Estimates of Plant Number of Maize Crop at Seedling from High-Throughput UAV Imagery

LIU Shuaibing[1], Yang Guijun[2]

[1]School of Surveying and Land information Engineering, Henan Polytechnic University, Jiaozuo, Henan, China
[2]National Center for agricultural information engineering and technology research, Beijing, China

A paper from the Proceedings of the
14th International Conference on Precision Agriculture
June 24 – June 27, 2018
Montreal, Quebec, Canada

Abstract. *The acquisition of such agricultural information as crop growth and output is of great significance for the development of modern agriculture. Using the image analysis is important to gain information on plant properties, health and phenotype. This study uses the unmanned aerial vehicle images about Maize breeding material collected in Beijing Xiao Tang mountain town in June 2017. The four color space transformation of RGB, HSV, YCbCr and L*A*B was used to divide the UAV image foreground (crop) with the background (soil background), and the classification of two values was obtained. The morphology of maize seedling was identified by skeleton extraction, and the morphological structure was refined by adding noise removal. According to the growth of crops, crops are divided into two categories (multiple leaves, few leaves). The results show that the Harris corner detection method has the highest recognition accuracy, the recognition rate of less leaf type reaches 96.3%, the recognition rate of multi leaf type reaches 99% and the overall recognition rate is 97.8%. The accuracy of the traditional image recognition is improved by 2~3%, and the accuracy is reliable. When dealing with multi leaf individual plants, the accuracy of identification can reach 99%. At the same time, under the overlapping overlapping of multiple leaves, the research method in this paper has good applicability.*

The authors are solely responsible for the content of this paper, which is not a refereed publication.. Citation of this work should state that it is from the Proceedings of the 14th International Conference on Precision Agriculture. EXAMPLE: Lastname, A. B. & Coauthor, C. D. (2018). Title of paper. In Proceedings of the 14th International Conference on Precision Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture.

Keywords: *Maize, unmanned aerial vehicle (UAV), number of plants, color, space, skeleton extraction, corner detection*

INTRODUCTION

Nowadays, the method of obtaining field information has become diversified and flexible with the rapid development of UAV (unmanned aerial vehicles) technology and its application in agricultural science (Floreano 2015). Compared with traditional satellite images, UAV images can effectively exclude the influence of cloud occlusion, and can also collect remote sensing image data in cloudy days (Zhang 2012). According to actual needs, the high-throughput UAV imagery can easily formulate the measurement plan, change the flight height, and get the high-resolution image data (Peña 2013). In addition, UAV remote sensing crop phenotypic platform can get high-throughput remote sensing images in a short time, saving time, manpower and economic cost (Tripicchio 2015), which provides strong support for the rapid collection and analysis of crop information in agricultural science field (Liu Jiangang 2016).

Pheonmics is a subject that studies the phenotype characteristics of organisms. Nowadays, the development of agricultural science has put forward more needs for spatial data acquisition, such as plant density, crop yield, and related soil properties, Pajares G and Grosskinsky were summarized that although the modern mechanization constantly improved, the traditional biomass, LAI (leaf area index) and yield of phenotypic parameters were still in the stage of manual operation, time-consuming, low efficiency, poor precision and limited the development of modern agricultural science. Barabaschi and Cobb J N pointed out that the genome revolution has greatly improved the understanding of gene composition in the past ten years. So it is significant to collect high-resolution images and study crop phenotypes which can provide data basis for genetics and plant breeding.

High throughput crop phenotypic platform is an effective tool for rapid acquisition of phenotypic information, including greenhouse and field types. Greenhouse high-throughput platform is equipped with VIS (visible light) imaging, IR (infrared) imaging, NIR (near infrared) imaging and laser 3D scanner and other sensors to obtain a large number of individual phenotypic information. However, its poor mobility and high cost are difficult to be used in the production conditions of large plant planting density and the changeable growth environment. The field platform is divided into agricultural machinery platform (agricultural machinery, agricultural vehicle, etc.), artificial mobile platform (trolley) and UAV platform. Barmeier G and Schmidhalter U successfully evaluated the biomass fresh weight and dry weight of East wheat and measured the nitrogen content and absorption rate of the plant by using the tractor platform. The object of this study was to use the UAV imagery to identify the field of corn seedings through unmanned aerial vehicles (UAV) images to solve the problem of low efficiency of artificial visual count.

MATERIALS AND METHOD

The Location

The experimental field is located in the national precision agriculture demonstration base of Xiaotangshan (116°26′10″~116°27′05″E), Changping District, Beijing, China, the altitude is about 50 m. The experimental data of unmanned aerial vehicle (UAV) were collected in June 8, 2017 (10:00-14:00). The weather was sunny and the sun radiation intensity and stability. The flight height was about 40m. The DJ-S1 000 eight rotor electric UAV is used, the total weight is 4.4kg, the flight load is 6000-11000 g, the battery is LiPo (6S, 10 000mAh~20 000 mAh, the smallest 15C), the size is 460 mm * 511 mm * 305 mm, hovering time is 15 minutes.

Image preprocessing

This research uses Agisoft PhotoScan software to process the UAV high definition digital image. A 30 cm 30 cm geometric reference board was set up between different aerial belt to maintain fixation throughout the whole growth period of corn. The central point of the geometric reference plate is the GPS control point, which provides the basis for the mosaic of different aerial images and improves the accuracy of image. With the help of the geometric correction function of Agisoft PhotoScan software, the image geometric correction based on the GPS control point of geometric reference plate is used to remove the image of the UAV attitude change and the atmospheric refraction. According to the planning of breeding materials plot, all the plots was cut by Adobe Photoshop CC 2017, and the feasible research areas were sorted out.

The analysis method

In this study, four color space models(RGB, HSV, YCbCr and L*A*B) are selected. Through comparative analysis, HSV color space is selected as a remote sensing image processing model. The image is transformed to the HSV color model by color transformation. According to the color characteristics of the crop, the edge information extraction is extracted by threshold segmentation, and the two value map after the crop soil separation is finally obtained. In this paper, the method of image skeleton extraction based on potential energy balance was used to study the skeleton extraction on the basis of two values of crop segmentation, and the morphological structure of crops was identified.

The image processing results showed that Harris corner detection could better extract the morphological corners compared with Moravec and Fast corner detection. Table 1 shows the code used in the main processing of this article.

Table 1 Pseudo code for this research method

This paper method pseudo code:

Input the original image i

phase1 read the image i

phase2 after transform the image into HSV color space and get the image t

phase3 the image t was segmented by threshold and got the classified binary image J

phase4 Skeleton extraction of image J and get the skeleton image K, then deburring the image K and get the skeletion morphologic image H

phase5 zooming and resampling the image H to get the denoising image F

phase6 use Harris corner detection to carry out the image F corner detection. Statistics the number of image information Y

output the number of the corner detection Y

Results and discussion

This study selected four color space models RGB(red, blue, green), HSV(Hue, Saturation, Value), YCbCr(Luminance, Cblue, Cred)for data processing. Through comparative analysis four color models, the HSV color space was selected as a remote sensing image processing model because it has the least noise points and the most accurate edge extraction for crop morphology.

In order to verify the feasibility of the method, the crop plots were counted according to the 1/2 plot, 2/3 plot, one plot, two plot and four plot to verify the feasibility and accuracy of the method. Fig. 1 shows the comparison of true plant number and computer automatic identification technology in each sample area

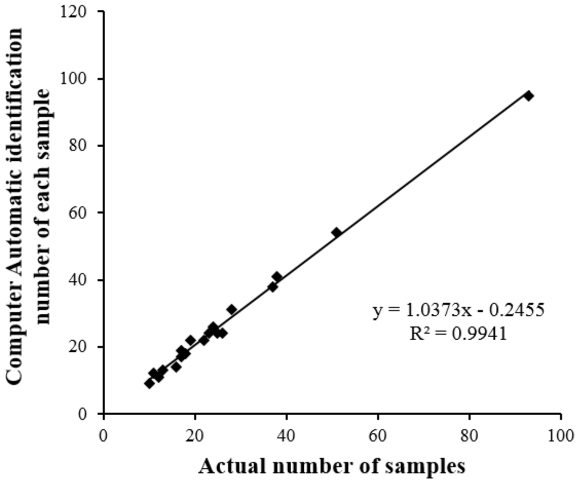

Fig.1 Computer recognition and comparison diagram under different areas

The number of computer recognized trees is very close to that of manual ones. The two sets of data are analyzed by linear regression, and the correlation index R^2 is about 0.99. It proves that the two sets of data have a higher fitting effect and a strong correlation, which proves that the method of this paper is reliable.

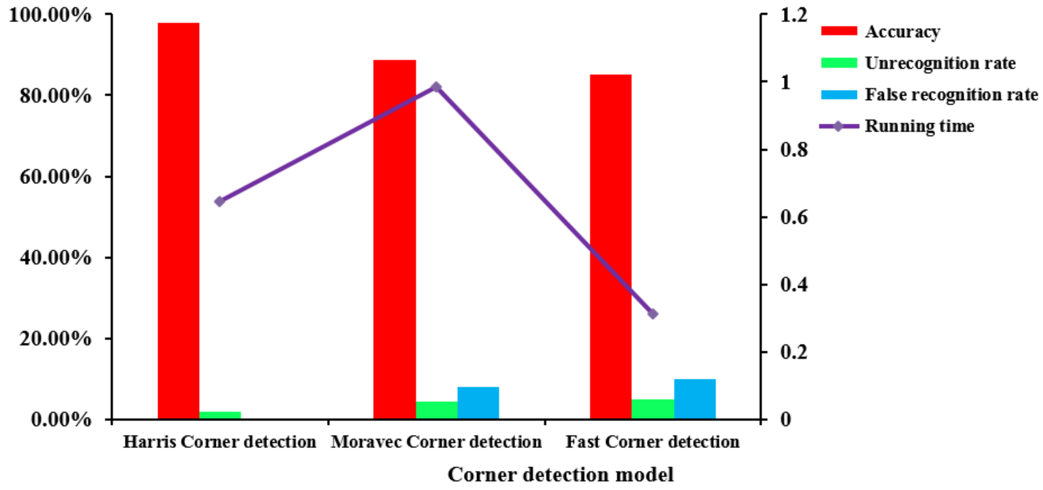

Fig.2 The effect of different Corner detection methods on the accuracy of the results.

It can be seen from Figure 9 that Moravec and Fast corner check have no good applicability and low accuracy for skeleton polygon graph. At the same time, on the overall recognition rate, the Harris corner detection accuracy reached 97.8%, and the average processing time of each breeding material plot was 0.646 seconds. Fast corner detection has the highest time efficiency but the lowest accuracy. To sum up, Harris corner detection has the highest accuracy and the most suitable for maize seedling number identification in field, so Harris corner detection is used to analyze the breeding material area.

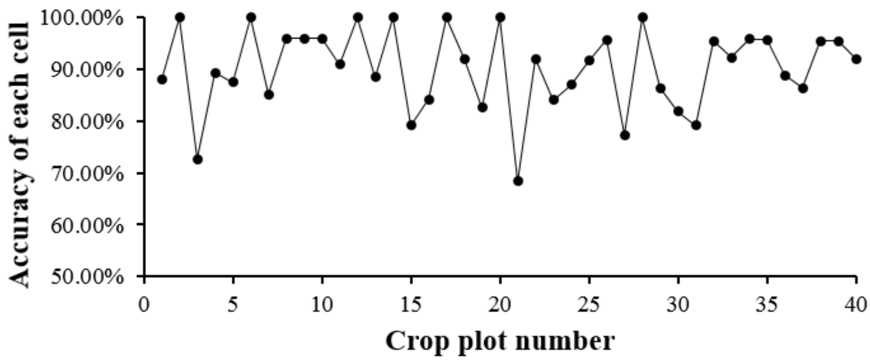

Fig.3 Precision statistics of crop material cell

It can be seen from Fig.3 statistics that the accuracy is reliable from Harris corner detection. There are 7 computer recognition values in the plot, which is exactly the same as the actual plant number in the material plot, reaching 100% and the accuracy of most of the communities is more than 80%.

The number of artificial count maize seedlings is 954, while the number of computer identification is 975 strain, and the error is 21 strain. Through Harris corner detection, the total recognition number is 97.8%, and the accuracy is reliable.

CONCLUSIONS

The study adopted the principle of digital morphology, through the threshold segmentation binary map, through the skeleton extraction algorithm, get the exact skeleton shape of the maize seedling stage, remove most of the noise point and skeleton bifurcation in the material area, and use the Harris corner detection to determine the specific number in the corn material area, saving the manpower and material resources. It provides strong support for large area measurement of seedling emergence and final yield estimation.

In the different material area, the correlation coefficient of automatic recognition of the number of plants and the number of artificial visual recognition R can reach 0.99 and the overall recognition rate is 97.8%. The accuracy of the traditional image recognition has been improved by 2~3% and the accuracy is reliable.

REFERENCES

Floreano D, Wood R J. Science, technology and the future of small autonomous drones.[J]. Nature, 2015, 521(7553):460-6.

Sankaran S, Khot L R, Espinoza C Z, et al. Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: A review[J]. European Journal of Agronomy, 2015, 70:112-123.

Zhang C, Kovacs J M. The application of small unmanned aerial systems for precision agriculture: a review[J]. Precision Agriculture, 2012, 13(6):693-712.

Peña J M, Torres-Sánchez J, de Castro A I, et al. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images[J]. Plos One, 2013, 8(10):e77151.

Tripicchio P, Satler M, Dabisias G, et al. Towards Smart Farming and Sustainable Agriculture with Drones[C]. International Conference on Intelligent Environments. IEEE, 2015:140-143.

Rez-Ortiz M, Jos A, Manuel, et al. Selecting patterns and features for between- and within- crop-row weed mapping using UAV-imagery[J]. Expert Systems with Applications An International Journal, 2016, 47(C):85-94.

Liu Jiangang, Zhao Chunping, Yang Guijun, et al. Review of field-based phenotyping by unmanned aerial vehicle remote sensing platform[J]. Transactions of the Chinese Society of Agricultural Engineering. 2016,32(24):98-106. (in Chinese with English abstract)

Yang Youxin, Yang Zemao, WU Caijun, Fan Shuying. Advances in plant phenomics research[J]. Acta Agriculturae Universitis Jiangxiensis. 2015,37(06):1105-1112. (in Chinese with English abstract)

Geesing D, Diacono M, Schmidhalter U. Site-specific effects of variable water supply and nitrogen fertilisation on winter wheat[J]. Journal of Plant Nutrition and Soil Science = Zeitschrift fuer Pflanzenernaehrung und Bodenkunde, 2014, 177(4):509-523.

Fu Y, Yang G, Wang J, et al. Winter wheat biomass estimation based on spectral indices, band depth analysis and partial least squares regression using hyperspectral measurements[J]. Computers & Electronics in Agriculture, 2014, 100(2):51-59.

Pajares G. Overview and Current Status of Remote Sensing Applications Based on Unmanned Aerial Vehicles (UAVs)[J]. Photogrammetric Engineering & Remote Sensing, 2015, 81(4):281-329.

Grosskinsky D K, Svensgaard J, Christensen S, et al. Plant phenomics and the need for physiological phenotyping across scales to narrow the genotype-to-phenotype knowledge gap[J]. Journal of Experimental Botany, 2015, 66(18):5429.

Barabaschi D, Tondelli A, Desiderio F, et al. Next generation breeding[J]. Plant Science An International Journal of Experimental Plant Biology, 2016, 242:3.

Cobb J N, Declerck G, Greenberg A, et al. Next-generation phenotyping: requirements and strategies for enhancing our understanding of genotype–phenotype relationships and its relevance to crop improvement[J]. Theoretical & Applied Genetics, 2013, 126(4):867-887.