EXTRACTION METHOD FOR CENTERLINES OF RICE SEEDLINGS BASED ON FAST-SCNN SEMANTIC SEGMENTATION

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基于 Fast-SCNN 语义分割的秧苗列中心线提取方法

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ABSTRACT

For the extraction of paddy rice seedling centerline, this study proposed a method based on Fast-SCNN (Fast Segmentation Convolutional Neural Network) semantic segmentation network. By training the FAST-SCNN network, the optimal model was selected to separate the seedling from the picture. Feature points were extracted using the FAST (Features from Accelerated Segment Test) corner detection algorithm after the pre-processing of original images. All the outer contours of the segmentation results were extracted, and feature point classification was carried out based on the extracted outer contour. For each class of points, Hough transformation based on known points was used to fit the seedling row centerline. It has been verified by experiments that this algorithm has high robustness in each period within three weeks after transplanting. In a 1280×1024-pixel PNG format color image, the accuracy of this algorithm is 95.9% and the average time of each frame is 158ms, which meets the real-time requirement of visual navigation in paddy field.

摘要

*为提取水田秧苗中心线，提出一种基于 Fast-SCNN (Fast Segmentation Convolutional Neural Network)语义分割网络的秧苗列中心线提取方法。通过训练 Fast-SCNN 网络，选取最优模型，将秧苗从图像中分割出来。将原始图像预处理后，采用 Fast(Features from Accelerated Segment Test)角点检测算法提取特征点。提取分割结果的所有外轮廓，基于提取到的外轮廓进行特征点分类，对于分类后的每类特征点，采用基于已知点的 Hough 变换拟合秧苗列中心线。经试验验证，本文算法在插秧后三周内各个时段，在杂草、缺株、反光等干扰时，均有较高的鲁棒性。处理每幅 1280*1024 像素的 PNG 格式彩色图像平均耗时 158ms，提取中心线的准确率为 95.9%，满足水田视觉导航的实时性要求。*

INTRODUCTION

Automatic navigation of agricultural machinery has been widely used in planting, cultivating, weeding, and harvesting. The navigation technology based on machine vision benefits from its low cost, good environmental adaptability, rich information, etc., which can effectively improve the operation quality and efficiency of agricultural machinery *(Meng et al., 2016)*. In the paddy field environment, the extraction of the centerline of rice seedlings is the core task of visual navigation. Since the working environment of agricultural robots is a typical unstructured environment and the working scene is complex, there are disturbances such as instability of natural light, lack of plants, weeds, etc. *(Yu et al., 2020)*. Therefore, designing a robust seedling centerline extraction algorithm for the specific environment of the paddy field is the focus and difficulty of visual navigation.

Many scholars have done research on the content of visual navigation line extraction in agricultural scenes. In view of the poor real-time performance and the difficulty of peak detection of the traditional Hough transform to extract the centerline, the researchers proposed a variety of improved Hough transform algorithms such as probabilistic Hough transform and Hough transform based on known points *(Chen et al., 2019; Mukhopadhyay et al., 2015; Zhang et al., 2017)*, which improve the efficiency to some extent. Least squares method is also a common method for crop row centerline detection *(Hou, 2020)*; in view of the shortcoming of this algorithm that is easily affected by noise points, some scholars have also improved it to improve its robustness *(Meng et al., 2013)*.

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In addition, scholars have also proposed some other methods of extracting the centerline of crop rows creatively, which have achieved good results in some specific scenes. *Guerrero et al. (2017)* proposed a crop row positioning method based on geometric constraints to reduce the interference of weeds on the accuracy of visual navigation line extraction, aiming at the problem that the spectral characteristics of crops and weeds are close to each other in corn field. *Liao et al. (2019)* used sub-regional statistics of seedling pixel point distribution to extract the characteristic points of seedlings, and realizes the clustering of characteristic points with the clustering method based on neighbor relations. *García-Santillán et al. (2018)* segmented the green pixels based on the color feature, and under the condition of detecting the starting point, used the regression algorithm to extract the corn crop line or curve.

In recent years, with the rise of deep learning technology, scholars have designed a variety of semantic segmentation networks based on deep learning to extract information in unstructured environments, and achieved good results. Semantic segmentation network structure is mainly based on Fully Convolutional Network (FCN) *(Long et al., 2017)*. However, the amount of parameters of classical semantic segmentation models is too large, which leads to poor real-time performance and requires powerful GPU support. Mobile robots require semantic segmentation networks to have high real-time performance, and require low memory usage, which can be deployed in embedded devices. Therefore, several lightweight and lightweight real-time semantic segmentation models such as ICNet *(Zhao et al., 2018)* and BiseNet *(Yu et al., 2018)* were born, which achieved high-precision segmentation at a faster speed on public data sets.

In this study, a method based on semantic segmentation was proposed to extract the seedling row centerline. The Fast-SCNN model was used to segment the seedlings according to the row from the image *(Poudel et al., 2019)*. The segmentation results were combined with FAST corner detection algorithm to extract the centerline of seedling row *(Rosten et al., 2006)*.

MATERIALS AND METHODS

In the face of traditional image algorithms that are difficult to ensure robustness in unstructured environment, the study proposed a centerline extraction algorithm for rice seedlings based on semantic segmentation. The seedlings were segmented by column from the background through training the semantic segmentation network, then the outer contours were extracted based on the connected region in the segmentation result. FAST corner points were extracted as feature points in original images after graying and binarization. By judging whether the corner points are included a certain contour, the feature points were classified. Finally, for each class of feature points, Hough transform based on known points was used to fit the navigation line. The flow of the algorithm is shown in Figure 1.

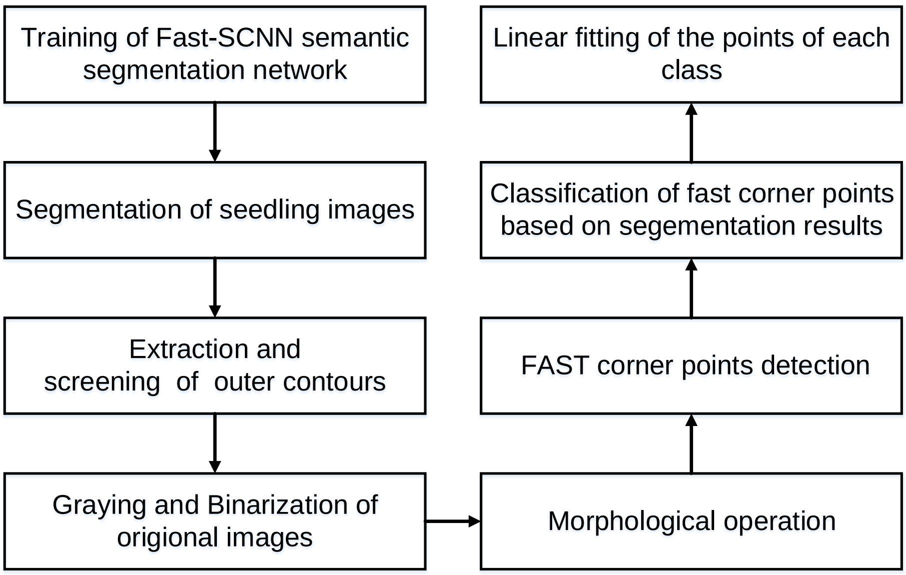


Fig. 1 - Flow chart of the algorithm proposed in this study

Production of paddy field image data set

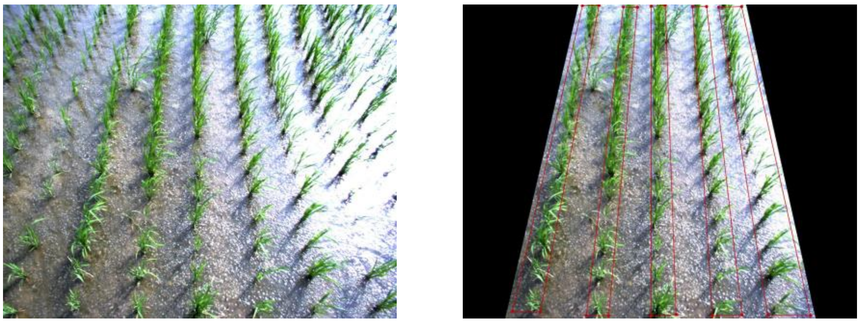
The planting address of paddy field pictures selected for the experiment in this study is Taiping Street, Xiangcheng District, Suzhou City. 800 pictures of rice seedlings in two typical periods: one week after transplanting and three weeks after transplanting, were collected in different periods of a day.

All 800 images collected were divided into three categories, training set, test set and verification set, as shown in Table 1. The proportion of the three types of sample data was 8:1:1, all the pictures were randomly divided.

Table 1

Type and number of data sets

Object	Training set	Validation set	Test set	Total
Amount	640	80	80	800



(a) (b)

Fig. 2 - Annotation of image

The semantic segmentation of images adopts the method of supervised learning, and a reasonable data annotation method is the premise of training convolutional neural network. In this study, 800 images collected were labeled with a software named Labelme. During the labeling of images, an irregular quadrilateral frame was used to frame the crop rows that appear completely in the images. In order to prevent the seedlings column in two sides of picture that were not labeled from causing ambiguity in training process, this study removed information that was outside the boundary lines and extended both sides to the outside by 15 pixels, filling with 0, as shown in Figure 2(b), and Figure 2(a) is the original color image. The boundary lines of every picture were determined by the left boundary of the leftmost crop row and the right boundary of the rightmost crop row, which were labeled and saved in a JSON format file. After annotation, labels were generated according to the four vertices of each quadrangle in the annotation information. The generated label was a single-channel image with the same size as the corresponding original image, the pixel value of background was set as 0 and the pixel value of the area of rice seedling was set as 1.

Segmentation of seedling images based on Fast-SCNN network

- Fast-SCNN network

On account of the relatively fixed distribution of rice seedlings in the field, this study used a semantic segmentation algorithm based on deep learning to segment the distribution area of seedlings from the background. The scene of the agricultural machinery's automatic operation in the paddy field is similar to the scene of autonomous driving, which requires real-time performance on embedded devices. Therefore, this study selected Fast-SCNN lightweight semantic segmentation network to segment crops from the background.

Fast-SCNN is a real-time semantic segmentation model, which is suitable for efficient computing on low-memory embedded devices. The Fast-SCNN network is characterized by a two-branch structure, using a shared shallow network to encode detailed information before branching. The network structure includes four parts: the learning down-sampling module, the global feature extraction module, the feature fusion module and the classifier module. It adopts cutting-edge convolutional neural network technologies such as Spatial Pyramid Pooling, Bottleneck, Distribution Shifting Convolution and Depthwise Separable Convolution. Fast-SCNN neural network achieves the balance between the quality and speed of segmentation.

- Model training and the selection of the optimal model

The images in training set were inputted into the network for training, and the parameters were iteratively updated through the backpropagation and gradient descent algorithm to meet the segmentation requirements. The original images were down-sampled to a size of 640*512 pixels before being inputted into the network, and BN (Batch Normalization) was used before the activation function of each layer to speed up the convergence and regularization. The study augmented the existing data before training to improve the generalization ability of the network. The data augmentation methods adopted in this study are showed as follows:

(1) Flip the original image horizontally with a probability of 0.5.

(2) Multiply each pixel in the original image by a random value between 0.8 and 1.3.
(3) Treat the original image with Gaussian disturbance whose variance is a random value between 0 and 3.

This study used an online augmentation method, which transformed the original pictures by the methods above before inputted into the network. During the training process, the model was saved every 10 rounds, the model effect is tested on the test set, and the effect is compared and the model with better generalization ability is selected. The training hyperparameters are shown in Table 2.

The value of the initial learning rate was set as 0.005, and the learning rate decay method was polynomial decay. The formula of the real-time learning rate when iterating to a certain round l_{rate} is shown as follows:

$$l_{rate} = base\_lr * (1 - n\_iteration/n\_max)^{pow} \tag{1}$$

where: $base\_lr$ -- initial learning rate
$n\_iteration$ -- the number of iteration rounds
n_max -- maximum number of iteration rounds
pow -- learning rate decay index

Table 2

Hyperparameter value of model training

Hyperparameter name	Value
Batch size	4
Gradient descent algorithm	SGD with momentum
Momentum	0.9
Weight decay coefficient	0.0005
Initial learning rate	0.005

In this study, the value of pow was set as 0.9, and the maximum number of iteration rounds was 6000. When the number of iteration rounds reached the maximum number, the learning rate dropped to 0 and the training stopped. After 6000 iterations of the weight parameters, the change of model loss is shown in Figure 3(a). It can be seen from the figure that the model was gradually stabilized after the 4000th iteration, and the loss value stabilized at about 0.04.

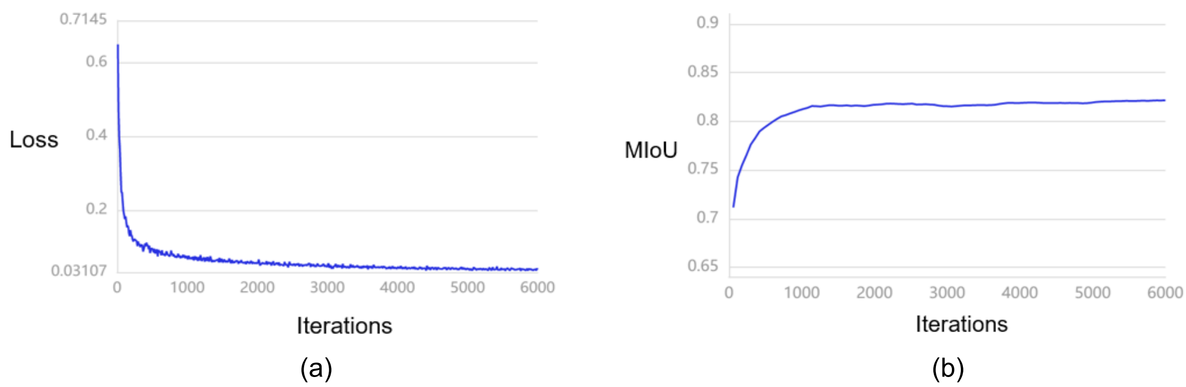


Fig. 3 - The curve of loss and MIoU with the number of iteration

In this study, the optimal model among all the models saved during training was selected as the final model. The evaluation indicators of semantic segmentation result include Mean Intersection over Union (MIoU), accuracy and so on; this study used MIoU as the basis for selecting the optimal model. The change curve of the value of MIoU with the number of iterations in the validation set is shown in Figure 3(b). It can be seen from the figure that after the 4000th iteration, the value of MIoU tended to stabilize around 0.82. Therefore, the model saved at the 4000th iteration was selected as the optimal model, and the MIoU was 0.8206.

Extraction of centerlines of seedling columns based on segmentation result

- Detection and screening of counters

Due to perspective projection and shooting angle, the two ends of the segmentation result image will produce mutual adhesion between the columns, resulting in some irregular contours, which cause interference for subsequent contour detection, as shown in Figure 4(b), so these areas need to be eliminated. By analyzing the pictures of segmentation results, the study used the trapezoidal mask to process the segmentation results to remove the interference areas on both sides. After multiplying the original image and the mask image, the middle trapezoidal region of interest (ROI) would remain unchanged, while the values of the pixels outside ROI would be 0. The mask image is shown in Figure 4(c), the regions that are not part of ROI are right trapezoids in 2 sides of the image, whose topline is 300 pixels and the baseline is 100 pixels.

(a) (b) (c) (d)

Fig. 4 - Screening of counters

After extracting the segmentation result for the ROI, a row of seedlings in ROI will form a connected region. The study used an algorithm based on boundary tracking to extract all the outer contours of segmentation results *(Suzuki et al., 1985)*, which stores all the extracted outer contours as a point set. However, segmentation results showed that there were a few of invalid contours in the ROI area, which would cause interferences. In order to prevent the interference of invalid contours in the ROI area, this study screened the detected outer contours. Three indicators were used in the screening: area, perimeter, and area-perimeter ratio. As shown in Figure 4(d), the contours that comply with the indicators are filled with red, which will be preserved, or the contours are filled with blue, which will be ignored. After screening, the number of outer contours finally retained was n, which was the number of rows of rice seedlings detected, and each contour extracted was saved as a point set.

- Feature point extraction based on FAST corner detection algorithm

The first step of feature point extraction was graying of original color images. This study noticed that comparing with the other area of original images, the green feature of the color of seedlings is more prominent. So the super green operator based on the RGB color space was used for graying *(Søgaard et al., 2003)*. Experiments showed that this method can accurately distinguish the seedlings from the background. The calculation formula of the super green operator is shown as follows:

$$\mathrm{I(x,y)} = \begin{cases} 0, & 2g-r-b<0 \\ 2g-r-b, & 0 \le 2g-r-b \le 255 \\ 255, & 2g-r-b>255 \end{cases} \tag{2}$$

where: $\mathrm{I(x,y)}$ -- The grayscale value of a pixel in the grayed image with coordinates of (x,y)

r, g, b -- The values of channels R, G, and B in the original color image

After graying, the maximum variance between classes (OTSU) algorithm was used for binarization *(OTSU, 1979)*, and the morphological operation was used for denoising. The morphological method was using the open operation with a structure element of 5*5 square. In this way, a binary image with only two gray values of 0 and 255 was obtained. The pixels with gray value of 255 represent seedlings, and the pixels with gray value of 0 represent backgrounds.

After the binary image had been obtained, feature points were extracted based on the binary image. This study used the FAST corner detection to extract the corner points in the binary image as feature points. The algorithm of FAST corner detection uses a 37-pixel circular template to scan each pixel of the gray image to be detected, and counts the difference between the detected pixel and the 16-point pixels of the circular template, the center of the circle being the detected pixel. FAST corner detection algorithm can be expressed by the formula as follows:

$$N = \sum_{x \in circle(a)} |I(x) - I(a)| > K \tag{3}$$

where: $I(x)$ -- the value of a certain pixel on the periphery of the circular template

$I(a)$ -- the gray value of the detected point a

N -- the total corner response

K -- the threshold value of the corner response

When N is larger than a certain threshold N_0 and the pixels on N form a continuous arc, point a is considered a FAST corner point. In this study, the value of K is 100 and the value of N_0 is 9.

- Contour-based feature point classification

FAST corner detection extracted the feature point cloud of seedlings, but the feature point cloud includes all the feature points of seedlings, so these feature points need to be classified to distinguish different seeding columns. This paper adopted a contour-based method to classify feature points, whose specific steps are as follows:

(1) Store all the FAST feature points extracted in a same set.

(2) For the first outer contour, traverse all the feature points and judge whether the feature points are within the contour.

(3) If a feature point is in the contour, classify it as the crop row represented by the contour, delete the point from the feature point set, and return to step (2). If it is not in the contour, go directly to step (2). After traversing the feature points, enter step (4).

(4) For all other outer contours, repeat steps (2)-(3) in sequence until all contours are traversed.

For the method used to determine whether a point is within the contour, this study analyzed the shape of the extracted outer contour. As shown in Figure 5, all of the extracted contour were convex in the Y direction generally, and there is almost no depression in the Y direction. So the number of intersections between a horizontal line on the X axis and any contour can only be 0, 1, or 2. Based on this reasoning, this study adopted the following method to determine whether a point is within a contour.

For the feature point to be detected, search the point set of the contour for the points that with the same Y coordinate value as the detected point. If there are 0, 1, or more than 2 such points, it is considered that the point is outside the contour. If there are 2 such points, compare the X coordinates of the detected point with the X coordinates of these two points, as shown in Figure 5, assuming the detected point as point $A(X_1, Y_1)$, draw a straight line through point A that is parallel to the X axis. The straight line and the contour intersect from left to right at point $B(X_2,Y_2)$ and point $C(X_3,Y_3)$. If the relationship among X1, X2, X3 satisfies any one of the following:

(1) X2>X1 and X3>X1

(2) X2<X1 and X3<X1

The detected point is outside the contour, otherwise the point is inside the contour.

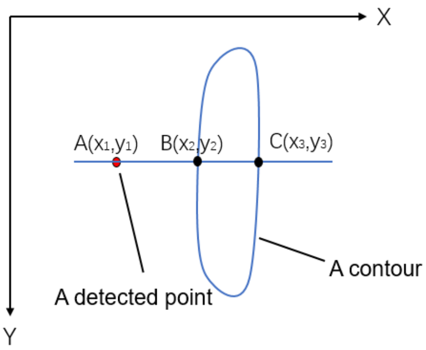


Fig. 5 - Determine of whether a point is within the contour

- Fitting of centerlines

After the feature point classification was completed, for the feature point set of each class, Hough transform based on known points was used to fit the centerline of seeding columns *(Zhang et al., 2012)*. This algorithm can avoid the disadvantages of traditional Hough transform with high time complexity and has high robustness. The fitting algorithm flow is as follows:

(1) For each feature point set, calculate the mean value of the abscissa and ordinate of all points to obtain the center point (X_{avg}, Y_{avg}) of the point set.

(2) Calculate the slope of the line determined by the point in each point set and the center point of the point set, calculate the maximum and minimum slopes, and take the minimum slope value and the maximum slope value as the upper and lower bounds of the interval, which is divided into 30 equal parts.

(3) Count the number of lines in each interval by means of regional voting, and find the interval with the most lines. Finally, take the average slope of all the lines in the interval as the slope of the seedling centerline represented by the point set, and the line goes through the class center point (X_{avg}, Y_{avg}).

RESULTS

Experiment platform

The experiment platform used in this study is configured with Intel Core i5 9400F CPU, whose basic frequency is 2.9GHz, 16GB memory, NVIDIA GTX1080Ti graphics card with 11GB video memory. The system of operating environment is Windows 10 (64-bit). The semantic segmentation model training environment is Python 3.6, Pytorch 1.2 framework, CUDA 10.0 parallel computing architecture and cuDNN7.6 deep neural network library. The development environment is Visual Studio 2017 and the development language is C++.

Determination of parameters

During the screening of contours, this study used three indicators to determine whether it is the contour of the seedling row: area, perimeter, and area-perimeter. The method for determining the three indicators is to count the area, perimeter, and area-perimeter ratio of all the contours of the seedling row from the segmentation results of 80 images in the test set. The area of contour is determined by the number of pixels inside the contour, and the perimeter of contour is determined by the number of pixels in the set of points that make up the contour. The extreme and average values of the indicators of valid contours are shown in Table 3.

From the data in the table, we can find the extreme values of the area, perimeter and area-perimeter ratio. This study took the highest and lowest values of the three indicators, with 1.1 margin coefficient as the criterion. The range of perimeter is 1964-3490, the range of area is 42307-111595 and the range of area-perimeter ratio is 19-46. The contour meeting all the three ranges is considered to be the contour of the seedling row, or it would be ignored.

Table 3

Statistics of area, perimeter and area-perimeter ratio

	Perimeter	Area	Area-perimeter ratio
Max value	3173	101450	41.74
Min value	2161	46538	21.28
Average value	2472	71667	31.11

The analysis of the semantic segmentation models' performance in the test set

The lightweight Fast-SCNN model used in semantic segmentation puts the pictures of the validation set into the trained model for verification. This study compared the effects of other two mainstream real-time semantic segmentation networks ICNet and BiSeNet. The experiment of other 2 algorithm used the same hardware and software conditions. The results on the test set are shown in Table 4.

Table 4

Test results of various semantic segmentation networks

Network name	Fast-SCNN	ICNet	BiseNet
MIoU (%)	82.06	84.48	79.40
Accuracy (%)	90.36	91.72	88.16
Time spent (ms)	24.04	53.25	31.82

From the comparison results, we can find that the MIoU value and accuracy of ICNet are a little higher than those of Fast-SCNN, however, the average time consuming of each frame is much higher. The segmentation quality and time consuming of BiseNet are both worse than Fast-SCNN. Therefore, in terms of segmentation quality and speed, Fast-SCNN performs better than the other two semantic segmentation networks in the application scenario of paddy field.

Results of centerline extraction

Through tracking and photographing the growth process of rice after transplanting, it can be found that there are three typical periods during rice growth. The first period is one week after transplanting, when the seedlings are very small and there is a large gap between the seedlings in each column. The second period is the third week after transplanting, when the seedlings in the same column are staggered and dense, and there is a wide gap between the columns. The third period is more than 5 weeks after transplanting, the seedlings grow densely, and the gaps between the columns are sealed by the seedlings. The weeding of rice seedlings mainly concentrated within 3 weeks after transplanting, weeding could not be carried out later than 3 weeks after transplanting because the seedlings seal the gaps. Therefore, this study researched the paddy field image within three weeks after transplanting, we used the paddy field images of one week after transplanting and three weeks after transplanting to test the extracted centerline of seedling columns.

In order to judge the accuracy of the extraction of seedling row centerlines with the algorithm in this paper, the method of comparing the extracted centerlines with the artificial fitting line was used as the basis of accuracy judgment. Draw the centerlines of the seedling manually, and calculate the angle deviation between them and the centerlines extracted with the algorithm proposed in this study. If the Angle deviation is greater than 5 degrees, the centerline is judged to be inaccurate.

- Extraction of centerlines one week after transplanting

At the period of one week after transplanting, the rice seedlings are very small, the distribution of seedlings is scattered, and there is no adhesion among seedlings. At this period, the main interference comes from reflection and bubbles on the water surface. This study selected 2 representative images from the images of this period for analysis, which were the strong light environment with serious reflection and the normal light environment, as shown in Figure 6(a) and Figure 6(f). They were processed with the following operations: the images were inputted into the trained Fast-SCNN network for segmentation, and the original image was grayed, binarized and morphologically denoised to extract fast corners, and then the fast corners were classified and fitted according to the screened contours of prediction results of segmentation.

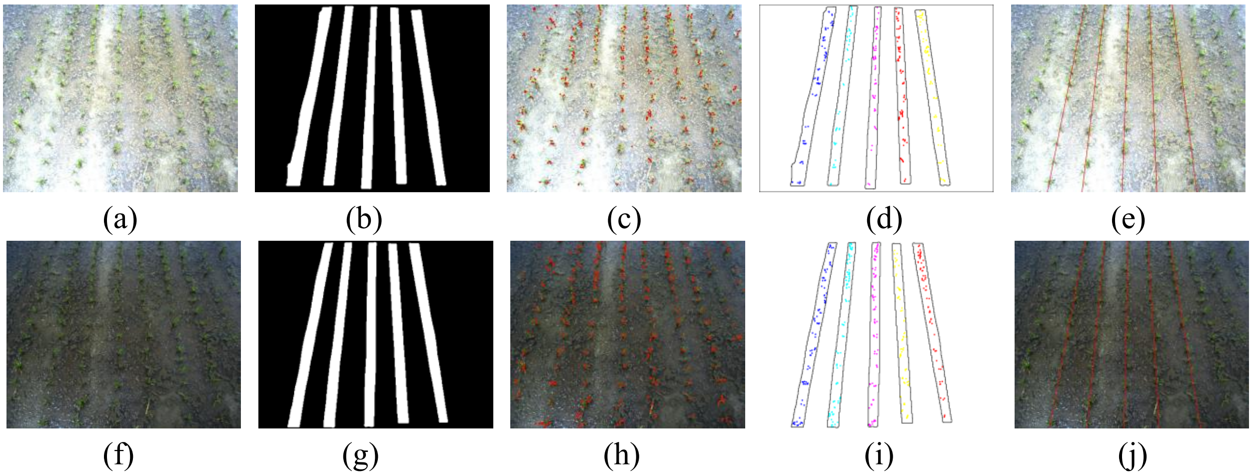


Fig. 6 - Extraction effect of centerlines 1 week after transplanting

Figure 6(b) and 6(g) are the results of counter extraction and screening; it can be seen from the figures that the Fast-SCNN semantic segmentation network can segment seedlings from the background by columns in both reflective and normal light conditions, and each column of seedlings can form a complete connected area. The feature points extracted by FAST corner detection are shown in Figure 6(c) and 6 (h). It can be seen that the feature points are concentrated in the seedlings' growth area, which represents the position of seedlings well. Feature points classification based on outer contours are shown in Figure 6(d) and 6(i). The results of classification show that the feature points that represent different column can be classified clearly, which can prevent the wrong clustering of a few of points caused by various clustering algorithms effectively. From the results of centerline extraction shown as Figure 6(e) and 6(j), we can find that the algorithm of this study can extract the centerlines of seeding columns in the middle section of picture accurately with high robustness. The average time spent per frame is 146ms, the accuracy is 96.4%, and the average angle error is 1.35 °.

- Extraction of centerlines three weeks after transplanting

At the period of 3 weeks after transplanting, the shape and distribution of seedlings are quite different from those at the period of one week after transplanting. The typical images shown in Figure7(a), 7(f) and 7(k) are three typical environments of weak light, normal light and strong light. It can be seen from the segmentation results in Figure 7(b), 7(g) and 7(l) that when the Fast-SCNN semantic segmentation network encounters the lack of plants and reflection, a row of seedlings can still form a complete connected area without being divided. No matter the size of weeds between seedling rows, they were predicted as the background by semantic segmentation network, thus effectively avoiding the influence of weeds on centerline extraction. It can be seen from the results of feature point extraction in Figure 7(c), 7(h) and 7(m) that the feature points extracted by FAST corner detection algorithm are all distributed in the seedling growth area, and feature points can be extracted in all the distribution areas of seedlings.

On account of the color characteristics of weeds between seedling columns are similar to those of seedlings, characteristic points can also be extracted in the area of weeds. However, the feature points generated by weeds are not within any contour detected in the result of semantic segmentation, so the feature points classification based on the outer contours of segmentation results can exclude the feature points generated by weeds, so as to avoid the influence of weeds on the centerline extraction. Feature points classification based on outer contours are shown in Figure 7(d), 7(i) and 7(n). From the fitting results of centerlines in Figure 7(e), 7(j) and 7(o), it can be seen that the algorithm proposed in this study can extract the seedling centerlines at the period of 3 weeks after transplanting in the middle section of picture accurately with high robustness. The average time spent per frame is 168ms, the accuracy is 95.5%, and the average angle error is 1.56°.

From the experimental results, it can be seen that the algorithm proposed in this study can extract the centerline of the middle 4-6 rows of seedlings with high accuracy in each stage of weeding operation, and the average time of each frame is 158ms, the accuracy is 95.9%. The speed meets the requirements of weeding robot navigation, which provides a reliable method for a visual navigation for agricultural robot.

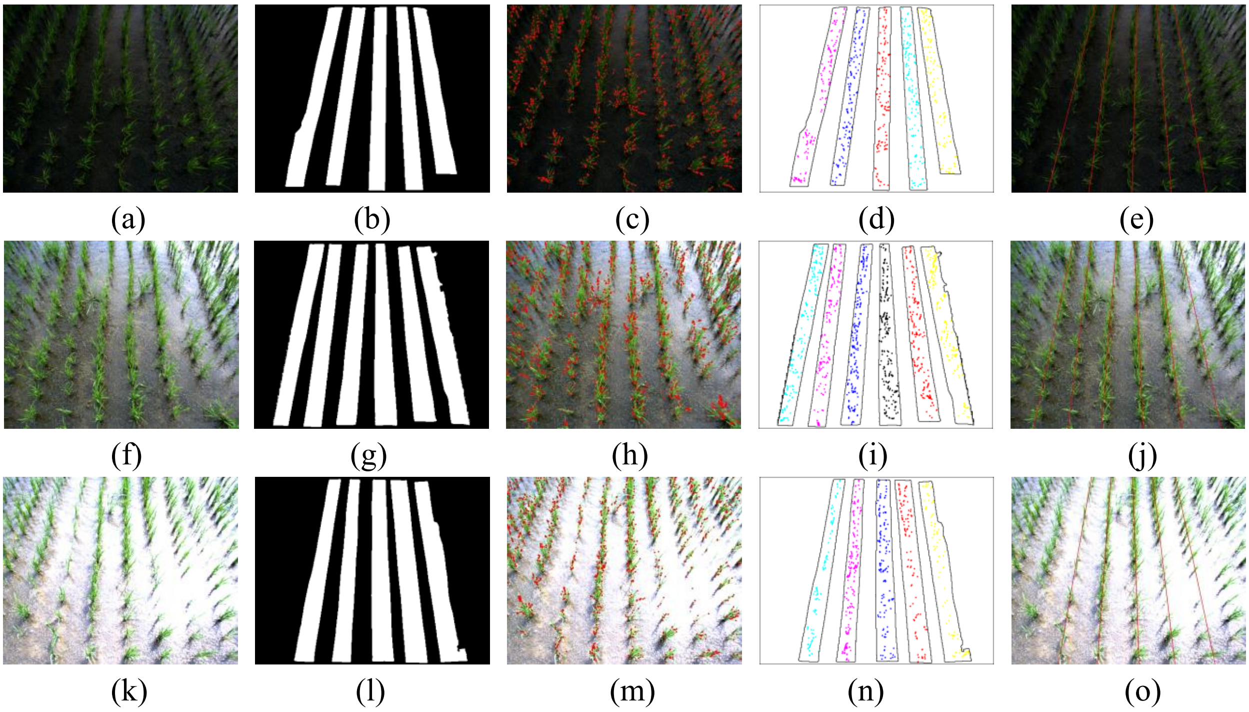


Fig. 7 - Extraction effect of centerlines 3 weeks after transplanting

CONCLUSIONS

(1) The images of rice seedlings with different brightness were collected at different period after transplanting, and the dataset was made by annotation of the images. Based on the dataset, the Fast-SCNN semantic segmentation network was trained, and the optimal model was selected to segment the seedlings from the background. Then contour detection was carried out based on the connected region in the segmentation results and the qualified outer contours were extracted as the contour of the seedling columns.

(2) The original image was grayed and segmented by super green operator based on RGB color space and Otsu algorithm. After the noise points were removed by morphological operation, the corner points in binary image were extracted as feature points of seedling image by FAST corner detection algorithm. The result of experiment showed that FAST corner points can respect the region of seedlings well.

(3) The extracted feature points were classified based on the contours, and each type of feature points were fitted by Hough transform based on known points. The results showed that the accuracy of the algorithm proposed in this study is 95.9%, and it takes 158ms to process a 1280*1024-pixel PNG format color image, which meets the real-time requirements of visual navigation.

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