. In 2015, 216.6 million people had moderate to severe visual impairment, and this is estimated to rise to 550 million people in 2050 [2]. In addition, it is estimated that 36 million people were blind in 2015 and that this figure will increase to 115 million people in 2050. Therefore, more support for individuals with visual impairment will be needed in the future. Currently, individuals with visual impairment are supported in various ways. Support is often provided by guide dogs and the use of white canes. According to the International Guide Dog Federation, there are 20,000 guide dogs serving in 31 countries [3]. However, this number is not enough for the 36 million individuals with visual impairment worldwide. In addition, it is unlikely that the number of guide dogs, which require training and management, will increase rapidly in the future. In contrast, white canes are readily available, but they may take time for users to master. Moreover, users must often walk the same course many times to be comfortable enough to walk it by themselves. Accordingly,

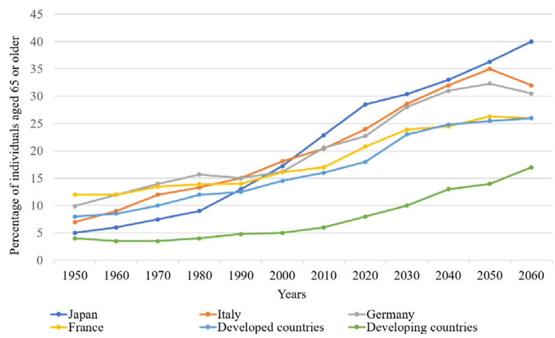

FIGURE 1. Changes in population aging rates.

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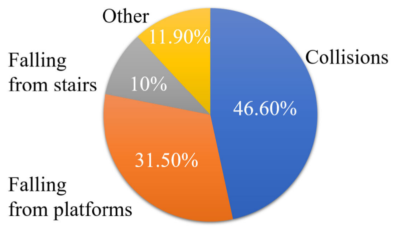


FIGURE 2. Details of accidents of blind people while walking.

when going out to unfamiliar places, individuals with visual impairment need to be accompanied by a caregiver. However, because providing this kind of assistance can cause stress for caregivers, many individuals with visual impairment choose to go out by themselves. According to one study, 76.6% of individuals with visual impairment walk alone without assistance from a caregiver or advanced technology help [4]. Figure 2 shows the percentage of individuals with visual impairment that fall from platforms at stations (31.5%) or have collisions while walking (46.6%). These data reveal the potential danger for individuals with visual impairment when walking alone [5].

In consideration of these circumstances, many studies have investigated ways to support the lives of individuals with visual impairment by proposing walking support systems. Research on walking support approaches for people with visual impairments has been conducted for more than 50 years. Although some of these studies are old and have not been applied in current research, they still present the basics for walking support systems [6]–[8]. Such support systems include the use of a white cane, traditionally used by people with visual impairments. The usability of white cane-related walking support systems is comparatively high because the system is installed in an object that they normally use [9], [10]. Moreover, some walking support systems target the protection of visually impaired people from collisions by recognizing only obstacles that are present during the walk. These systems are developed by using sensing devices such as stereo cameras and ultrasonic sensors. They do not provide route guidance for the visually impaired. However, they can protect visually handicapped people from collisions. Moreover, methods for sending instructions to visually impaired people have also been reported in the literature. Some of them provide audio instructions [11]–[13]. The other types are based on electro-tactile or vibro-tactile stimulators [14]–[16]. The implementation in the real world appears difficult because hardware has to be installed in a usable range.

Recently, many support systems for individuals with visual impairment have focused on the use of tactile paving. Tactile paving is installed in many public places to assist individuals with visual impairment in navigating these spaces. Therefore, support systems for individuals with visual impairment can take advantage of this infrastructure by automatically detecting tactile paving and obstacles and providing corresponding guidance. This paper focuses mainly on problems related to detecting tactile paving. For example, one proposed method detects tactile paving by using color information with fixed thresholds [17]. However, this approach is not reliable under varying lighting conditions, which can lead to large changes in the color and saturation values of objects in captured images. Moreover, differences in the color of tactile paving in different locations might also affect detection results. Accordingly, this study focuses on detecting tactile paving by onboard processing of images captured by the system's camera. Following our observations, the color of the tactile paving varies according to countries. The main goal of this work is to recognize those tactile paving under different conditions in real time. We tackled this problem by image processing introducing a new image processing algorithm. Moreover, finally, the end is to guide the direction of Braille blocks to the visually impaired for safe walking. In the algorithm, approximate straight borderlines of a tactile paving in the image are detected. Then, the HSV histograms of only the color information of the tactile paving are extracted by picking a small window within the borderlines. Based on the HSV histograms, dynamic thresholds are statistically determined. Finally, these thresholds are applied to detect tactile paving region from the images. In this proposal, the thresholds are determined by acquiring the information on the spot. Therefore, the algorithm is very much effective for the target tactile paving detection problem. This paper makes the following contributions: 1) proposed algorithm obtained a high accuracy of 91.65% when it was tested with worldwide tactile pavement images and images without tactile pavements, which represents a detection accuracy higher than that of existing methods in the literature, 2) furthermore the proposed algorithm obtained a detection rate of 93.36% when it was tested with the same worldwide tactile images, 3) the proposed method is robust because it can detect indoor/outdoor tactile paving with different colors, under the different lighting conditions.

II. RELATED WORK

Many studies of tactile paving detection have been conducted. For example, Yamanaka *et al.* [18] and Jie *et al.* [19] proposed systems for detecting only yellow tactile paving, which is common in Asian countries. Additionally, Einloft *et al.* [20] and Woo *et al.* [21], [22] detected the tactile paving specific to Brazil and Korea, respectively. However, because there is no global standard for tactile paving, its characteristics may vary from country to country and region to region. In addition, even when there is a national standard in place, very little tactile paving will appear exactly the same color in captured images due to fading or because the lighting is reflected differently depending on usage conditions. Therefore, the fixed threshold methods used in these studies are not sufficiently robust across the wide range of conditions a person with visual impairment is likely to encounter.

Ghilardi *et al.* [23] dealt with different colors by setting two types of threshold in order to eliminate the effects of differences among countries and regions. First, a histogram of the entire image is created, and then the thresholds are deter-

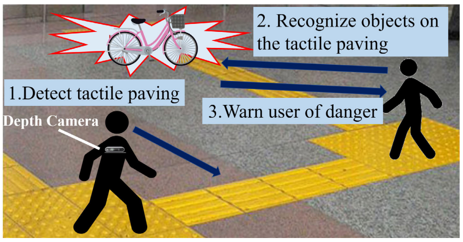


FIGURE 3. Main functions of the system.

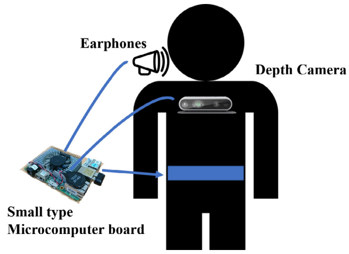


FIGURE 4. The proposed device, as worn by a user.

FIGURE 5. Depth camera.

mined by looking at the peak. Accordingly, when other large areas of the same color are detected, a false/unsuitable threshold could be generated since the peak of the histogram does not match the information from the tactile paving. Moreover, in their method, if the number of pixels detected as regions of interest is less than 10% or more than 40% of the image, the detection is considered as false. This is a vague definition because ROI size may vary according to the user's camera holding position and image resolution. Yamanaka *et al.* [18] also used the same tactile paving detection algorithm in their study. They reported an unsatisfactory detection rate after experiments under a variety of circumstances. Thus, the tactile paving detection algorithms in these studies may not be sufficiently robust.

Other studies have proposed supporting independent walking in individuals with visual impairment by using RFID tags that can transmit information about where the user is [24]–[28]. In addition, Khalifa [29] proposed a system to help individuals with visual impairment identify objects in the environment using QR codes. As long as RFID tags or QR codes are fixed somewhere, they can be detected without having to consider the influence of different colors and sizes or regional differences. However, these tools must be installed everywhere for individuals with visual impairment to be able to walk completely independently. This method is difficult to implement due to the large investment of time and money that is required.

In addition, most studies that have investigated visual detection of tactile paving used high-spec laptops, which are too big for individuals with visual impairment to carry.

Building on these previous studies, we developed a system that enables individuals with visual impairment to walk independently anywhere by detecting tactile paving, regardless of differences in color, size, and country or region. We do this by implementing a method that recognizes color in real time and accurately detects tactile paving by generating histograms from a small window around the center point coordinate of each tactile paving block. Lastly, we constructed a device that is light enough for individuals with visual impairment to carry easily.

III. PROPOSED SYSTEM

An illustration of the proposed system is shown in Fig. 3, and the placement of the system on a user is shown in Fig. 4. The system consists of a depth camera, a small microcontroller that performs image processing and other calculations, and small earphones that guide the user. The main functions/steps are 1) detect tactile paving, 2) recognize objects on the tactile paving, and 3) warn the user of danger.

The goal of the proposed system is to enable independent walking by individuals with visual impairment. To achieve this, we use a depth camera to ascertain the conditions of the area around the user. Accordingly, the fundamental function of the system is to detect the tactile paving because doing so facilitates the guidance of the user. The user receives information through the earphones when a potential danger is detected, thereby preventing accidents beforehand. To implement the system, we developed an image processing algorithm that uses images captured by the camera to detect the tactile paving. This paper discusses the first step, which uses the RGB sensor of the depth camera.

A. DEPTH CAMERA

In this project, we used an Intel RealSense D435 depth camera (Fig. 5). The camera has stereo vision and measures depth by using infrared rays combined with millimeter radar based on the principle of triangulation (similar to human depth vision) [30], [31]. In addition to its depth sensor, it is equipped with an RGB sensor and an IR projector. Power is supplied via USB. While the RGB sensor is being used to detect the tactile paving (step 1), the depth sensor acquires the distance to obstacles, as well as their shape (step 2). Having multiple sensors in a single, light unit simplifies the task, which is the reason we selected the RealSense D435 for this project. Dimensions and weight of the device are 90 mm$\times$ 25 mm $\times$ 25 mm (length $\times$ depth $\times$ height) and 72 g, respectively.

B. MICROCONTROLLER BOARD

There are many recent studies on compact system development using small, lightweight hardware [32]–[35]. In the present study, we used an AEEON UP microcontroller board (Fig. 6). Because the board is about the size of a credit card,

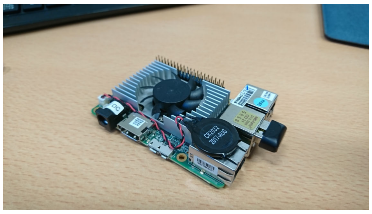


FIGURE 6. AEEON UP microcontroller board.

it can easily be held by the user. The board comes equipped with a 64-bit Intel Atom x5-Z8350 processor having a clock speed of 1.92 GHz [36], 4 GB of memory (RAM), and 32 GB of storage. These features make the AEEON UP microcontroller board ideal for our aims.

IV. TACTILE PAVING DETECTION

In this study, we used RGB images obtained from the RealSense D435 depth camera to detect tactile paving. The system is operated by a program we created using C++ as the scripting language together with the open-source image processing library OpenCV. Our general aim is to detect tactile paving by extracting its characteristic color, a process that comprises three stages. First, the original image from the camera is cropped by 30% on all sides to remove noise and leave only the central tactile paving in the image. Then, the Hough line transform is applied to find the straight borderlines of the tactile paving [37], [38]. Additionally, start and end points of all detected borderlines are determined. Furthermore, the center point of these all points is obtained. Then, a small area around the center point located on the tactile paving is extracted from the image and its HSV-based histogram is calculated to determine the color constellation of the tactile pavement. We used HSV color space, which is used in many color detection systems and is widely available and easy to implement with RGB-to-HSV codes. In the second stage, six dynamic thresholds (the upper and lower bounds of the HSV color space) are determined statistically based on the previously derived histograms. The purpose of these thresholds is to capture the characteristic color of the tactile paving. Finally, a mask image is generated based on the dynamic thresholds. Additionally, morphological operations are applied to the mask image to reduce noise. A flowchart of the algorithm is shown in Fig. 7.

A. HISTOGRAM GENERATION

The purpose of the first stage is to generate HSV histograms of the tactile paving for dynamic threshold determination. Given that tactile paving blocks are rectangular, we can detect their straight borderlines by using line detection. However, this approach might also detect lines inside the tactile paving. In the next step, the coordinates of the start and end points of all the detected straight lines are obtained. By averaging these coordinates, we can obtain the center point of the tactile paving in the image. This process is shown in Fig. 8.

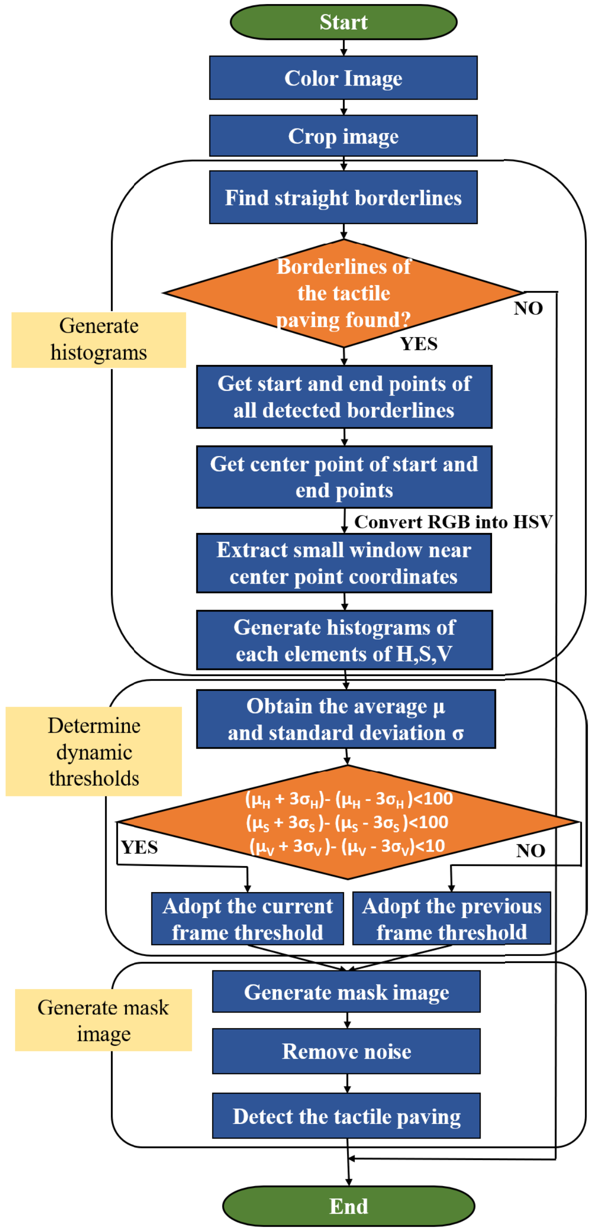


FIGURE 7. Flowchart for the tactile paving detection process.

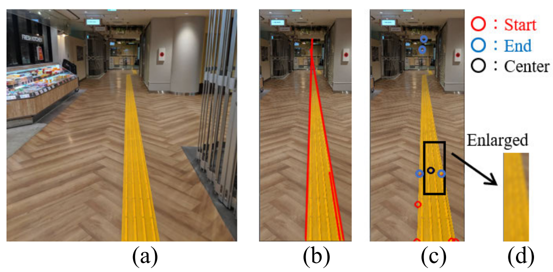


FIGURE 8. (a) Original image; (b) cropped original image and detection lines; (c) coordinates of the start points (red circles), end points (blue circles), average center point (black circles), and small window size (black vertical rectangle); and (d) enlarged small window.

Next, HSV histograms are generated based on a small window around the center point coordinate of the tactile

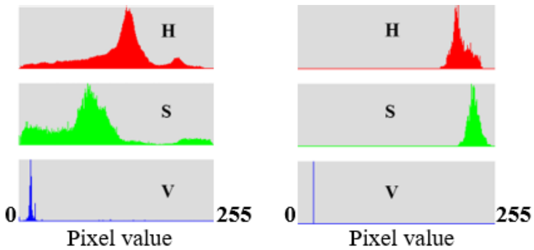


FIGURE 9. Histogram of the original image (left) and the extracted image/window (right).

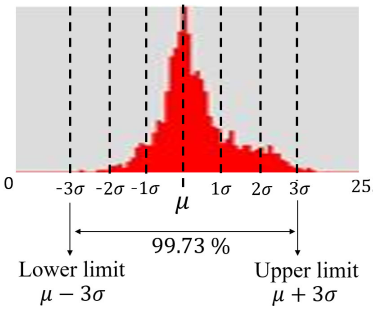


FIGURE 10. Determination of threshold upper and lower limits.

paving tile (Fig. 8d). The shape of the window is a rectangle (height $\times$ width $=$ 100 $\times$ 20 pixels), which allows us to extract only the data (i.e., the tactile paving color and shape information) required to create the histograms. Experimentally, we found that this is the maximum window size that could cover only tactile paving. Figure 9 shows a comparison of histograms for a full image and the small window inside the tactile paving.

B. DYNAMIC THRESHOLD DETERMINATION

The purpose of the second stage is to determine the dynamic thresholds based on the generated histograms. First, the average (μ) of each histogram is obtained. Then, the standard deviation (σ) of each histogram is obtained by Eq. (1).

$$\boldsymbol{\sigma} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} \tag{1}$$

Next, the lower limit of the dynamic threshold is determined to be the value of $\mu - 3\sigma$, and the upper limit is set to $\mu + 3\sigma$. That is, when each histogram approximates the normal distribution, the value within the 99.73% credible interval is determined as the dynamic threshold. The determination of the upper and lower limits of the dynamic thresholds is shown in Fig. 10.

It is very important to distinguish whether the center point is located on the tactile paving to prevent false detection due to incorrect threshold adaptation. If the center point coordinate is not located on the tactile paving, the histogram (color information) will substantially differ from that of the window covering only the tactile paving. Hence, false/unsuitable thresholds would result from distributions being too large. Thus, to determine the correctness of the center point position, we focused on the difference in the

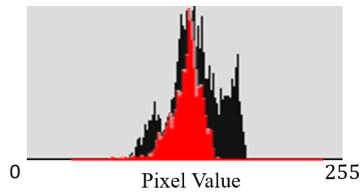


FIGURE 11. Comparison of histograms for images in which the center is (red) and is not (black) located on the tactile paving.

distribution of the histograms when the center point was and was not located on the tactile paving. By using the value of $\boldsymbol{Th} = (\boldsymbol{\mu} + 3\boldsymbol{\sigma}) - (\boldsymbol{\mu} - 3\boldsymbol{\sigma})$, which is the difference between the upper and lower thresholds, we quantify the spread of the distribution and estimate the position of the center point quantitatively. Figure 11 shows a comparison of the histograms in these two scenarios.

Next, we describe an approach to prevent false threshold determination by successfully distinguishing whether the center point is located on the tactile paving. First, the difference between the upper and lower limits of the dynamic thresholds is obtained by Eq. (2).

$$\boldsymbol{Th} = (\boldsymbol{\mu} + 3\boldsymbol{\sigma}) - (\boldsymbol{\mu} - 3\boldsymbol{\sigma}) \tag{2}$$

Then, the position of the center point is estimated according to the value of CP by Eq. (3).

$$\boldsymbol{CP} = \begin{cases} 1, & \boldsymbol{Th} < 100 \\ 0, & \boldsymbol{Th} \geq 100 \end{cases} \tag{3}$$

When the center point is located on the tactile paving, the distribution of the histogram is narrow and very sharp because the small window around the center point contains only the yellow of the tactile paving. Therefore, the average $\boldsymbol{Th}$ in this case is 65-75. On the other hand, when the center point is not located on the tactile paving, the distribution of the histogram is wide because the color information of the small window around the center point will not be uniform. Therefore, the average $\boldsymbol{Th}$ in this case is 120-130, and thus the decision as to whether the center point is on tactile paving is based on the value between them, $\boldsymbol{Th} = 100$. If CP is 1, the center point is estimated to be on tactile paving given that the deviation σ is small and thus very likely represents the specific tactile paving color. If CP is 0, the center point is estimated to not be located on tactile paving, given that the deviation σ is large ($\boldsymbol{Th}$ is large). Moreover, if the center point is determined not to be located on tactile paving, the upper and lower threshold limits obtained from the current frame are replaced by those from the previous frame. In so doing, we can prevent the occurrence of high false rates when the center point is not located on tactile paving. In the proposed algorithm, first it acquires the original image and crops 30% of the ends. This cropping removes noise by leaving only central tactile paving in the image. By the way, pedestrians can turn their body to any direction while walking straight on the tactile paving. So, the camera may not only look at the

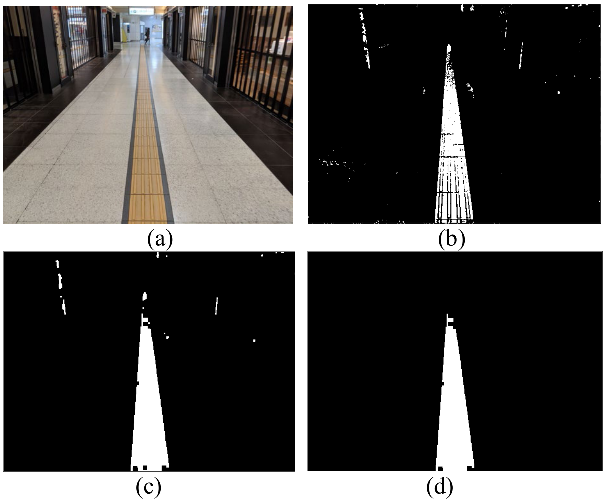


FIGURE 12. (a) Original image and masked image after (b) applying the dynamic threshold, (c) applying the morphological opening, and (d) removing all contours/areas except the largest one (tactile paving) and eliminating contours other than those of the tactile paving.

straight forward view and tactile pavement may not be captured to the center area of images. In this case, if the full/part of the tactile pavement is within the un-considered image area by cropping, threshold for tactile pavement extraction may not be updated. However, as mentioned in the algorithm, if the current threshold is not updated, tactile pavement is detected by applying previously determined threshold. Here, in the final extraction stage, tactile pavement is extracted from the original image and the cropping process does not affect the final extraction. On the other hand, if there is a similar object as tactile pavement that was captured to the center area of the image during the user's body turning, false threshold updating can also be happened. As a result, false detection of tactile pavement can occur. According to the experiments in different environments minor false detections occurred due to this reason.

C. MASK IMAGE GENERATION

The purpose of the third stage is to generate the mask image and apply a morphological opening operator to reduce noise. However, total elimination of noise is not always possible. Hence, we also distinguish each contour and calculate the area. The largest area is assumed to represent the tactile paving. Finally, all remaining contours/areas are removed to obtain a mask image consisting only of the tactile paving (without noise). This process is shown in Fig. 12.

V. EXPERIMENTAL EVALUATION

A. EXPERIMENTAL ENVIRONMENT

We performed experiments using the proposed system and evaluated its performance. The experiments were conducted using 870 images taken at several indoor and outdoor environments in several countries. This includes 470 images of tactile paving in Europe (Germany, Italy, Spain, and France), 400 images in Asia (Japan, China, Korea, Indonesia, Taiwan, and Thailand). We calculate the true positive rate (TP) and false negative (FN) rate using them. In addition to that we use 172 images that do not include tactile pavements to confirm the false positive (FP) rate and true negative (TN) rate. Furthermore, experiments were conducted using the 182 images of tactile paving that are under an obstacle. The images were taken at a height of 1.0 m and a 45° angle relative to the ground, as shown in Fig. 13.

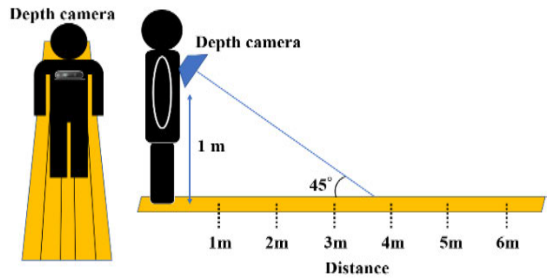


FIGURE 13. Experimental environment.

TABLE 1. Accuracy evaluation results of proposed algorithm.

		Actuality	
		Present	Absent
Predicted	Tactile Paving	811(TP)	28 (FP)
	No Tactile	59 (FN)	144 (TN)
Accuracy	(TP+TN)/(P+N)	91.65 %	

B. EVALUATION

Table 1 shows the following evaluation results: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). TP and TN correspond to images in which the presence or absence of tactile paving was correctly recognized. FP and FN correspond to images in which the presence or absence of tactile paving was not correctly recognized. We evaluated the identification results according to accuracy, which is also shown in Table 1. The calculation of accuracy was done following the definition in Table 1. The accuracy was 91.65% when the proposed algorithm is tested with worldwide tactile pavement images and images without tactile pavements. Hence, the proposed method detected tactile paving in both environments with good accuracy and a comparatively low FP rate. In addition, the accuracy of our results was higher than those of previous studies. For example, Yamanaka *et al.* [18] had an average accuracy of 57.65% and Ghilardi *et al.* [23] achieved 88.48% (Table 2). Therefore, it is confirmed that ours is the most effective method. Moreover, the obtained processing rate was 10.51 fps, which leaves some room for improvement. However, considering the walking speed of most individuals with visual impairment, the current value may be sufficient. The experiment results can be confirmed through the submitted video as well.

Some of experimental images and detection result images are shown in Fig. 14. In addition, these detection result

TABLE 2. Comparison of the accuracy obtained in this study with those of previous studies.

Methods	Accuracy
Yamanaka et al. [18]	57.65 %
Ito et al. [17]	74.00 %
Ghilardi et al. [23]	88.48 %
This method	91.65 %

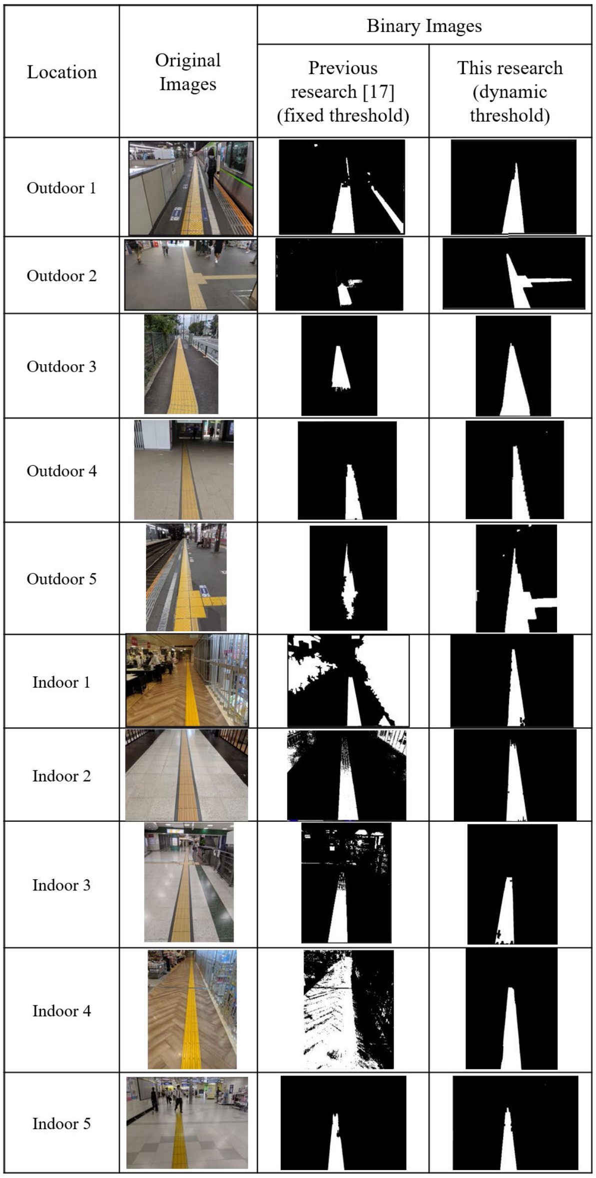


FIGURE 14. Some of original images and detection result images in Japan.

images are compared with those of previous studies that detected tactile paving by fixed thresholds.

Because tactile paving originated in Japan, tactile paving in many other parts of the world is similar to the paving on which we experimented. Therefore, this approach is effective in many countries. However, some tactile paving in the world is different from that in the images we have taken. Therefore, detection experiments using tactile pavement images from Europe (Germany, Italy, Spain, and France), Asia (China, Korea, Indonesia, Taiwan, and Thailand) including Japan were performed. Some of detection results are shown in Fig. 15 and regional based detection rates are shown in Table 3. As shown in table 3, the detection rate ($\frac{TP}{TP+FN}$) was 92.13% (433 out of 470 were detected) in Europe, 94.50% (378 out of 400 were detected) in Asia. According to this, the proposed algorithm obtained a detection rate of 93.36% when it tested with worldwide tactile pavement images. The results of these experiments proved that the detection rate of the tactile paving did not change much for different countries. Therefore, the proposed method works regardless of country or region. Some of the results can be confirmed from the submitted video.

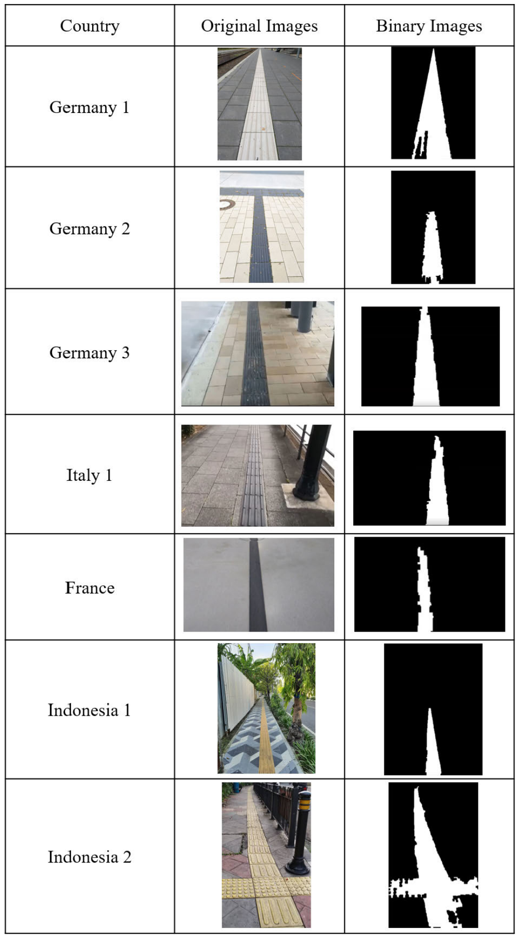


FIGURE 15. Some original images and detection result images of tactile paving in other countries.

Moreover, we conducted experiments to detect tactile paving under an obstacle, assuming a complex environment with barriers on tactile paving. These some of experimental results are shown in Fig. 16. As a result, the detection rate (TP/(TP + FN)) was 93.96% (171 out of 182 were detected) in the case that tactile pavement is covered by obstacles.

TABLE 3. Regional based evaluation results of tactile paving detection.

Region	Detection rate
Asia (Japan, China, Korea, Indonesia, Taiwan, and Thailand)	94.50 %
Europe (Germany, Italy, Spain, and France)	92.13 %

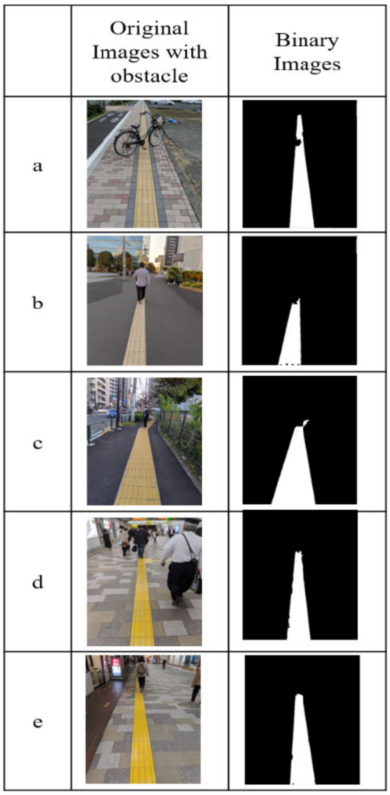


FIGURE 16. Some original images with obstacles and detection result images.

In these experiments, tactile paving up to the obstacle is detected accurately because the obstacle hides the tactile paving. Even if the center point is located on the obstacle, false thresholds are not determined by the process described in Section IV.B. Therefore, false detection of tactile paving due to obstacles does not occur. Moreover, If the obstacle is within the tactile paving area (Fig. 17), in the binary image before morphological opening, only the area of the obstacle can be removed. Therefore, obstacles can be recognized by detecting this area. However, in the future, we plan to use three-dimensional information to detect obstacles to improve detection accuracy.

The differences in detection rate according to distance are shown in Fig. 18. The detection rate is high when the distance between the camera and tactile paving is 1 to 3 m but drops when the distance is 5 m or greater. This is because the near-field color environment is different from the environment for which the threshold was determined.

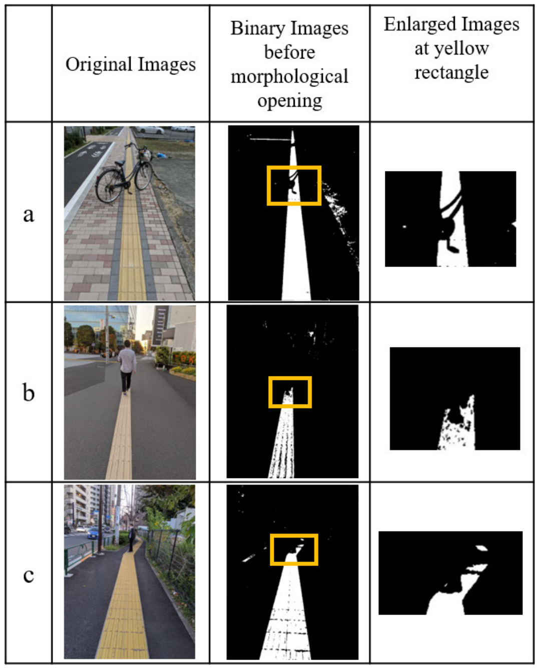


FIGURE 17. Some of original images with obstacle and enlarged images near obstacles.

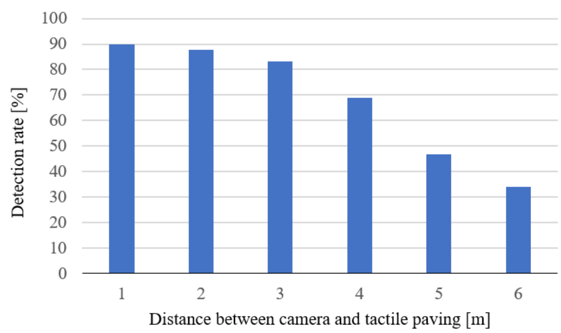


FIGURE 18. Difference in detection rate depending on the distance.

The determined threshold may not recognize the nearby tactile paving and will result in false detection. However, a distance of 4 m is sufficient for the system to function effectively. The experimental results in multiple locations under different conditions can be confirmed through the attached video as well.

C. ERROR ANALYSIS

In this study, experiments were conducted under various circumstances. Therefore, some false positives from the experiments were found (Fig. 19). As a result of analyzing these errors, both previous studies and this study showed that the detection accuracy was significantly reduced in some cases under certain environmental conditions. Specifically, detection accuracy was reduced under the following three conditions:

- Nighttime
- Illumination by intense light sources
- Ground and background having the same color as tactile paving

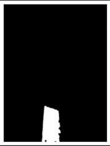
Cases	Original Images	Binary Images
At night		
Illumination by intense light sources		
Ground and background of the same color as tactile paving		

FIGURE 19. False detection under three conditions.

Under these circumstances, it is very difficult to extract the color information of only the tactile paving from the whole image, which reduces the detection accuracy. We have analyzed each of the three conditions in detail. At night, it is difficult to differentiate the color information between the tactile paving and the rest of the image because the entire image is black. Color information that is recognized by hue and saturation in daylight outdoors is not available at night. Under intense light sources, tactile paving made of synthetic rubber or porcelain reflects the light source. As a result, the colors are obscured in the image and the characteristic color information of the tactile paving is lost and cannot be detected accurately. Finally, when the ground and background are the same color as the tactile paving, even if the color information of the tactile paving can be acquired and an accurate dynamic threshold can be set, the color information of the background and the ground will also be within the threshold, so they will be detected together, and it will be difficult to detect the tactile paving separately. If the ground and background of the same color as the tactile paving are separated from the tactile paving, only the ground or background with an area larger than that of tactile paving will be detected. A complete solution to these errors has not yet been established. Therefore, solving these errors is an issue for improving the detection rate in the future.

VI. CONCLUSION

In this paper, we proposed a new tactile paving detection method employing a dynamic threshold approach as part of a support system for individuals with visual impairment. Images are captured by a portable depth camera fixed to the user's body and are processed by a microcontroller board. The proposed system correctly detected tactile paving 91.65% of the time in both indoor and outdoor environments under varying lighting conditions. In the future, we aim to further improve the detection rate and processing speed and will conduct experiments involving individuals with visual impairment.

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