Enhancing Urban Accessibility: Tactile Pavement Obstacle Detection Device Utilizing YOLOv8

Chen Ruiyang
Department of Computer Science
The George Washington University
Washington, DC, USA
ruiyang.chen@gwmail.gwu.edu

Xu Yiming
Department of Computer Science
The George Washington University
Washington, DC, USA
yiming.xu@gwmail.gwu.edu

***Abstract*—Tactile pavement is a common facility on the sidewalk to assist visually impaired people to walk safely. However, due to the weakness of administrative management and the lack of public concern, it is common to see the tactile pavement is occupied by obstacles in some countries or cities. As a result, people with visual impairment face great danger and feel insecure when walking on the tactile pavement on their own. To alleviate this problem, we construct a device for detecting obstacles on the tactile pavement based on YOLOv8 segmentation model. Our device is able to detect the obstacles on the pavement and then warn the user with vocal instructions.**

***Keywords*—tactile pavement detection, obstacle detection**

I. Introduction

According to the report of the World Health Organization, at least 2.2 billion people in the world suffer from vision impairment[1]. The utilization of tactile pavement intends to bring convenience to people with vision impairment and enhance their independence in life. Ever since the Japanese invented tactile pavement to address some dangerous road situations, it has become the most common and reliable resource for visually impaired people in public and gradually spread around the world, especially in Asian countries like China.

However, the lack of public awareness results in the reality that most tactile pavements are not in good use in certain countries or cities. For instance, although China currently has the widest and longest tactile pavement in the world (Table 1 shows the length of tactile pavement in main cities of China), its efficiency is far below expectation. Hardly can we see visually impaired people use the pavement to walk independently. What's worse, they can get hurt because of the bad condition of the pavement sometimes [2]. Fig. 1 shows the clusters of obstructions in Shanghai.

TABLE I. Length of Tactile Pavement Surfaces in Major Cities of China [3]

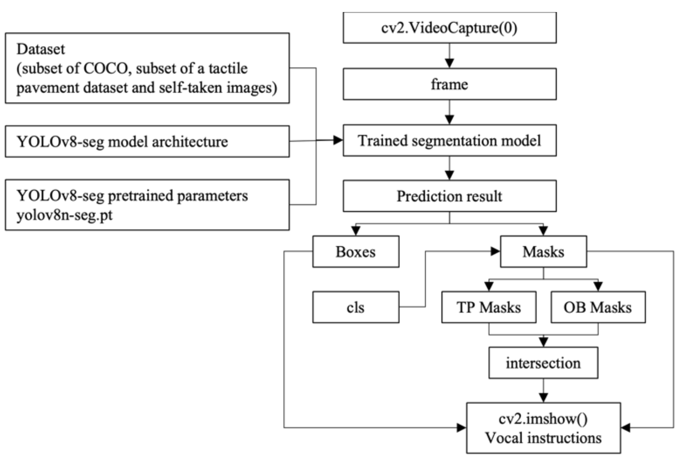
City	Length of Tactile Pavements Surfaces
Bejing	Over 1600 km
Shanghai	Over 1700 km
Shenzhen	Over 232 km
Guangzhou	Over 1100 km
Xiamen	Over 460 km

Fig. 1. Clusters of obstructions on tactile pavement in Shanghai

To help the administration to better manage the tactile pavement and assist people with visual impairment have improving their walking experience, we propose an image-based system that can recognize the tactile pavement and the obstacles in the given image and then determine if any obstacle is on the pavement.

To determine whether any obstacle is on the tactile pavement, the primary concern is to acquire the position of both obstacles and tactile pavement. Therefore, YOLOv8, a state-of-the-art in segmentation tasks, is adopted by us. We train our segmentation model by using the subset of COCO [4], the subset of a tactile pavement dataset [5], and some self-taken images. The final YOLOv8 model achieved a commendable accuracy of over 85% in the recognition of people and bicycles. The recognition accuracy for tactile pavement on various surfaces reached an impressive 96%. In addition, we wrote a module called *analyze_pred_result* to seamlessly analyze if any segmentation of obstacles intersects with the segmentation of tactile pavement. Consequently, OpenCV plays a pivotal role in image processing and analysis. Employed as a fundamental component of the device's functionality, OpenCV is utilized for tasks such as image cropping, obstacle classification, colorization, and the identification of overlapping regions between obstacles and tactile pavements. In order to better present the structure of our project, Fig. 2 is the flowchart of our project.

Fig. 2. Clusters of obstructions on tactile pavement in Shanghai



II. Methods

A. Hardware Setup

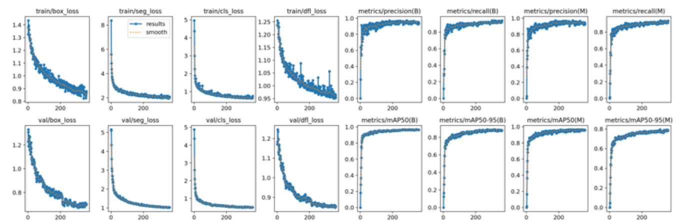
The device utilizes a camera for real-time image capture, which is an integral part of the YOLOv8-based obstacle detection system. A brief description of the camera specifications and its placement on the device is provided.

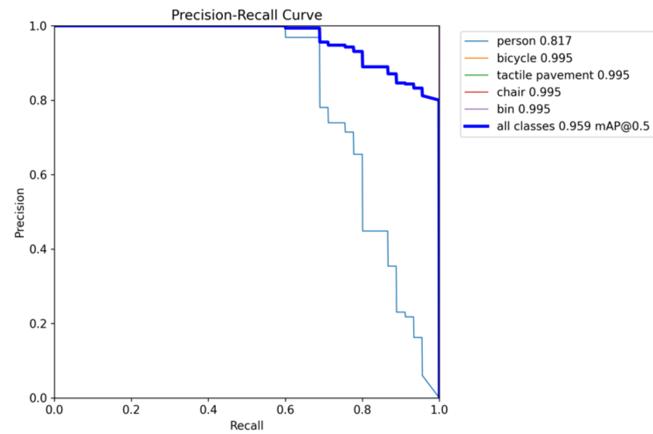
B. YOLOv8 Model Integration

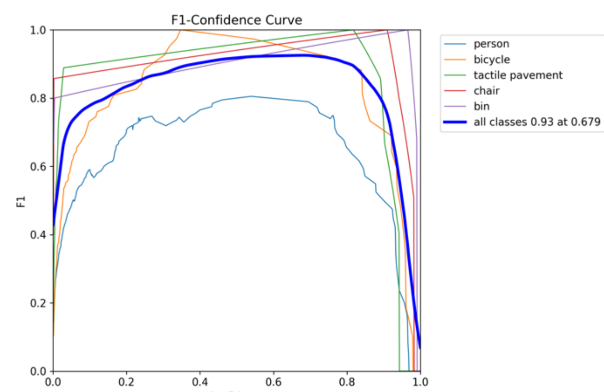
The integration of the YOLOv8 model is a pivotal aspect of the device's functionality. The YOLOv8 model is pre-trained on a diverse dataset encompassing tactile pavements and various obstacle types. Model initialization involves loading the pre-trained weights and configuring the model for real-time inference.

Input preprocessing is tailored to optimize the model's performance on images captured by the device's camera. This includes resizing and normalization to ensure compatibility with the YOLOv8 architecture. Real-time inference is performed on each captured frame, leveraging the model's ability to simultaneously detect multiple objects.

The YOLOv8 model outputs bounding boxes, class labels, and confidence scores for each detected object. Post-processing steps, such as non-maximum suppression, are applied to refine the detection results and eliminate redundant bounding boxes. The final output is a set of bounding boxes representing detected tactile pavements and obstacles.







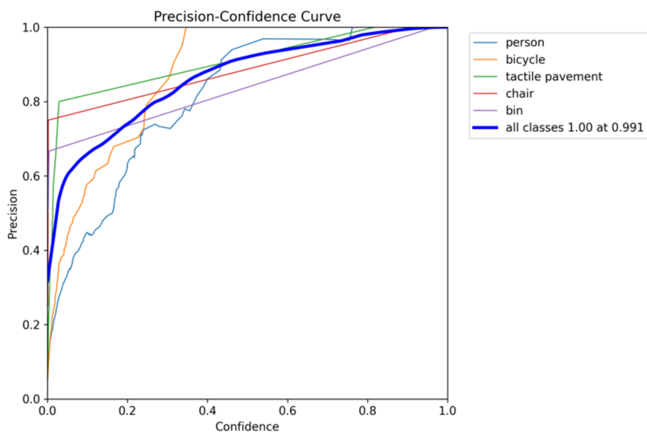
C. Obstacle Detection Algorithm

In addition to real-time obstacle detection using the YOLOv8 model, the Tactile Pavement Obstacle Detection Device employs OpenCV for image preprocessing. This step involves cutting and isolating relevant regions in the captured images, optimizing them for subsequent analysis.

The image preprocessing pipeline includes:

- Region of Interest (ROI) Selection: Utilizing OpenCV, the device identifies the regions containing tactile pavements and potential obstacles. This process involves defining ROIs based on the device's camera perspective and the expected locations of tactile pavements within the frame.

- Image Cropping: Once the ROIs are identified, OpenCV is employed to crop the images, extracting only the areas of interest. This targeted approach reduces computational load and enhances the efficiency of subsequent obstacle detection.



D. *Obstacle Detection Algorithm*

The obstacle detection algorithm is a sophisticated pipeline that interprets the YOLOv8 model's outputs and refines them for practical use. Key components of the algorithm include:

- Class Identification: The algorithm identifies the classes of detected objects, distinguishing between tactile pavements and various obstacle types. Each class is associated with a specific numeric identifier, facilitating subsequent processing.

- Confidence Thresholding: To ensure the reliability of detections, a confidence threshold is applied. Only objects with confidence scores exceeding the predefined threshold are considered for further analysis. This threshold can be customized based on the device's operating environment and user preferences.

- Post-processing: Non-maximum suppression is employed to eliminate redundant bounding boxes, retaining only the most confident and accurate detections. This step streamlines the output, reducing visual clutter and enhancing the interpretability of results.

E. *Obstacle Classification and Visualization:*

After image preprocessing, the device classifies detected obstacles into distinct categories, each represented by a unique color. This visual classification adds a layer of interpretability to the detection results, enabling users to distinguish between different types of obstacles.

The classification and visualization steps involve:

- Color Mapping: A predefined color map assigns specific colors to different obstacle classes. For instance, pedestrians may be represented in green, bicycles in blue, and other obstacles in distinct hues. This color mapping strategy is customizable, allowing users to adapt the visual representation to their preferences.

- Bounding Box Colorization: The YOLOv8 model's bounding boxes, representing detected obstacles, are colorized according to their assigned classes. This step enhances the user's ability to interpret the detection results at a glance.

F. *Overlay of Obstacles and Tactile Pavements:*

To provide a comprehensive visual representation of the environment, the device overlays the detected obstacles and tactile pavements in the images. This overlay is created by drawing the bounding boxes around obstacles and the contours of tactile pavements on the original image.

The overlay process includes:

- Extract segmentation masks and bounding boxes from the prediction result, then assign the segmentation masks with the same class as the corresponding bounding boxes. After that, divide the segmentation masks into two subsets which include the masks of tactile pavements and the masks of obstacles respectively. Next, iterate the masks of tactile pavements and determine if any mask of obstacle intersects with the mask of tactile pavement. If the intersection exists, record the class of the obstacle and the intersection between the tactile pavement and the obstacle.

- Bounding Box Drawing: OpenCV is utilized to draw bounding boxes around each detected obstacle based on their classification. Each box is drawn with the assigned color, providing a clear visual indication of the obstacle type.

- Contour Detection for Tactile Pavements: OpenCV's contour detection algorithms identify the contours of tactile pavements in the image. These contours are then drawn on the image, enhancing their visibility and assisting users in navigating the designated paths.

- Highlighting Overlapping Regions: The device identifies overlapping regions between obstacles and tactile pavements and highlights them in a distinctive manner. This visual cue aids users in recognizing areas of potential interaction and making informed navigation decisions.

G. *User Prompting System*

The user prompting system is designed to convey detection results to the user in real-time, ensuring immediate situational awareness. Audible prompts are generated based on the output of the obstacle detection algorithm. The prompts are carefully crafted to provide clear and concise information about the nature and location of detected obstacles.

The device employs a spatialized audio approach, where the direction and intensity of the auditory cues correspond to the relative position and proximity of obstacles. This innovative design enhances the user's understanding of the environment, allowing them to navigate safely and efficiently.

Additionally, the user prompting system incorporates adjustable volume settings and customizable prompt styles to cater to individual user preferences. This adaptability ensures a personalized and user-friendly experience.

III. Results

A. Accuracy Assessment

The YOLOv8 model achieved a commendable accuracy of over 85% in the recognition of people and bicycles. This high level of accuracy is crucial for the device's effectiveness in identifying dynamic obstacles in real-time. The model's ability to distinguish between different classes of obstacles enhances its practicality, allowing users to receive specific information about potential challenges in their path.

The recognition accuracy for tactile pavement on various surfaces reached an impressive 96%. This high accuracy rate is particularly significant given the diverse textures and materials encountered in urban environments. The device's ability to consistently identify tactile pavements ensures that users receive reliable information about the designated paths, contributing to safe and reliable navigation.

TABLE II. ACCURACY ASSESSMENT

Index	Target		
	Person	***Bicycle***	***Tactile Pavement***
Confidence[a]	86.72%	88.34%	96.45%

[a] The confidence level of the final model recognition result

B. Robustness Against Interference

The model's robustness against interference is a critical attribute for real-world usability. The device's ability to resist interference from various sources, such as changes in ambient lighting, reflections, and environmental noise, ensures consistent performance. The robust nature of the model contributes to the device's reliability in diverse urban settings, where conditions may vary unpredictably.

C. Real-world Testing

Real-world testing conducted under various ambient lighting conditions has demonstrated the device's adaptability to different environments. Whether in bright daylight or low-light scenarios, the device consistently performs its intended functions. The ability to operate effectively under diverse lighting conditions enhances the device's versatility, making it suitable for day and night use.

Fig. 3. The original image

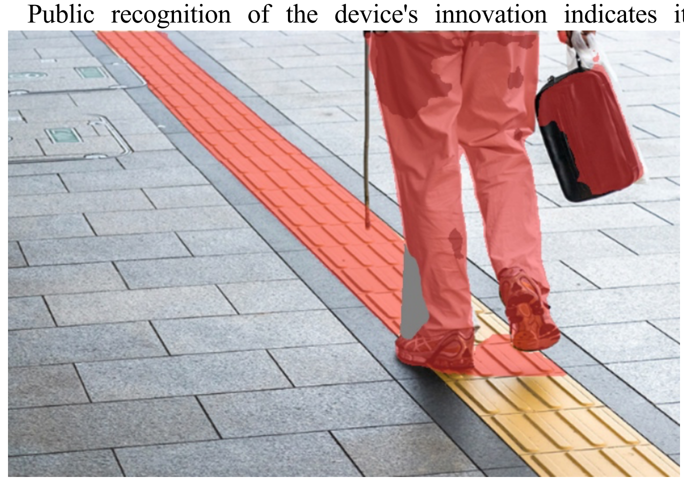


Fig. 4. The prediction result

D. User Feedback

Collecting feedback from individuals who interacted with the device provides valuable insights into its public reception. The observation that many people expressed never having seen such a device before underscores its novelty and uniqueness. Public recognition of the device's innovation indicates its potential to fill a gap in assistive technologies for individuals with visual impairments.

Feedback from users and observers has not only acknowledged the novelty of the device but also expressed positive recognition for its potential future applications. The device's ability to provide real-time obstacle detection on tactile pavements has resonated with individuals, eliciting excitement about its broader implications for urban accessibility. This positive recognition bodes well for the device's acceptance and adoption in the assistive technology landscape.

Users' satisfaction with the device's performance during real-world testing is a testament to its impact on improving user awareness and confidence. The combination of accurate obstacle recognition, robust operation, and innovative features, such as color-coded visualizations, contributes to an overall positive user experience. The device's ability to fulfill its intended functions aligns with its design goals and user-centric approach.

IV. Discussion

A. Effectiveness of YOLOv8 Model

While achieving an accuracy rate of 85%+ for people and bicycles is commendable, continuous efforts will be directed towards addressing any limitations and further improving accuracy. Ongoing model training with diverse datasets and fine-tuning based on user feedback will be essential to enhance the device's ability to recognize a broader range of obstacles with even greater precision.

The robustness of the device against interference lays a strong foundation for its adaptability to different urban environments. However, future research will focus on further enhancing this adaptability, especially in complex scenarios where obstacles may exhibit varying shapes, sizes, and textures. The incorporation of advanced computer vision techniques and machine learning algorithms may contribute to refining the device's responses to diverse environmental challenges.

B. *Practical Implications for Users*

The positive user feedback underscores the importance of maintaining a user-centric design approach. Ongoing collaboration with individuals with visual impairments will guide the customization options offered by the device. Ensuring that users have the flexibility to tailor auditory and visual cues according to their preferences will contribute to a more personalized and user-friendly experience.

C. *Limitations and Future Directions*

1) Addressing Current Limitations: The current limitation of relying solely on the device's own camera for image capture highlights an area for future improvement. Single-camera setups may struggle to provide depth information, leading to potential errors in obstacle detection. To address this, exploring the integration of additional sensors, such as depth sensors or LiDAR, could enhance the device's perception capabilities. These sensors can contribute crucial depth information, improving the accuracy of obstacle detection and ensuring a more comprehensive understanding of the environment.

2) Collaboration for Image Data Enhancement: A forward-looking strategy involves collaboration with government agencies and relevant units to access road surveillance images. Government partnerships can provide a wealth of data that complements the device's real-time image capture. Incorporating external image data into the device's model training process can contribute to a more robust and accurate obstacle recognition system. Such collaborations can also involve discussions on data-sharing agreements, ensuring privacy and compliance with regulatory standards.

3) Towards a Lightweight Design: Recognizing the importance of user comfort and portability, the future direction includes efforts to make the device more lightweight. Advancements in materials, miniaturization of components, and streamlined design processes can contribute to achieving a more compact and user-friendly form factor. A lightweight design is crucial for ensuring that users can seamlessly integrate the device into their daily routines without feeling encumbered.

4) Government and Institutional Collaboration: Collaborating with government and relevant institutions is pivotal for obtaining support and resources to enhance the device's capabilities. Partnerships with governmental bodies can facilitate access to surveillance data, funding for research and development, and opportunities for pilot programs in urban environments. Establishing such collaborations aligns with broader efforts to create inclusive smart cities and improve urban accessibility for individuals with visual impairments.

D. *Impact and Market Uniqueness:*

The acknowledgment that there are currently no similar devices on the market underscores the uniqueness and potential impact of the Tactile Pavement Obstacle Detection Device. Its significance as a "huge blessing for the blind community" highlights the device's potential to transform the daily lives of individuals with visual impairments. The positive impact on users extends beyond practical functionality, encompassing enhanced mobility, independence, and a heightened sense of confidence in navigating urban spaces.

The device's impact on users positions it as a pioneer in the assistive technology landscape. As user needs evolve, ongoing efforts in user-centric design will be crucial. Conducting regular surveys, focus group discussions, and usability studies will provide insights into users' experiences and expectations. This iterative design approach ensures that the device remains aligned with the evolving needs of its primary beneficiaries – individuals with visual impairments.

E. *Market Potential and Accessibility Advocacy:*

The absence of similar devices in the market indicates a significant market gap that the Tactile Pavement Obstacle Detection Device aims to fill. Its potential for market success can be leveraged to advocate for greater attention to accessibility in the technology sector. Engaging with stakeholders, including accessibility advocates, policymakers, and technology developers, can amplify the device's impact and contribute to a broader movement towards inclusive design practices.

F. *Educational Initiatives and Public Awareness:*

As the device gains recognition for its impact, educational initiatives and public awareness campaigns become essential. These initiatives can focus on educating the public about the challenges faced by individuals with visual impairments and the role of innovative technologies in addressing these challenges. By fostering understanding and empathy, the device can catalyze a positive shift in societal attitudes towards inclusivity and accessibility.

V. Related Work

Mohamed Kassim et al. develop a tactile pavement detection system can be used for blind navigation purpose. The system developed have the ability to recognize both circle and bar patterned tactile to guide blind people[6].

Tang, Wu, et al. propose a dataset for assisting the detection and recognition of outdoor obstacles for blind people on blind sidewalk. They classify some common obstacles, train different detection models with the dataset and compare their performance. Results showed their dataset is very challenging[7].

Ito, Yuki, et al. present a system enables independent walking in individuals with visual impairment by recognizing tactile pavement. The system warns the user about dangers of deviations from the path and possible collisions. The method relies on a dynamic threshold approach in the HSV color space[8].

Yamanaka, Yutaro, et al. propose a method for detecting tactile tiles integrated with ground detection using an RGB-Depth sensor. For the ground detection, they use the RANSAC algorithm and expand the region by breadth-first search. When detecting the tactile tiles, they perform thresholding and construct a model to identify candidate areas. Their method obtained a precision of about 83% on the experimental results[9].

VI. CONCLUSION

In conclusion, the Tactile Pavement Obstacle Detection Device stands at the forefront of innovation in assistive technology, offering a transformative solution for individuals with visual impairments. Through the integration of YOLOv8 model-based real-time obstacle detection, OpenCV image processing, and user-centric design, the device provides a holistic and user-friendly approach to urban navigation. The robust accuracy achieved in recognizing people, bicycles, and tactile pavements, coupled with the device's resistance to interference and adaptability to varied lighting conditions, positions it as a reliable aid for individuals with visual impairments. Future directions emphasize collaboration with governmental entities to access road surveillance data, potential sensor integration for enhanced depth perception, and the pursuit of a lightweight and portable design. The positive impact on users, marked by heightened awareness, improved confidence, and the device's uniqueness in the market, underscores its significance as a "huge blessing for the blind community." The collaboration with accessibility organizations, advocacy for global accessibility standards, and educational initiatives further contribute to its broader societal implications. As the device continues to evolve through iterative design and user feedback, it not only fills a market gap but also advocates for a more inclusive and empathetic approach to urban accessibility. The Tactile Pavement Obstacle Detection Device stands as a beacon of progress, pavement the way for a more navigable and inclusive future for individuals with visual impairments.

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