Tactile Tile Detection Integrated with Ground Detection using an RGB-Depth Sensor

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Keywords: Industrial Applications of AI, Tactile Tile, Ground Detection, Visual Impairment.

Abstract: Tactile paving is a system used to help visually impaired individuals walk safely. However, it is difficult to recognize the surrounding tactile tiles on a first visit to an area. In this study, we propose a method for detecting tactile tiles integrated with ground detection using an RGB-Depth sensor. For the ground detection, we use the RANSAC algorithm and expand the region by using the breadth-first search. When detecting the tactile tiles, we perform thresholding and construct a model to identify candidate areas. Experimental results showed that the proposed method obtained a precision of about 83% in detecting tactile tiles on a paved asphalt road. It was possible to correctly distinguish tactile tiles from other objects by combining ground detection in many cases. On the other hand, there were many false detections of tactile tiles in challenging environments, and the processing speed should be improved for real-time navigation.

1 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 vision impairment or blindness. Generally, it is risky for visually impaired individuals to go out alone. Therefore, a guide with professional qualifications is often asked to accompany them. Nevertheless, they sometimes feel overburdened because they have to worry about both their surroundings and the labor of hiring the guide. Even when going out to unfamiliar places with a guide, they are concerned about their surroundings and experience a lot of stress. For such individuals, a tactile paving system is indispensable for walking safely. As they walk, they use a white cane or the sole of the shoe to recognize the protrusions on the surface of the tactile paving. This system is used in many countries due to its usefulness in safely guiding visually impaired people. However, tactile paving has a problem in that the tiles cannot be recognized unless the individual is standing on them. Hence, it is difficult to search for surrounding tactile tiles in unfamiliar places. Simply installing these tiles is not enough to ensure the safety of visually impaired individuals walking alone. Considering the above, there is a need for a guide system that can provide the visually impaired with information on the surrounding environment, including tactile tiles. By providing information for different environments and helping with navigation, such a system will help them go out safely and easily.

When detecting tactile tiles, two features must be considered: color and shape. As the international standard (ISO 23599, 2012) defines, the color of tactile tiles is typically yellow, as this color is easy to distinguish from paved asphalt roads. As for shape, the surface of each tile is lined with linear protrusions for guidance or point-like protrusions for calling attention. A previous work proposed detecting tactile tiles from images of the sidewalk by means of computer vision algorithms (Ghilardi et al., 2016). Our work extends this method so that it can be applied in outdoor environments where multiple objects exist.

In any guide system for the visually impaired, false detection is a very serious problem. For example, if a tactile tile is falsely detected on a wall and that navigation information is transmitted to the visually impaired, they will walk in that direction and may actually collide with the wall. Generally, tactile tiles are installed on flat ground. If a tactile tile is detected at a location that is not estimated to be flat ground in the image, the navigation information should not be transmitted. We propose a method that detects both tactile tiles and flat ground in parallel by using an RGB-Depth sensor. Our contributions are

Yamanaka, Y., Takaya, E. and Kurihara, S.
Tactile Tile Detection Integrated with Ground Detection using an RGB-Depth Sensor.
DOI: 10.5220/0009092907500757
In *Proceedings of the 12th International Conference on Agents and Artificial Intelligence (ICAART 2020) - Volume 2*, pages 750-757
ISBN: 978-989-758-395-7; ISSN: 2184-433X

summarized as follows.

- We detect tactile tiles in outdoor environments where various objects exist.
- We reduce false detection of tactile tiles compared to the case of detecting them in an entire image by detecting flat ground and narrowing the detection range.
- Processing time can be shortened compared to the case of serial processing by executing two processes in parallel: ground detection and tactile tile detection.

2 RELATED WORK

Many approaches to the detection of specific objects have been proposed for navigation systems used by the visually impaired. In some approaches, the segmentation of flat ground is performed using an RGB-Depth sensor. Yang, Wang, Hu, and Bai proposed a method to estimate normal vectors and extend regions from depth information after detecting the plane by using the RANSAC algorithm (Yang et al., 2016). This method makes it possible to perform the navigation by detecting areas where the visually impaired can pass. The ground detection process in our work draws on this technique. Caraiman et al. introduced a method to detect specific objects such as doors, stairs, and signs after completing the ground segmentation (Caraiman et al., 2017).

Other approaches detect the tactile tiles from a color image. Kassim et al. developed a method to determine the types of protrusion on the surface of a tactile tile by deriving the metric that represents the geometrical characteristics of the figure (Kassim et al., 2018). Jie, Xiaochi, and Zhigang detected the straight lines of a tile by thresholding, edge detection, and Hough transforming (Jie et al., 2010). Ghilardi, Macedo, and Manssour proposed a method that detects a tactile tile from sidewalk images using computer vision algorithms and a decision tree (Ghilardi et al., 2016). Our work extends these ideas for application to outdoor environments where there are multiple objects besides tactile tiles.

Some approaches detect multiple objects simultaneously by semantic segmentation using a convolutional neural network. Among these, a representative example is a method by Yang et al. that detects objects such as sidewalks, stairs, and cars by means of a unique model architecture (Yang et al., 2018). When providing navigation for the visually impaired, it is crucial to detect multiple objects simultaneously. In our work, we also find semantic segmentation to be effective for detecting multiple objects. However, we need to devise additional approaches for objects such as tactile tiles, where false detection can be a serious problem.

3 PROPOSED METHOD

The flow chart of the proposed method is shown in Figure 1. In this section, we describe the RGB-Depth sensor we use for our experiment (Sec 3.1), ground detection (Sec 3.2), tactile tile detection (Sec 3.3), and the comprehensive judgment for determining whether tactile tiles do indeed exist (Sec 3.4).

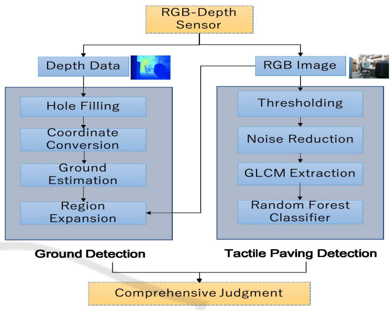


Figure 1: Flow chart of proposed method.

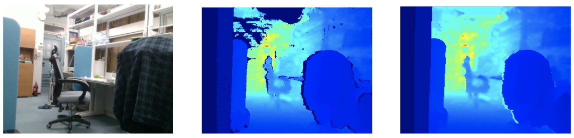
3.1 RGB-Depth Sensor

We use the Intel RealSense Depth Camera D435i as the RGB-Depth sensor (Figure 2). This is a stereo vision camera that can measure depth. It is equipped with two depth sensors, an RGB camera, and an active IR projector that illuminates the object. It can also acquire linear acceleration and angular velocity synchronously with depth information, as it is equipped with an inertial measurement unit (IMU). As shown in Figure 3(b), there are some parts of the image where the depth information is not obtained accurately due to noise and lack of data. In this work, we remove the noise and compensate for the lack of data by using the hole-filling filter that comes with RealSense SDK. The effect of this filter is shown in Figure 3(c).

Figure 2: RealSense D435i.

3.2 Ground Detection

This subsection describes the coordinate conversion (Sec 3.2.1), ground estimation (Sec 3.2.2), and estimated region expansion (Sec 3.2.3) in detail.



(a) (b) (c)

Figure 3: (a) Color image acquired by RGB camera (RealSense D435i). (b) Original depth image. (c) Depth image after applying hole-filling filter to (b).

3.2.1 Coordinate Conversion

We use a three-dimensional point cloud calculated from the depth information to detect the ground. This point cloud is acquired as coordinates in the camera coordinate system, so we need to convert it to coordinates in the global coordinate system. When converting the coordinates, a rotation matrix based on the attitude of the camera is required. We use the quaternions to express the posture. The quaternions are a four-dimensional vector that extends the complex number, which is used to express the posture of an object in 3D space. The quaternion $\boldsymbol{q}$ is shown in Equation (1), where q_0, q_1, q_2, and q_3 are real numbers, and $\boldsymbol{i}$, $\boldsymbol{j}$, and $\boldsymbol{k}$ are the basic quaternion units. We use the Madgwick filter (Madgwick, 2010) to derive the quaternions. According to Equation (2), the point (X, Y, Z) in the camera coordinate system is converted into the point (X_w, Y_w, Z_w) in the global coordinate system by using the quaternion $\boldsymbol{q}$ obtained by the Madgwick filter (Diebel, 2006). In Equation (2), $\mathbf{R}$ is equivalent to the rotation matrix.

$$\boldsymbol{q} = q_0 + q_1\boldsymbol{i} + q_2\boldsymbol{j} + q_3\boldsymbol{k} \tag{1}$$

$$\mathbf{R} = \begin{bmatrix} q_0^2+q_1^2-q_2^2-q_3^2 & 2(q_1q_2-q_0q_3) & 2(q_0q_2+q_1q_3) \\ 2(q_0q_3+q_1q_2) & q_0^2-q_1^2+q_2^2-q_3^2 & 2(-q_0q_1+q_2q_3) \\ 2(q_1q_3-q_0q_2) & 2(q_2q_3+q_0q_1) & q_0^2-q_1^2-q_2^2+q_3^2 \end{bmatrix}$$

$$\begin{bmatrix} X_w \\ Y_w \\ Z_w \end{bmatrix} = \mathbf{R} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \tag{2}$$

3.2.2 Ground Estimation

We estimate the ground by using the random sample consensus (RANSAC) algorithm (Fischler and Bolles, 1981), a robust estimation algorithm that considers outliers in the given data and suppresses their effects. RANSAC estimates the model parameters by dividing a set of data into inliers (a set of data that the model fits) and outliers (a set of data that the model does not fit). The plane model of the point cloud in the global coordinate is expressed in Equation (3) using four parameters A, B, C, and D. The condition to be regarded as inliers is defined by Equation (4) and consists of the threshold T for the distance between the estimated plane and the point cloud. First, three points are randomly selected from the point cloud. Then, the parameter estimation is performed repeatedly by RANSAC. (See the work of Zeineldin and El-Fishawy (Zeineldin and El-Fishawy, 2016) for a detailed explanation of how the parameters are estimated.) When the angle between the estimated plane and the XY plane in Equation (5) is abnormally large, (i.e., not considered to be the ground), we will return the processing to the beginning of the loop to reduce calculation time. In this way, ground with a small angle between the XY plane is estimated. Figure 4(b) depicts the estimated ground region.

$$AX_w + BY_w + CZ_w = D \tag{3}$$

$$\frac{|AX_w + BY_w + CZ_w + D|}{\sqrt{A^2+B^2+C^2}} < T \tag{4}$$

$$= \arccos \frac{|B|}{\sqrt{A^2+B^2+C^2}} \tag{5}$$

3.2.3 Estimated Region Expansion

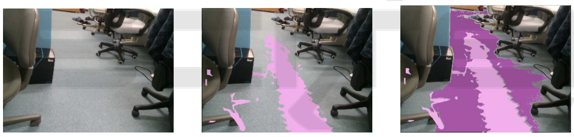
As shown in Figure 4(b), only a part of the ground is estimated by RANSAC. Hence, we need to expand the estimated region. In this work, we do this by choosing seeds and performing the breadth-first search. Algorithm (1) describes the details. First, several points are randomly selected if two conditions are satisfied: one, points belong to inliers in the model estimation by RANSAC, and two, one or more four-connected neighbors of them belong to outliers. Pixels of the color image corresponding to those points are adopted as seeds S. If one of those pixels exists at the outer edge of the color image, it is not adopted as a seed. Then, the breadth-first search starts from the first element of S, and the pixel visited in the search is regarded as the ground. If a pixel meets at least one of the following four conditions, we do not search further from that pixel.

- The point in the point cloud corresponding to the visited pixel p belongs to inliers.
- The visited pixel p has already been searched
- The difference between the hue h_p of the visited pixel p and the average hue h_{avg} of pixels that have corresponding points belonging to inliers is greater than or equal to the threshold H.
- The visited pixel p is located at the Canny edge (Harris et al., 1988) of the color image.

The search is repeated for all the elements in S. The result of the estimated region expansion is shown in Figure 4(b) and 4(c), which depicts the expansion of the region that is considered to be the ground.

Algorithm 1 : Region Expansion based on Breadth-First Search.

Seeds $S = [S_1, \ldots, S_N]$
h_{avg} = average hue value of inliers
for $i = 1$ **to** N **do**
  Initialize Queue Q
  Add S_i to Q
  while Q is not empty **do**
    q = the first element of Q
    Remove q from Q
    for p = four-connected neighbors of q **do**
      if p is not in the inliers and p is not visited and $|h_p - h_{avg}| < H$ and p is not at the Canny edge of the image **then**
        Add p to Q
        $p \leftarrow$ visited
      end if
    end for
  end while
end for



(a) (b) (c)

Figure 4: (a) Color image acquired by RGB camera (RealSense D435i). (b) Region estimated to be ground by RANSAC (pink). (c) Region added to (b) by expansion (purple).

3.3 Tactile Tile Detection

This subsection describes the thresholding (Sec 3.3.1), noise reduction by DBSCAN clustering (Sec 3.3.2), and model construction by extracting features (Sec 3.3.3) in detail.

3.3.1 Thresholding

From the viewpoint of visibility, the color of tactile tiles is usually yellow. First, we convert the RGB image into an image in the YCbCr color space, which is robust to light conditions, as a previous work (Ghilardi et al., 2016) showed. The YCbCr color space expresses the color with the luminance (Y), the blue-difference chroma (Cb) obtained by subtracting the luminance from blue, and the red-difference chroma (Cr) obtained by subtracting the luminance from red. Thus, we can perform thresholding regardless of the brightness of the image because the hue and brightness are independent in the YCbCr color space. Second, we create a histogram for Cb and Cr and perform thresholding. Figure 5(b) and (e) shows the thresholding results.

3.3.2 Noise Reduction

When candidate areas are detected by thresholding, a small area is sometimes found, as indicated in Figure 5(b) and (e). Small areas like this are considered a noise in the detection of tactile tiles because they exist in a large area of candidate areas. We reduce the noise with DBSCAN clustering (Ester et al., 1996) in the pixel coordinate system with the upper-left of the image as the origin. Since DBSCAN clustering is a density-based clustering method, which makes it unnecessary to determine the number of clusters in advance, it is robust against outliers. In the result of DBSCAN clustering against remaining pixels as candidate areas, some pixels do not belong to any clusters. These pixels are considered noise and are removed. Figure 5(c) and (f) shows the result of noise reduction. Identification after the noise reduction is necessary because multiple clusters sometimes exist as candidate areas in outdoor environments.

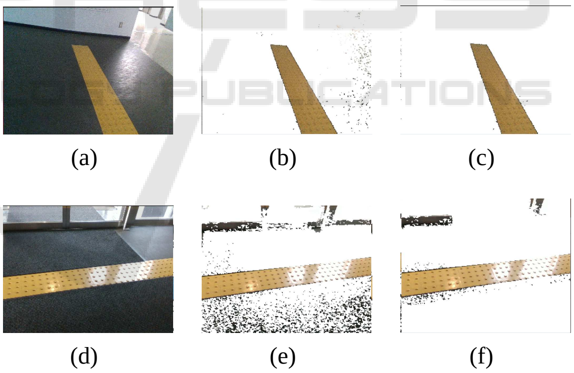


Figure 5: (a), (d) Color image acquired by RGB camera (RealSense D435i). (b), (e) Color image including noise after thresholding. (c), (f) Denoised color image by DBSCAN clustering, where one cluster in (c) and three clusters in (f) exist as candidates areas.

3.3.3 Model Construction

The shape of the tactile paving surface is unique compared with other objects in an outdoor environment. Constructing a model that captures this feature is key for determining whether or not a tactile tile exists in a candidate area. We use a random forest classifier (Breiman, 2001) based on a decision tree as the model to judge its existence. The image texture features calculated from the gray-level co-occurrence matrix (GLCM) are adopted as features of the model. First, the GLCM is calculated for each offset defined by different distances and angles. Second, the image texture features are acquired by extracting statistic information from these GLCMs. In this work, we obtain them through the following procedure.

1. Several pixels are chosen randomly from near the center of one candidate area.
2. Twenty-five-pixel square images are cropped from the original image (Figure 5(a) and (d)) around these pixels. These images are regarded as patches
3. Steps 1 and 2 are repeated for each candidate area.
4. For each patch, the image texture features are obtained by calculating the GLCM with the determined offsets.

Pixels are selected from near the center of candidate areas in step 1 so that we can create patches that capture the major part of the candidate area. We use three different distances (1, 2, and 3 pixels) and four different angles (0, 45, 90, and 135 degrees) as an offset and extract six different statistic information, so a total of 72 features are generated from each patch. Then, we label these patches as to whether they contain tactile tiles or not. Lastly, the learning of the model is initiated.

3.4 Comprehensive Judgment

The calculation time to process ground detection and tactile tile detection in series is long. If these two processes are executed in parallel, we can reduce the calculation time. In the result of parallel processing, we obtain outputs of the ground detection and tactile tile detection separately. Hence, it is necessary to make a comprehensive judgment as to whether the tactile tile does exist. In this study, we count the number of patches if the following two conditions are satisfied.

- The model (Sec 3.3.3) prediction of the patch is positive.
- The center of the patch is considered to be the ground in the ground detection (Sec 3.2).

If this number is equal to or greater than a certain percentage (P) of the number of patches in the area, the candidate area is considered to be a tactile tile.

4 EXPERIMENTS

This section gives an overview of the experiments we performed to evaluate the proposed method (Sec 4.1) and reports the results for the effectiveness of incorporating ground detection processing (Sec 4.2), the parallelism of the proposed method (Sec 4.3), and the robustness to environments (Sec 4.4).

4.1 Overview of Experiment

To evaluate the proposed method, we performed the following three experiments.

- Evaluation of the effectiveness of incorporating ground detection (Sec 4.2).
- Evaluation of the parallelism of the proposed method (Sec 4.3).
- Evaluation of the robustness to environments (Sec 4.4).

We held the RGB-Depth sensor at a height of about 1.5 m from the ground surface using a handheld tripod. We tilted it from the horizontal at an angle of about 45 degrees toward the ground. Figure 6 shows the experimental scene. We performed the processing of the proposed method by a laptop computer with an Intel Core i7 processor and 16GB of memory. The parameter values are listed in Table 1 and we created five patches (See Sec 3.3.3) per candidate area. The identification results of candidate areas are labeled as True Positive (TP), True Negative (TN), False Positive (FP), or False Negative (FN).

Regarding an area that is not a tactile tile as positive (FP) is a serious problem. Therefore, the precision shown in Equation (6) is used to evaluate the identification results.

Figure 6: Experimental scene in outdoor environment.

Table 1: Parameter values used in experiment.

T (Sec 3.2.2)	0.03 m
(Sec 3.2.2)	10°
N (Sec 3.2.3)	50
H (Sec 3.2.3)	20
P (Sec 3.4)	40 %

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

4.2 Effectiveness of Incorporating Ground Detection

4.2.1 Experimental Design

To evaluate the effectiveness of incorporating ground detection, we took videos with the RGB-Depth sensor in the following two environments.

- Tactile tiles on a paved asphalt road in a sunny area (measuring distance: about 200 m) (Env 1).
- Tactile tiles on a paved asphalt in a shaded area (measuring distance: about 200 m) (Env).

When identifying candidate areas in each frame, we performed two operations simultaneously: narrowing the detection range of tactile tiles incorporating ground detection, and detecting them from the entire image. We examined the following four cases.

1. Detecting the ground and narrowing the detection range of tactile tiles in Env 1 (Case 1).
2. Detecting tactile tiles from the entire image without ground detection in Env 1 (Case 2).
3. Detecting the ground and narrowing the detection range of tactile tiles in Env 2 (Case 3).
4. Detecting tactile tiles from the entire image without ground detection in Env 2 (Case 4).

In Cases 2 and 4, only the first condition of the comprehensive judgment (Sec 3.4) was valid. We calculated the precision of the identification results and compared them.

4.2.2 Results and Discussion

Table 2 lists the results of the candidate area identification for each of the four cases. As shown, the precision was higher when ground detection was performed in both Env 1 and Env 2. We conclude that incorporating ground detection is effective for reducing false detections of tactile tiles.

Table 2: Effectiveness of ground detection.

Case	TP	FP	FN	TN	Precision
1	171	31	155	164	**0.8465**
2	206	73	120	122	0.7384
3	95	20	183	398	**0.8261**
4	162	124	116	294	0.5664

4.3 Parallelism of Proposed Method

4.3.1 Experimental Design

In the proposed method, ground detection and tactile tile detection are performed in parallel. To evaluate the parallelism, we performed an experiment where two processes are performed in series for comparison. First, we excluded pixels that were not considered ground in the ground detection (Sec 3.2). Second, we performed tactile tile detection (Sec 3.3) on the remaining pixels. As a result, two processes were performed sequentially. We took videos with the RGB-Depth sensor in Env 1. For these two cases, we calculated the average processing time per frame and compared it.

4.3.2 Results and Discussion

Table 3 lists the average processing time per frame for these two experiments. As shown, the processing time per frame can be shortened by processing in parallel.

Table 3: Evaluation of parallel processing.

Type	Processing time per frame
Serial	1.5904 sec
Parallel	**1.4832** sec

4.4 Robustness to Environments

4.4.1 Experimental Design

We investigated whether the proposed method can be applied in various environments. We took videos with the RGB-Depth sensor in Env 1, Env 2, and the following three environments.

- Tactile tiles with a small luminance ratio with the road (measuring distance: about 80 m) (Env).
- Tactile tiles on a tiled sidewalk (measuring distance: about 80 m) (Env 4).
- A tiled sidewalk with no tactile tiles (measuring distance: about 80 m) (Env 5).

For each environment, we calculated the precision of identification results and compared them.

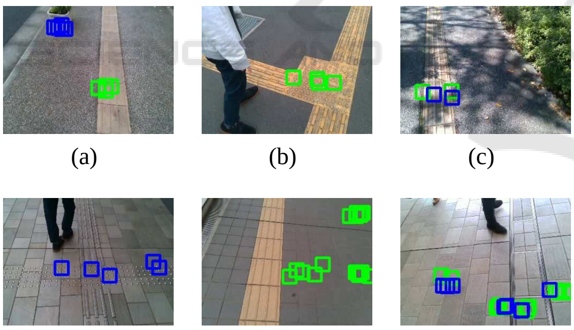
4.4.2 Results and Discussion

Table 4 lists the identification results of candidate areas in various environments. Figure 7 shows the results of tactile tile detection by the proposed method, where green and blue boxes indicate positive and negative patches by comprehensive judgment (Sec 3.4), respectively. As Figure 7(a)-(c) shows, the candidate area was identified relatively accurately, and the precision was high: 84.7% in Env 1 and 82.6% in Env 2. In contrast, as Figure 7(d)-(f) shows, there were many false detections of tactile tiles in Env 3, Env 4, and Env 5, and the precision was low.

As mentioned in the international standard (ISO 23599, 2012), the tactile tile should have a high luminance ratio with the road. The tactile tile in Env 3 did not follow this standard. It seems that these tactile tiles were not detected correctly because the proposed method expected them to follow the standard. In Env 4 and Env 5, we presume that tiled sidewalks were the problem; specifically, the shape of the tiles on the sidewalks was similar to the surface of the tactile tiles for guidance. We also think that most of the pixels remained due to the tile color after thresholding. Furthermore, the model prediction probably gave false positives because the training data lacked data that had negative labels of the tiles on the sidewalks.

Table 4: Identification results in each environment.

Env	TP	FP	FN	TN	Precision
1	171	31	155	164	**0.8465**
2	95	20	183	398	**0.8261**
3	20	37	59	12	0.3509
4	22	37	12	95	0.3729
5	0	39	0	47	0



(a) (b) (c)

(d) (e) (f)

Figure 7: Detection results in each environment. (a), (b) Env 1. (c) Env 2. (d) Env 3. (e) Env 4. (f) Env 5.

5 CONCLUSIONS

In this paper, we have proposed a method of detecting ground and tactile tiles in parallel by means of an RGB-Depth sensor to provide information on the surrounding tactile tiles to the visually impaired. Experimental results showed that the proposed method obtained the precision of about 83% on a paved asphalt road.

In future work, we aim to improve the detection performance of the model and the real-time performance of the processing. Moreover, it is vital to devise an actual navigation method. To improve the detection performance, we will use pictures of tactile tiles in various environments as training data for the model. Also, although we shortened the processing time by parallel processing in this study, the speed was insufficient for real-time navigation. Therefore, we will optimize the processing or consider another faster method. Lastly, the information derived from the detection results should be conveyed to the visually impaired through voice and so on. This required information includes the direction and distance of tactile tiles from the current standing point. For the distance, the depth information acquired by the RGB-Depth sensor should be useful. We will examine a concrete navigation method and develop a prototype that incorporates an RGB-Depth sensor.

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