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Correlation analysis-based image segmentation approach for automatic agriculture vehicle*

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Abstract: It is important to segment image correctly to extract guidance information for automatic agriculture vehicle. If we can make the computer know where the crops are, we can extract the guidance line easily. Images were divided into some rectangle small windows, then a pair of 1-D arrays was constructed in each small windows. The correlation coefficients of every small window constructed the features to segment images. The results showed that correlation analysis is a potential approach for processing complex farmland for guidance system, and more correlation analysis methods must be researched.

Key words: Image segmentation, Machine vision, Correlation analysis, Guidance
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INTRODUCTION

In recent years, harvesting crop by combine has become more and more popular in China. In 2003, combines were used to harvest 23% of rice and 71% of wheat. The work described here is part of a project aimed at researching automatic combines who follow the cut-uncut edge of the crops automatically to reduce the driver's fatigue from the intensive work.

Much attention has been focused on vision-based automatic agriculture vehicle. Image segmentation is the key to extracting the guidance line. Helped by near-infrared (NIR) images, the work has become easier (Searcy and Reid, 1987; Marchant and Brivot, 1995). Reid segmented images of cotton rows by dynamic threshold and a Bayes classifier. Marchant (1996) used Hough transform to get parameters of three row-lines, with the results not being affected by weeds. Ollis and Stentz (1997) used a color camera to track the edge of cut/uncut alfalfa. A discriminant, the ratio of red/green of individual pixels, was used to identify the different regions. Color transformation, HIS, also was used to distinguish the crop area (Torii *et al*., 1996). Using a multispectral camera, Benson found that a hue_{NIR}-based segmentation was shadow independent and offered advantages not found in common monochrome cameras (Benson, 2001). In China, Shen (2003) used the morphology to segment farmland images. Debain *et al*.(2000) had even developed a statistics-based segmentation algorithm which divided the field image into $n\times m$ sites, and 4 statistical parameters of the each site: the maximum of the histogram, the second moment, the homogeneity and entropy, were integrated by the Markov fields to get the edge results. Besides that, stereovision for automatic guidance also was developed (Francisco, 2003; Kise, 2004). Francisco used the disparity map to segment image. Kise reconstructed images to an elevation map, and then got the guidance line. As we can see that lots of methods segmented image only based on a single pixel. But

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the real field images are complex, for example, the crops are no longer green, and weeds cover the field in harvest season. Those cases will increase the difficulty of imaging segmentation. New features, such as relationship between neighbor pixels or the structural features of plant, must be researched.

Correlation analysis, which describes the correlation between two arrays, is an effective method used in pattern recognition, and successfully segmented SAR images (O'Sulliran and Montagnino, 2004). This paper is aimed at investigating correlation analysis-based approaches for segmenting farmland images.

MATERIALS AND METHODS

A color camera (Kodak CX4200), was used to take images. We used a tripod in the early experiment, and a test platform was made and used in the later experiment. Fig.1 shows the platform. The camera was mounted above the cut-uncut edges. Its height and tilt angle were adjust to get a suitable image. Thus we could obtain the field images shown in Fig.2.

Fig.1 The test platform

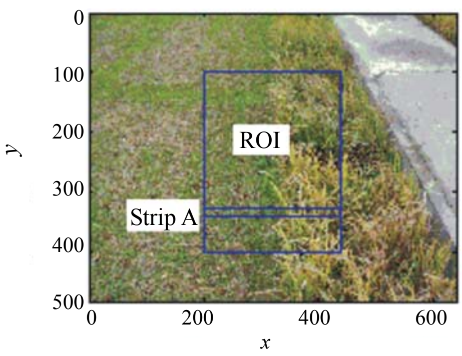

Fig.2 The field image, the strip A is used for analysis as an example in the next figure

Here, we define two classes in a field: one is crop, and another is background (weeds and soil). This approach aimed to segment the two classes (regions) correctly. To decrease the image processing time, only the pixels in the center of the image, the region of interest (ROI), were analyzed.

We also defined ROC (region of crop) and ROB (region of background). The correlation analysis method is described in the next section, and the result of segmentation will also be shown.

Correlation analysis

Correlation analysis can be used to find the relationship between two variables. We can recognize the leaves depended on the similarity of leave intensities. It is also possible for the computer to distinguish plants from soil by correlation analysis as the neighbor pixels inside one leaf have higher correlation than those inside soil. And it is also possible for the computer to recognize crops from weeds by knowing their different size and shape. In this paper, we divided the image into small windows and rearranged them to a pair of 1-D arrays. The correlation coefficients of two arrays express the feature of crops, weeds and soil. The steps are as follows.

Step 1: Preprocess. The color image should be transformed to the intensity image at first. The transformed equation is:

$$F=0.299R+0.587G+0.114B \tag{1}$$

where F is the set of intensity, and R, G, B is the set of red, green, and blue.

Step 2: Divide the image into small windows and construct a pair of 1-D arrays. The size of the small windows depends on the morphological feature of the crop. For example, the shape of rice is narrow and long: their width ranged from 2 to 6 pixels, and their length ranged from 20 to 60 pixels in our images. So, the size of small windows was set to 20×3 (m×n). A pair of 1-D arrays X_d, and Y_d were constructed in every small window. The first array X_d started from the first pixel in the first column, and ended at the (n–d) pixel in the last column. And the array Y_d started from the (d+1) pixel in the first column, and ended at the last pixel in the last column. That is

$$X_d=[f(1,1),f(2,1),\ldots,f(m,1),f(1,2),f(2,2),\ldots,f(m-d,n)]$$

Y_d=[$f(d+1,1),f(d+2,1),\ldots,f(m,1),f(1,2),f(2,2),\ldots,$
$f(m,n)$]

Where d is the distance of two arrays, X_d and Y_d.

Step 3: Calculate the correlation coefficients. If we analyzed the coefficients of the small window in the same level, we found that most of the coefficients in ROC were larger than those in ROB. So it is easy to segment the image by a threshold. Fig.3 shows the coefficients of small windows in the strip A in Fig.2.

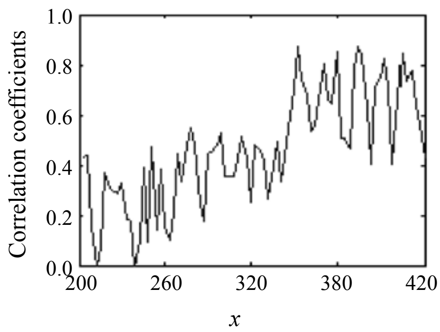

Fig.3 The correlation coefficients of small windows inside the strip A in Fig.2

Edge detection

The edge detection process can be implemented after the correlation analysis. Since the difference between two regions was clear, thresholds were selected based on the mean of correlation coefficients in the ROI. The steps are as follows.

Step 1: Label by the threshold. If the correlation coefficient of the small window was bigger than the threshold, all pixels in it were set to 255 and shown as white blobs. The others were set to zero. Fig.4 shows the labeled image.

Step 2: Remove the small black area blobs by morphological closing operation and small white blobs by morphological opening operation.

Step 3: Detect edge, and use linear regression to extract the edge-lines.

RESULTS AND DISCUSSION

The methods described in this paper were tested using 170 images. Images of rice and corn were acquired in different seasons from 2003 to 2004 at the test field of Zhejiang University, China. The images were taken under different light condition, including sunny and cloudy days.

Ability to distinguish crop, weed, and soil

Autumn rice is always harvested from October to November. It is possible that weeds grow up with high density, and the color of weeds is greener than that of crops, which makes the intensities of crops and weeds change in the same range. Fig.4 shows the method's ability to identify crops and green weeds.

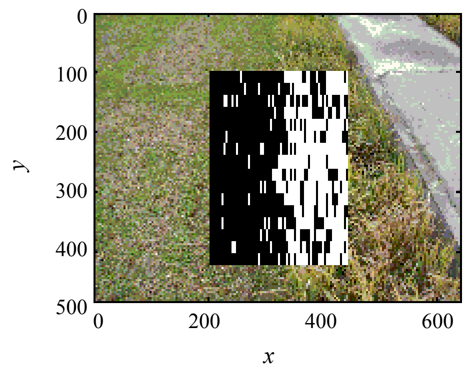

Fig.4 Crop image taken at November 2004. The size of small windows is 20×3, and the white blobs represent the detected leaves. Some white blobs in the ROB can be removed by morphologic operations

It is also possible that crop colors become yellow while dry soil in cut regions are yellow too. In this case, the intensities of crops and soil are very close to each other. Fig.5a is a typical rice field image in harvest season, Fig.5b shows the correlation coefficients in strip A, and Fig.5c shows the labeled and morphologic processed result.

This method can also be advantageously used for segmenting other types of crops whose leaves are narrow and long, such as the corn crop, shown in Fig.6a. Fig.6b shows the correlation coefficients inside a strip with the distance of arrays for correlation analysis is 1. Fig.6d shows the labeled result that regions of corn and background were clearly segmented.

Threshold of segmentation

The threshold is decided on the type of crops, the parameters of camera, and the distance of arrays for correlation analysis. The threshold of rice is smaller than that of corn, as the size of rice leaves is smaller than that of corn leaves. The camera also must be mounted correctly that most leaves are clearly seen, which improves the correlation features. The distance of arrays for correlation analysis should be as small as possible. Fig.6c shows that when the distance increases to 2, the correlation coefficients decreased. Fig.6e shows the segmented result. We found that it does not work correctly any more when the distance is larger than 3 pixels. So the segmentation threshold can be reliably obtained only when the distance is less than 3 pixels.

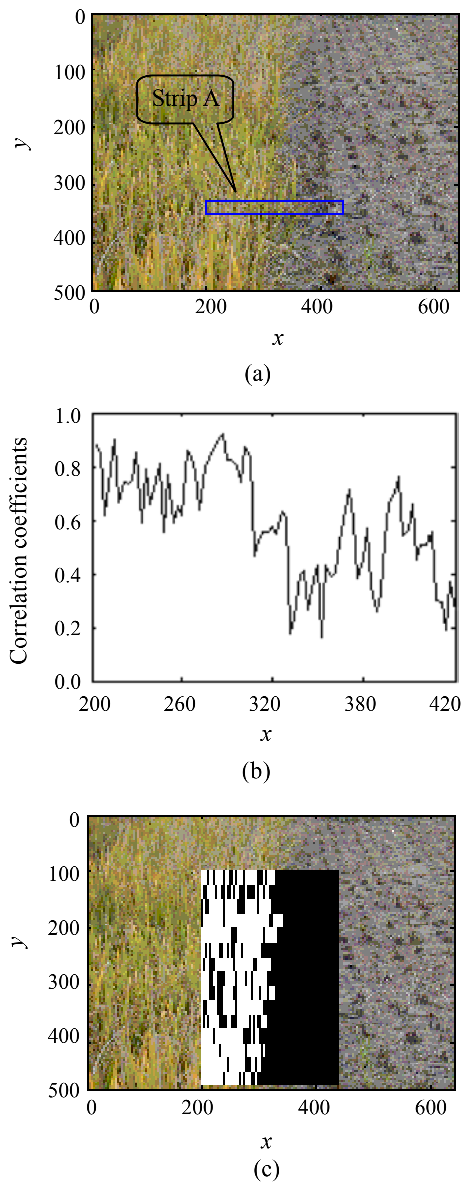

Fig.5 Crop image with yellow crops and dried-soil background
(a) The original image; (b) The correlation coefficients inside the strip A with the distance of arrays for correlation analysis is 1; (c) The labeled result

Size of the small windows

The size of small windows also is decided on the type of crops and their growing stage, i.e. the

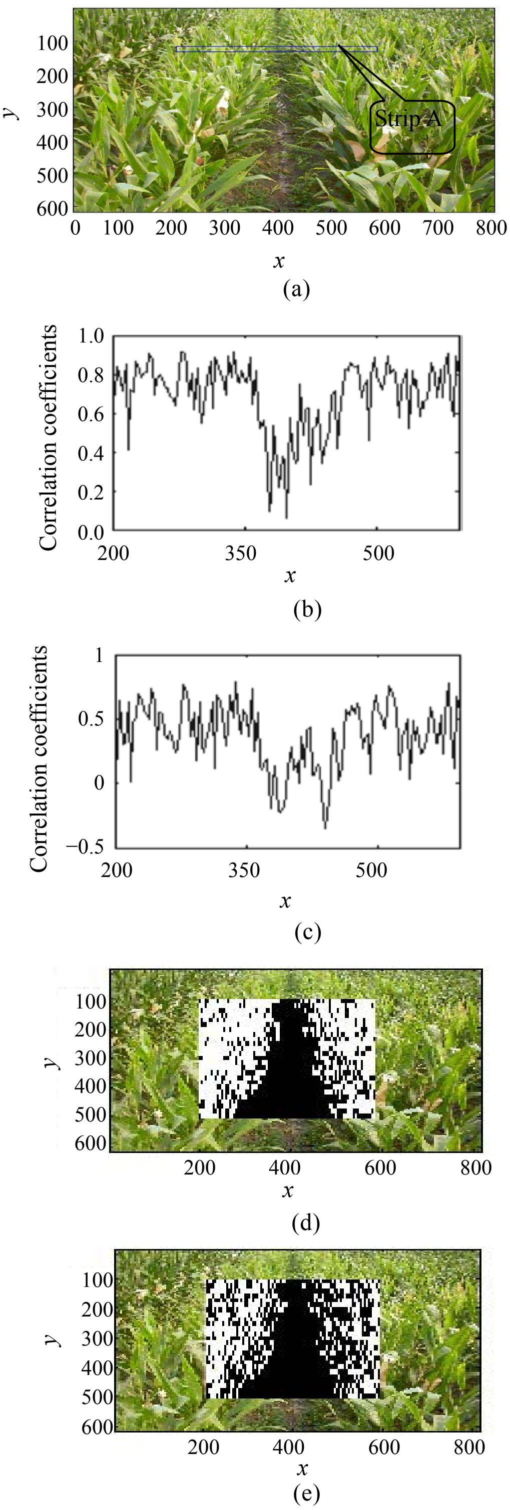

Fig.6 Segment cornfield image by the correlation coefficients-based method
(a) The original image; (b) The correlation coefficients inside the strip A with the distance of two 1-D arrays is 1; (c) The correlation coefficients inside the strip A with the distance of arrays for correlation analysis is 2; (d) The labeled result in case; (e) The labeled result in case (c)

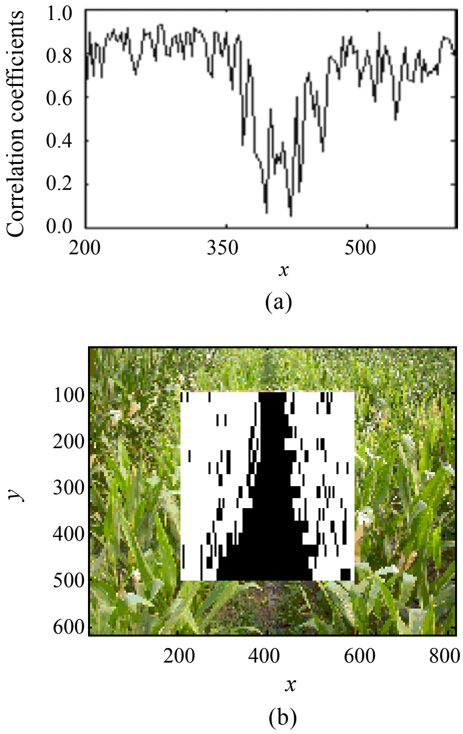

Fig.7 Segment cornfield with larger size window (25×3)
(a) The correlation coefficients inside the Strip A with the distance of correlation analysis pixels is 1; (b) The labeled result

large sampled windows are suitable for large leaves crops. Fig.7a shows that when the size of small windows increases from 16×3 to 25×3, the correlation coefficients are smoother compared to the coefficients in Fig.6b, and Fig.7b shows that more robust result can be obtained. In future work, some methods to find the suitable small window size need be developed.

Method to construct 1-D arrays

Other types of 1-D arrays can also be constructed. For example, every single column can also be taken as a 1-D array, and the correlation coefficients can be computed, but the difference between crop and background cannot be determined.

CONCLUSION

We divided the crop field image into small windows and construct 1-D arrays, then the correlation coefficients of every small window constructed the features to segment images. It was shown that the correlation analysis approaches based on the homogenous characteristic of crop could reliably segment the field image. This significantly increases the range of operating conditions that may be tolerated when compared with the previously reported methods. Correlation coefficient-based segmentation method is suitable for segmenting the field image in harvest season. In future work, other correlation analysis methods and improved algorithms on how to speed up the processing time for real-time application must be researched.

References

Benson, E.R., 2001. Vision Based Guidance of an Agricultural Combine. Ph.D Thesis, UIUC, p.116-123.

Debain, C., Chateau, T., Berducat, M., Martinet, P., Bonton, P., 2000. A guidance-assistance system for agricultural vehicles. *Computers and Electronics in Agriculture*, **25**:29-51.

Francisco, R.M., Zhang, Q., Reid, J.F., 2003. Automatic Navigation with Stereo Disparity. ASAE Annual International Meeting. Las Vegas, Nevada, USA.

Kise, M., Zhang, Q., Francisco, R.M., 2004. Stereovision-based 3D Field Recognition for Agricultural Vehicle. Proceedings of the CIGR International Conference, Beijing, Session V.

Marchant, J.A., 1996. Tracking of row structure in three crops using image analysis. *Computers and Electronics in Agriculture*, **15**:161-179.

Marchant, J.A., Brivot, A.R., 1995. Real-time tracking of plant rows using a Hough transform. *Real-Time Imaging*, **1**:363-371.

Ollis, M., Stentz, A., 1997. First Results in Vision-based Crop Line Tracking. Proceedings of the IEEE Robotics and Automation Conference, Minneapolis, Minnesota, USA, **1**:951-956.

O'Sulliran, J.A., Montagnino, L.J., 2004. Azimuth Correlation Models for Radar Imaging. Proceedings of SPIE—Algorithms for Synthetic Aperture Radar Imagery, **5095**:45- 53.

Searcy, S.W., Reid, J.F., 1987. Vision-based guidance of an agricultural tractor. *IEEE Control Systems*, **12**:39-43.

Shen, M.X., Li, X.Z., Ji, C.Y., 2003. Detection of areas of cropland scenery using morphology. *Transactions of the Chinese Society for Agricultural Machinery*, **34**(1):92-94.

Torii, T., Kanuma, T., Okamoto, T., 1996. Image Analysis of Crop Row for Agricultural Mobile Robot. Proceedings of AGENG96, Madrid, Spain, p.1045-1046.