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Vision-Based Edge Detection Between Plant and Soil of Ningxia Vineyard

Wei Li*and Dong-yang Huang**

Keywords： edge detection, image processing, plant and soil, automatic navigation, vision.

ABSTRACT

Realizing mechanical automation is a necessary path for the scale and precision of vineyard production, and solving the automatic navigation problem of universal mobile platforms in unstructured environments is the key to realizing mechanical automation. In order to adapt to the unstructured road environment in the vineyard, this paper proposes a vision-based edge detection method between plant and soil of Ningxia vineyard. To study the composition of the road scene in visual perception, the road scene is mainly divided into plant elements and soil elements, and is segmented at pixel level by convolutional neural network to obtain semantic information and achieve end-to-end pixel level prediction, based on which, binarization is performed and the noise is reduced, and then an edge extraction model based on RGB color is established according to the visual features, the edge between plant and soil is extracted. The results show that the average accuracy of edge detection is 96.39%, and the average running time of edge detection is 0.2319s. The method can effectively realize edge detection and make the proposed edge detection technique applicable to a complex, dynamic and multi-variable scene, which can intervene and proactively adapt to unstructured environments, which is of great practical significance.

INTRODUCTION

Cultivation of grapes is a traditional industry in Ningxia, which is considered to be one of the best wine-producing regions in China (Li et al., 2021), and the area of grapes planted in the eastern foothills of the Helan Mountains reaches 38,000 hectares (Li et al., 2022; Zheng et al., 2022). In recent years, with the further expansion of grape growing area, the problems of low efficiency, labor shortage and weak automation are becoming more and more prominent. During the growing period of grapes, currently it mainly relies on traditional semi-automated mechanical equipment with low working efficiency. During the harvesting stage, a large number of personnel are needed for cleaning, pruning branches and fertilizing (Hao et al., 2016), but there is a relative shortage of labor in the production area. In plant protection, mechanical operations for burying and digging vines are needed to prevent frostbite from occurring easily during the wintering period, which requires more precise control. Therefore, realizing the automation of mechanical operations is an urgent task for the development of the grape industry in Ningxia (Li et al., 2022), and visual perception and image processing are important research contents (Zhou et al., 2022; Tang et al., 2023), which are of great significance to improve the development of the grape industry.

The development of automated production towards “universal mobile platform + operation module” (Li et al., 2019) in Ningxia vineyards, universal mobile platforms are becoming the basis of production, and solving the problem of automated navigation on universal mobile platforms in vineyard environments is the key to realizing machinery automation. Automatic navigation is an important development direction in recent years, in order to adapt to the complex unstructured road environment, the existing automatic navigation methods mainly include GNSS navigation, LiDAR navigation, multi-source information fusion navigation and vision navigation. Li et al. (2019) and Wang et al. (2021) and Han et al. (2020) realized autonomous navigation via GNSS for mobile vehicles. GNSS navigation is generally aimed at the integrated field crops of rotary plowing, planting, and weeding. GNSS signals in vineyards are susceptible to the environment, and the instability of the signals tends to give the auto-navigation accuracy. Jones et al. (2019) and Velasquez et al. (2020) and Nehme et al. (2021) investigated the navigation system through LIDAR sensors with good results. In addition, more and more current studies synthesize the information fusion of multi-source sensors, Reina et al. (2021) and Kanagasingham et al. (2020) developed a navigation system through the

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* *Zhejiang College of Security Technology, Wenzhou, Zhejiang 325016, Peoples R China.*

** *School of Computer Science, Xi’an Polytechnic University, Xi’an, Shaanxi 710699, Peoples R China.*

fusion of information from multiple sensor devices, which can effectively sense the environment. However, in recent years, the trend of mechanical operations in vineyards has been toward automation and intelligence, which requires that the navigation system must be able to understand the environment, and therefore, computer vision is a key direction of research (Tang et al., 2022). In visual navigation, Radcliffe et al. (2018) and Yue et al. (2020) and Opiyo et al. (2021) proposed important image processing methods, but the research targets of image processing are specific plants and environments, which are difficult to be transplanted and applied to vineyard scenes. Li et al. (2020) and Zhang et al. (2017) and Yu et al. (2021) proposed techniques for visual navigation, these visual sensors are mounted higher than the crops, and the visual sensors shoot lower height crops at a tilted angle at the top, so that they can recognize multiple rows of crops in the image, which provides the basis of recognition for visual inspection. Under this condition, multiple rows of crops can be processed, and researchers usually perform gray scale or Gaussian filtering, then determine the navigation area by the characteristics of the crops, and finally extract the navigation path based on the Hough Transform or Least Squares method, which has a good recognition effect.

However, the grapes in Ningxia are planted in a shelf planting manner, the height of the plants is different from that of the aforesaid crops, and if the visual sensor is installed from a position higher than that of the grape crop, the sensor is installed too high and the image will fluctuate drastically due to the unevenness of the road surface, and at the same time, the vineyard of the non-structured planting will cause inaccuracy of information acquisition, and these factors are not conducive to the subsequent image processing. Therefore, the image acquisition of the vineyard in Ningxia is different from the crops mentioned above, according to the planting characteristics of the grape crop, in order to realize the automatic navigation of the universal mobile platform adapting to the environment, the better solution is that the visual sensor is installed at a lower height than the grape crop, which is installed in such a way that the perceived environment mainly contains the planting area on both sides and the soil area in the middle, therefore, research on edge detection between plant and soil was conducted to facilitate the navigation system to understand the environment.

In order to promote the further development of the industry, it is necessary to realize the automation of mechanical operation, and it is necessary to realize the automatic navigation of universal mobile platforms in complex unstructured environments, for this reason, this paper investigates the vision-based edge detection between plant and soil of Ningxia vineyard, which can effectively detect the edges between plant and soil, and provide the basis for automatic navigation, which is of great practical significance.

MATERIALS AND METHONDS

Visual Navigation Methods

Realizing automatic navigation is the basis for promoting mechanical automation and intelligence in Ningxia vineyard industry, which is the common and common need problem of mechanical operation. The navigation schematic of universal mobile platform in vineyard is shown in Fig. 1, the navigation system perceives the environment through visual sensors, so realizing the edge detection and scene information understanding is the key of visual navigation. In the vineyard environment, the main process of navigation is as follows:

(1) Sensing environmental information for edge detection between plant and soil in Ningxia vineyard.

(2) Planning an automatic navigation path based on edge detection.

(3) Calculate lateral deviation and heading angle in combination with position, and carry out motion planning.

(4) Outputting control decisions to realize automatic navigation.

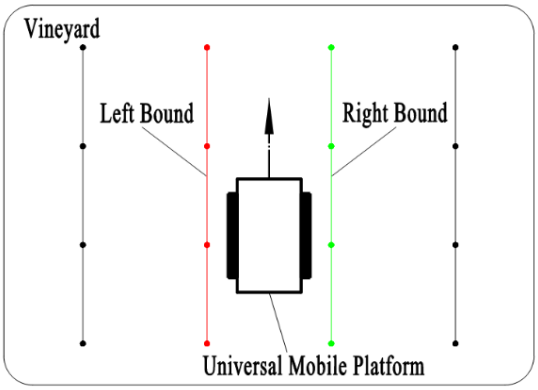


Fig. 1. The navigation schematic of universal mobile platform in vineyard.

In the vineyard environment information, Ningxia vineyard for the shelf planting mode, the width of the vineyard road is about 3 m, in which the plant is located in the two sides of the area, the soil is located in the middle area, the edge between the plant and the soil forms the navigation area of the road in the field environment, therefore, the realization of the edge detection between the plant and the soil in the road is the key and premise of the visual navigation, the use of the environment is semantic information to more accurately mechanical operation, in-depth understanding of the environment, which also provides an effective basis for the realization of intelligence. At the same time, visual navigation should be adapted to different production processes, including plant growth, plant harvesting, vine covering and vine digging.

Categorization of elements in navigation scenarios

Vineyard road is an unstructured scene, the condition of the road surface has complex, dynamic and variable characteristics, and is affected by the season and the production cycle, these complex factors for the recognition of the road to bring greater difficulties, to realize the vineyard scene based on the vision of the automatic navigation, the need for multiple processing to distinguish between the vineyard road and the surrounding environment. Fig. 2 shows the density distribution image of the vineyard road scene, there are obvious peaks in the figure (Chen, 2017), this is because in the image perceived by the visual sensor the main environmental features are plants and soil, the two sides of the road environment are plants, in the middle of the plant area is soil, the road is divided into the plant area and the soil area, which lays the foundation for the recognition and judgment of the environment.

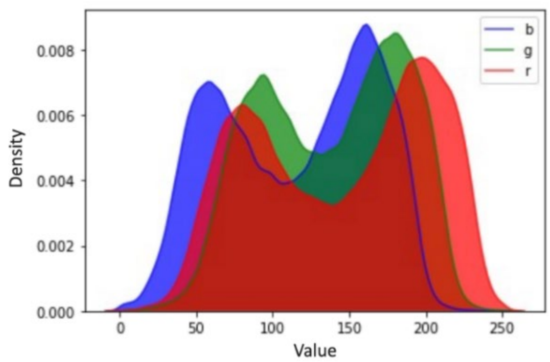


Fig. 2. Vineyard road scene density distribution image.

Table 1. Main classification elements.

Key constituent	Description
Background	Refers to the portion that is not part of the plant element or the soil element.
Plant area	It refers to the plant columns on both sides of the road environment, which are the areas of plant cultivation, and the existence of overlapping areas with the background of hedgerows, soil, debris, and obstacles, etc. The plant areas are affected by the production cycle, and the operations of burying and digging vines to protect against the cold are carried out during the overwintering period.
Soil area	It refers to the soil area in the middle of the road environment, where the road surface is mostly in an unstructured state, and is an autonomous movement area for a general-purpose mobile platform.

According to the composition of environment in the navigation scene, the elements in the vineyard road are classified into background, plant area and soil area, and the definitions of the main classified elements are shown in Table 1, which classify plant and soil to facilitate the subsequent operations of path planning, obstacle avoidance and autonomous movement in visual navigation. The classified elements are used as semantic information to facilitate machine understanding of the environment, and the classification of elements allows the automatic navigation system to further learn characteristics of the elements, independently understand and interpret the environment, and adapt to the complex, dynamic and changing unstructured vineyard environment.

Processing of images

In order to effectively improve the data quality, increase the diversity of data features, and make the generalization ability of the model better, the acquired vineyard road images are processed (Qi et al., 2021). Firstly, the acquired images are processed by color transformation and geometric transformation methods to reduce the dependence of edge detection methods on certain curing features, to highlight the details in the image or to enhance the blurred details, and the obtained pixel intensities are shown in Fig. 3, Fig. 3(a) is the original image, Fig. 3(b) is the brightness processing effect, Fig. 3(c) is the contrast processing effect, Fig. 3(d) is the sharpness processing effect, Fig. 3(e) is the chromaticity processing effect, and Fig. 3(f) is the geometric transformation effect of the image. By emphasizing the relationship between plant elements and soil elements through the processing method of data enhancement, it can further strengthen the system is judgment and recognition effect on the image.

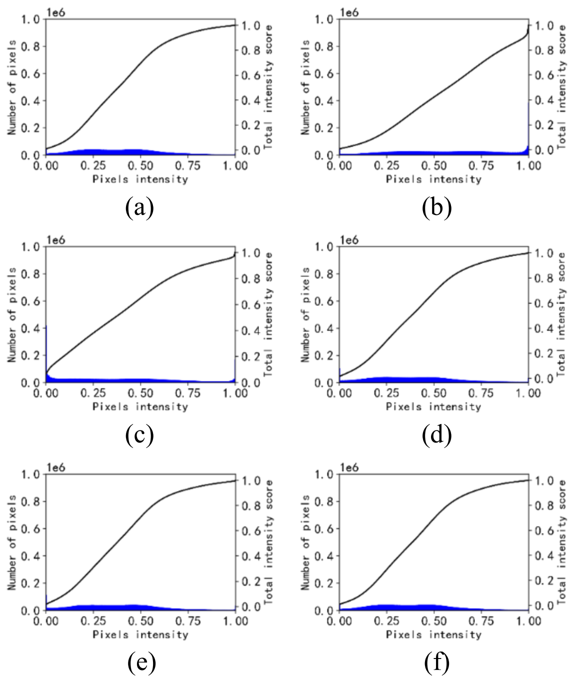


Fig. 3. Pixel intensity.

Dataset

The processed road images themselves have no semantics or labels and need to be manually segmented and labeled to form a dataset for edge detection. The images were collected at a grape growing base in the eastern foothills of the Helan Mountains in Ningxia, and then the collected images were labeled according to the way the elements were segmented in Table 1 using the labelme annotation tool (Russell et al., 2014) developed by MIT CSAIL. Plant elements are labeled with “grape” and soil elements are labeled with “soil”, plant elements and soil elements are labeled to effectively delineate the plant column and soil, and the JSON file after labeling the original image performs the conversion of the data. As shown in Fig. 4, Fig. 4(a) is the labeled original image, Fig. 4(b) shows label.png, Fig. 4(c) shows label_viz.png, and the RGB three-channel parameters of the labeled elements are shown in Table 2, which provides the basis for supervised learning by establishing the dataset.

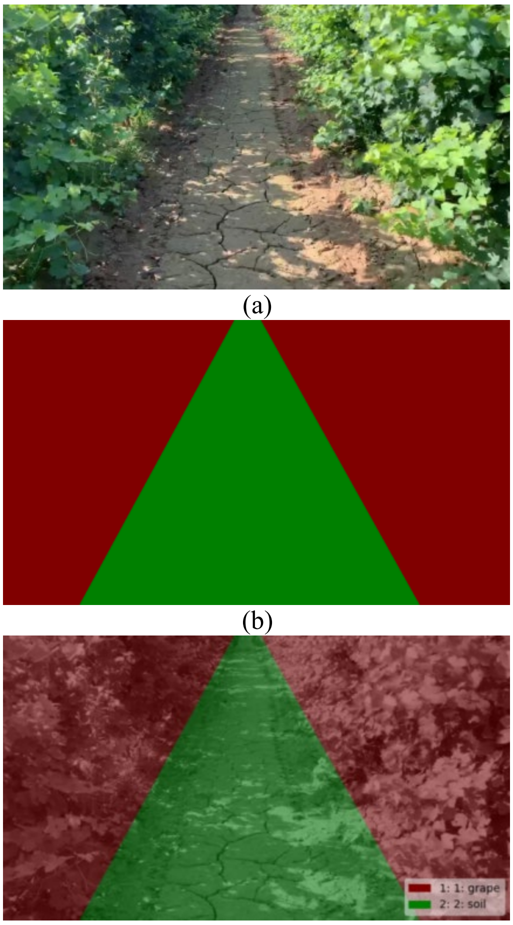


Fig. 4. Conversion results of data.

Table 2. Contents of the label.

Key constituent	Serial number	R	G	B
Background	0	0	0	0
Plant area	1	128	0	0
Soil area	2	0	128	0

Network infrastructure

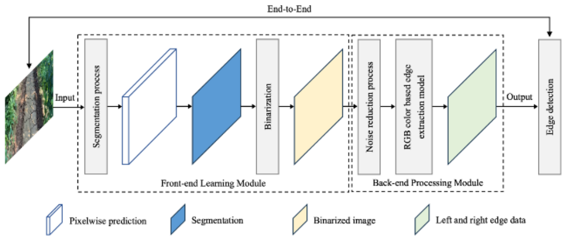


Fig. 5. Network structure.

For the complex unstructured road environment in the vineyard, the edges between the elements contain intrinsic information, as shown in Fig. 5, which is used to guide the edge detection through the constructed network model. In this paper the environmental information captured by the visual sensor is used as input, the pixel level segmentation is performed by a convolutional neural network (Simonyan et al., 2014) to achieve end-to-end pixel level prediction of a fully convolutional network (Long et al., 2015), the input image is downsampled, the convolutional layer of the network is used to extract local features, and the pooling layer is used to pool for the extracted feature information for dimensionality reduction to reduce computational complexity and thus improve network efficiency, further feature information is extracted to obtain a high-dimensional feature map, de-convolution is used to upsample the feature map of the last convolutional layer to restore it to the same size of the input image and retain the spatial information in the original input image, which produces a prediction at the pixel level, combining the semantic information from the deeper layers and representational information from the shallower layers to perform more accurate and fine-grained element segmentation at the semantic level, giving the model the ability to discriminate elements independently. It is used to guide edge detection to obtain semantic information. On this basis, in order to further accelerate the processing efficiency of the data, as shown in Eq. (1), the image continues to be binarized (Tensmeyer et al., 2020), and the binarized image has the same size and type as the original image, and the processed image is denoted as $dst(x,y)$, which forms the front-end learning module.

$$dst(x,y) = \begin{cases} maxval, src(x,y) > thresh \\ 0, other\ \ situations \end{cases} . \tag{1}$$

Where: $maxval$ denotes the set maximum value and the value is set to 255. $thresh$ denotes the selected specific threshold value and the value is 127.

Then, in order to avoid the noise from interfering with the detection of edges, the noise is removed by morphological (Dougherty, 2020; Dey, 2018) processing, expressed as shown in Eq. (2), which encompasses the change of structural elements with the processing.

$$f_{noise} = (Marker \oplus SE) \cap Mask. \tag{2}$$

Where: the $Marker$ denotes the image that is continuously and iteratively inflated, the SE denotes the inflated structural element, and the $Mask$ image denotes the graph that constrains the result of the inflation.

On this basis, the edge extraction model based on RGB color is then established according to the visual features, the edge points are obtained after traversing the pixel level of the image one by one, the edge features of the elements are extracted, and the process of traversing is repeated until all the edge points in the plant and the soil are retrieved, and at this time, the set of the edge points between plant area and soil area in the image constitutes the edge data of the image. As shown in Eq. (3), these edge pixel points form an ordered set, which detects and labels the edges of the road data perceived by the visual sensor, and the consecutive edge pixel points in turn constitute the edges of plant and soil, forming the back-end processing module.

$$f_{edge} = \{(x, y) | x = g(y), y \in [0, h]\}. \tag{3}$$

Where: $x = g(y)$ denotes the correspondence between edge pixel points, h denotes the number of vertical pixels of the image.

Above realized the network architecture design of edge detection between plant and soil, convolutional neural network is a very powerful visual model in the field of feature layering, and in the edge detection technology based on the visual way, the edge between plant and soil in the vineyard is extracted through the visual perception, image processing and deep learning methods, and the edge detection is further realized, which provides an important research on the automatic navigation in the unstructured environment.

ANALYSIS OF EDGE DETECTION MODEL TESTING

Relevant environment

In this paper, in the hardware level, the CPU of the computer is 12th Gen Intel(R) Core(TM) i5-12500H, and the GPU is NVIDIA GeForce RTX 3050. In the software level, the open source Python distribution is used, and the related development environment is also installed, and the version of Python is 3.7, using the TensorFlow (Pang et al., 2020) machine learning open source tool developed by Google, and the version of OpenCV is 4.5.5.

Performance of edge detection

Verify the edge detection between plant and soil in Ningxia vineyard, in the production link of vineyard, the binarized image of the road is shown in Fig. 6, Fig. 7 and Fig. 8, the black region in the image indicates the plant element and the white region indicates the soil element, with the change of environment, some black region is embedded into the white region because the elements of the plant region are extended to the region of the road, the same way, some white region embedded in the black area because the elements of the road area extend to the area of the plant. Machine learning can effectively segment and recognize the classified elements in different periods, adapt to the complex, dynamic and changing situation of the vineyard, lay the foundation for the environment perception of automatic navigation, and realize the understanding of environmental information by the system.

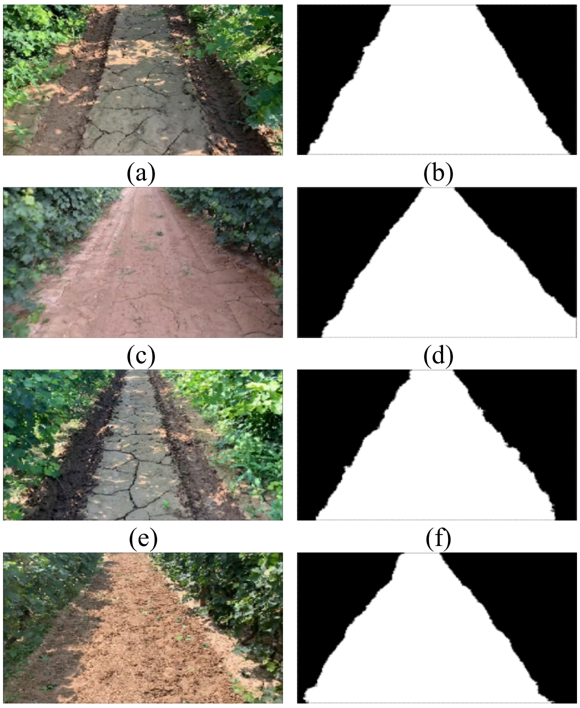
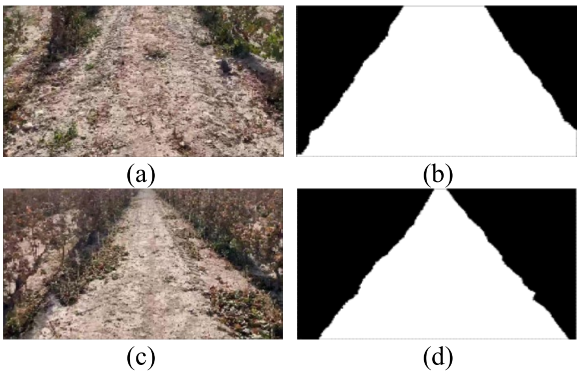


Fig. 6. Original and binarized images of plant growth links.



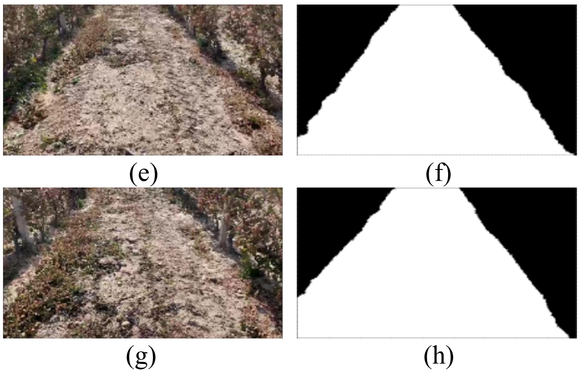


Fig. 7. Original and binarized images of the harvesting links.

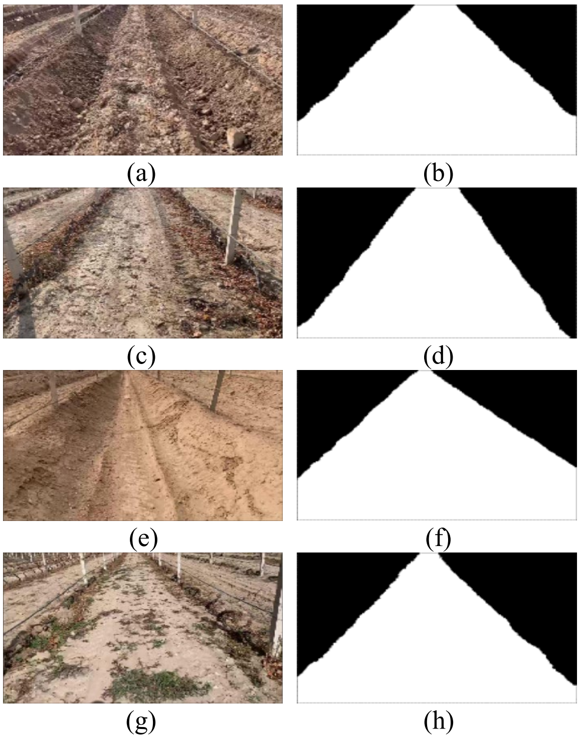


Fig. 8. Original and binarized images of burying and digging vines links.

In the process of edge detection, the vineyard environment exists in a complex, dynamic and variable situation, in Fig. 6(a, c, e, g), Fig. 7(a, c, e, g) and Fig. 8(a, c, e, g) is the original image, and in Fig. 6(b, d, f, h), Fig. 7(b, d, f, h) and Fig. 8(b, d, f, h) corresponds to the binarized image, on the whole, segmentation and processing can be better realized in the plant growth session, plant harvesting session, burying vine and digging vine sessions. In order to avoid the interference of the noise in the complex environment on the edge detection, after the morphological processing, the noise interference can be effectively suppressed to exclude the uninteresting noise edges, and only the real edges that respond to the structure of the elements are retained.

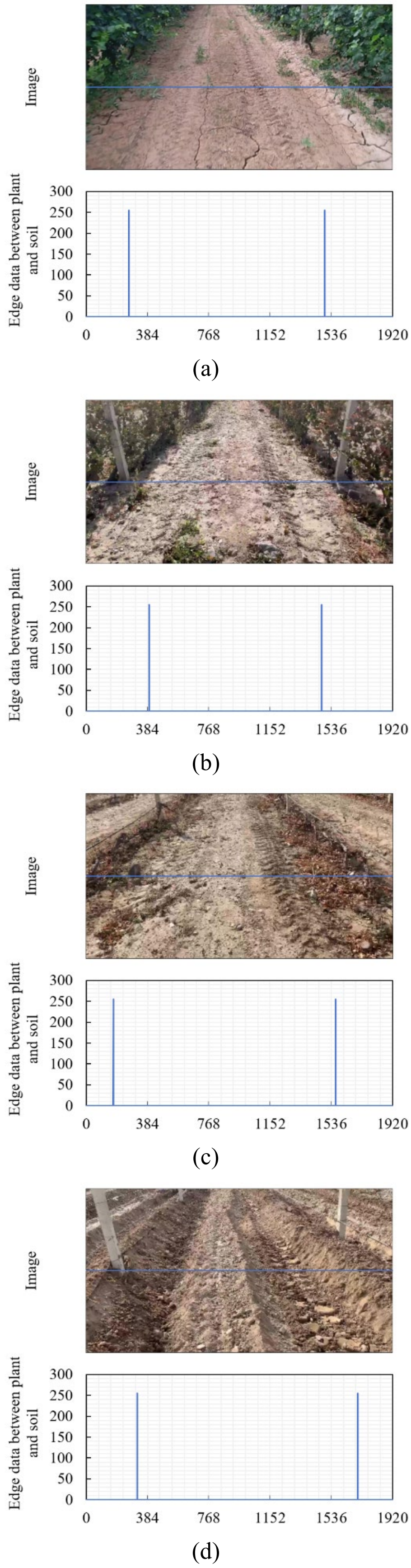


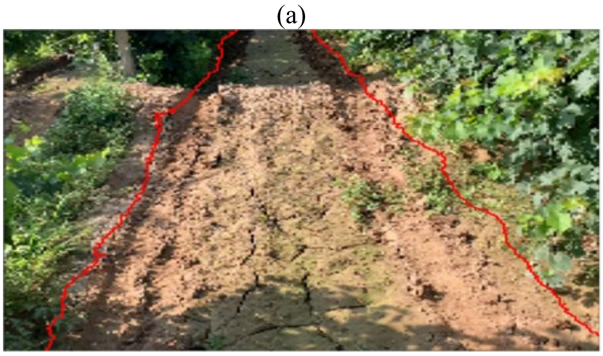
Fig. 9. Edge data between plant and soil.

On this basis, the edge extraction model based on RGB color is established to extract the boundary between the elements, as shown in Fig. 9, at this time, there will be obvious boundary features between plant and soil, on the mark of the original image, the edge data in the figure corresponds to the edge of the left side and the right side respectively, which is located in the junction of plant and soil, and the successive features constitute the continuous edge of plant and soil.

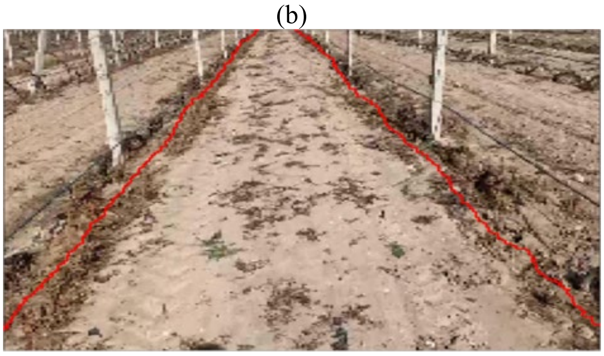
The effect of edge detection

Edge detection of plant and soil in the vineyard environment is shown in Fig. 10 for data visualization, the solid line in the figure indicates the extracted left edge and right edge of plant and soil, and the perceived edges are persistent and effective throughout the covered area, which reflects the effect of boundary feature processing between plant and soil, and is able to adaptively judge the environmental information, and the edges are able to be detected more accurately and completely under the conditions of different production sessions, and the edge detection is effectively carried out.

(a)



(b)



(c)

(d)

Fig. 10. Schematic of edge detection between plant and soil in vineyard.

RESULTS AND DISCUSSION

The edges detected by the model were compared with the manually calibrated edges as shown in Eq. (4), and the lateral deviation of the edge detection results and the manually calibrated edges between the plant columns and the soil were used as the edge detection quality evaluation coefficient and for assessing the effectiveness of edge detection.

$$f_{precision} = \frac{e_p}{H} \times 100\%. \tag{4}$$

Where: e_p denotes the horizontal pixel difference and H denotes the number of pixel points in the horizontal direction of the image.

The proposed method is applied to 100 randomly selected images, and the edge detection quality evaluation coefficients are given in Table 3, and the closer the value of the result is to 1, the better the effect. Moreover, the end time t_e as well as the start time t_s of edge detection are obtained, and the running time of the edge detection method is obtained by $t_{total} = t_e - t_s$ calculation, and the running time using the edge detection model is given in Table 4.

Table 3. Edge detection quality evaluation coefficients.

Serial number	Results	Serial number	Results
1	96.83%	51	95.69%
2	96.59%	52	98.92%
3	98.29%	53	98.99%
4	97.56%	54	97.57%
5	97.51%	55	96.01%
6	97.89%	56	95.64%
7	98.11%	57	98.50%
8	97.12%	58	95.01%
9	97.39%	59	98.36%
10	97.67%	60	94.62%
11	95.01%	61	95.74%
12	96.01%	62	94.90%
13	96.11%	63	95.13%
14	96.16%	64	96.32%
15	94.77%	65	96.86%
16	96.33%	66	96.50%
17	94.82%	67	95.58%
18	97.67%	68	96.97%
19	96.35%	69	97.40%

20	96.18%	70	98.88%
21	95.96%	71	96.55%
22	95.53%	72	92.14%
23	97.56%	73	95.19%
24	93.86%	74	94.90%
25	96.06%	75	95.96%
26	95.45%	76	95.26%
27	94.67%	77	96.46%
28	96.11%	78	98.50%
29	97.74%	79	96.06%
30	97.42%	80	98.39%
31	96.29%	81	96.19%
32	95.11%	82	96.22%
33	97.28%	83	95.15%
34	96.58%	84	96.21%
35	96.43%	85	97.13%
36	95.93%	86	95.35%
37	96.57%	87	96.03%
38	94.92%	88	98.02%
39	94.94%	89	95.42%
40	98.08%	90	97.67%
41	95.97%	91	96.07%
42	95.87%	92	95.69%
43	97.30%	93	97.00%
44	96.44%	94	96.46%
45	98.07%	95	95.78%
46	96.04%	96	95.56%
47	94.74%	97	96.18%
48	96.06%	98	95.93%
49	95.87%	99	97.17%
50	95.21%	100	97.90%

Table 4. Runtime of edge detection.

Serial number	Runtime	Serial number	Runtime
1	0.2545s	51	0.2258s
2	0.2365s	52	0.2115s
3	0.1930s	53	0.2184s
4	0.2029s	54	0.2075s
5	0.2151s	55	0.2412s
6	0.2372s	56	0.2313s
7	0.2023s	57	0.2352s
8	0.2257s	58	0.2632s
9	0.2189s	59	0.2276s
10	0.2424s	60	0.2120s
11	0.2423s	61	0.2391s
12	0.2460s	62	0.2309s
13	0.2422s	63	0.2290s
14	0.2578s	64	0.2521s
15	0.2411s	65	0.2445s
16	0.2437s	66	0.2227s
17	0.2346s	67	0.2365s
18	0.2482s	68	0.2275s
19	0.2428s	69	0.2091s
20	0.2450s	70	0.1906s
21	0.2286s	71	0.2388s
22	0.2404s	72	0.2434s
23	0.2018s	73	0.2230s
24	0.2412s	74	0.2522s
25	0.2753s	75	0.2397s
26	0.2382s	76	0.2337s
27	0.2301s	77	0.2402s
28	0.2076s	78	0.2053s
29	0.2191s	79	0.2635s
30	0.1946s	80	0.2227s
31	0.2140s	81	0.2343s
32	0.2420s	82	0.2340s
33	0.2125s	83	0.2352s
34	0.1990s	84	0.2446s
35	0.2574s	85	0.2394s
36	0.2518s	86	0.2470s
37	0.2372s	87	0.2312s
38	0.2304s	88	0.2137s
39	0.2339s	89	0.2358s
40	0.2398s	90	0.2235s
41	0.2443s	91	0.1944s
42	0.2204s	92	0.2389s
43	0.2046s	93	0.2306s
44	0.2545s	94	0.2402s
45	0.2264s	95	0.2458s
46	0.2097s	96	0.2281s
47	0.2493s	97	0.2427s
48	0.2497s	98	0.2102s
49	0.3141s	99	0.2181s
50	0.2364s	100	0.2079s

(1) Table 3 gives the edge detection quality evaluation coefficients, and the average accuracy of edge detection using the model is 96.39%, which can effectively realize edge detection. Table 4 gives the runtime of edge detection, the average processing time of a single frame image is 0.2319s, these runtimes satisfy the navigation requirements of generalized mobile platforms. This demonstrates the effectiveness of the proposed method for edge detection between plant and soil in the Ningxia vineyard environment.

(2) The effect of edge detection is shown in Fig. 10, these four images are under different production links, the plant elements on both sides and the soil elements in the middle can be recognized effectively, and the edge detection of plant and soil is realized, which shows that the model has a strong adaptability to the changes of production links. Meanwhile, the two images shown in Fig. 10(a) and Fig. 10(b) are the detection effects of the images under shadows, and the two images shown in Fig. 10(c) and Fig. 10(d) are the detection effects of the images under light and achieve better results, which shows that the model has strong adaptability to the changes of light.

(3) The edge detection process can still be effective when the environment changes because the environment can be understood and deep semantic information can be provided through the learning process. After the front-end learning process, the semantic information given can understand the environment for the navigation system and promote the refinement of mechanical operations. After the back-end processing process, the extraction of edges between plant and soil in Ningxia vineyard is realized based on the visual features, with the ability of autonomous recognition, autonomous judgment and autonomous cognition of the environment.

(4) For complex, dynamic and multi-variable working scenarios, which is one of the most challenging structural tracking scenarios in precision agriculture, edge detection between plant and soil for automatic navigation in vineyard environments is proposed, the main practical advantage of this edge detection is that this makes the proposed edge detection technique applicable to a multi-variable scenario, intervening in different types of environments, adapting to unstructured environments, and being able to further promote the industry is high-quality development, which has a key practical

significance and research value.

CONCLUSIONS

Solving the problem of automatic navigation for universal mobile platforms in unstructured environments is the key to realizing automated production. In order to adapt to the unstructured road environment in vineyards, this paper proposes a vision-based edge detection method between plant and soil of Ningxia vineyard, which makes the proposed edge detection technique suitable for a complex, dynamic and multi-variable scenario, and is able to intervene and proactively adapt to the unstructured environment. The results show that the average accuracy of edge detection is 96.39% and the average running time of edge detection is 0.2319s, which makes the method effective in realizing edge detection, which is of key practical significance and research value. There are some subsequent work to be done, (1) Ningxia has windy weather and a small amount of foggy weather every year, and sometimes there is dusty weather, in these extreme conditions, it is difficult to solve the vineyard image segmentation problem. (2) Combine the edge detection method with the navigation line detection method and conduct navigation experiments to further realize the scene understanding and the full utilization of semantic information.

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基於視覺的寧夏葡萄園植物與土壤邊緣檢測

李偉
浙江安防職業技術學院

黃冬楊
西安工程大學

摘要

實現機械自動化是葡萄園生產規模化與精準化的必經之路,解決非結構化環境中通用移動平臺的自動導航問題是實現機械自動化的關鍵。為了適應葡萄園內非結構化道路環境,本文提出了一種基於視覺的寧夏葡萄園植物與土壤邊緣檢測方法。研究視覺感知中道路場景的組成,將道路場景主要分為植物要素和土壤要素,通過卷積神經網絡進行像素級別的分割,獲取語義信息,實現端對端像素級預測,在此基礎上,進行二值化處理,並且降低噪聲,然後根據視覺特征建立基於RGB顏色的邊緣提取模型,提取植物與土壤之間的邊緣。結果表明,邊緣檢測的平均準確度為96.39%,邊緣檢測的平均運行時間是0.2319s,該方法能夠有效的實現邊緣檢測,並使得所提出的邊緣檢測技術適用於一個復雜的、動態的與多變化的場景,能夠介入並主動適應非結構化環境,這具有重要的現實意義。