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Proposed Digital Images Methods for Cotton Identification using Image Processing: A Review

Arpita Pandya¹, Dr.Priya Swaminarayan²

Research Scholar, Computer Science, RAI University, Ahmedabad, Gujarat, India¹

Research Guide, Computer Science, RAI University, Ahmedabad, Gujarat, India²

ABSTRACT: India is generally an agricultural country. Agriculture is the single most important contributor to the Indian economy. Agriculture crop production depends on the season, biological, and economic cause. The prognosticating of agricultural yield is a challenging and desirable task for every nation. The image segmentation performs a significant role in the field of image processing because of its wide range of applications in the agricultural fields. Crop production is a complex phenomenon that is influenced by agro-climatic input parameters. Agriculture input parameters varies from field to field and farmer to farmer. This paper proposes the algorithms in image processing of the cotton to extract the feature, modelling and matching. Image Processing for Segmentation, feature measurement such as invariants, size and shape, texture and scene analysis.

KEYWORDS: Image Processing techniques, Cotton Identification, Ycber color space, Color subtraction module, Dynamic freeman chain coding and Machine vision.

I. INTRODUCTION

Cotton is an important cash crop and India cultivates the highest acreage in the world. It provides the basic raw material (cotton fibre) to the cotton textile industry. Cotton also known as 'White Gold' dominates India's cash crops, and makes up 65 per cent of the raw material requirements of the Indian textile. Cotton plays a vital role in economy in many cotton producing nations. India is the major cotton producing nation with 27 million bales production which is approximately account for 24% of global cotton production (2014). India has tripled cotton production form 13 million bales to 40 million bales and has doubled its market share of global cotton production form 12% in 2002 to 25% in 2014, representing a quarter of total global cotton production. The major cotton growing states in India are Punjab, Haryana, Rajasthan, Madhya Pradesh, Gujarat, Maharashtra, Andhra Pradesh, Tamil Nadu and Karnataka.

With the development of computer vision, more practices with respect to precision agriculture (PA) have evolved, such as intensive crop production, viticulture and horticulture. Research associated with cotton detection is of great necessity. For one thing, harvesting cotton needs highly intensive labour and is becoming less sustainable with high cost and shortage of skilled labour. For another thing, the retrieval of growth stage information mainly depends on manual records, requiring frequent observations and professional knowledge. Both of the above issues can be solved through automatic cotton detection assisted by computer vision technologies, with the advantages of efficiency improvement and artificial error reduction. Image segmentation in agriculture is a fundamental issue of computer vision, which can be applied to many directions, such as plant or weed identification, crop growth stage prediction and fruit detection. As a result, image segmentation technology can also play a big role in cotton detection in the field. However, present related segmentation methods, such as crop segmentation in the field, cannot be applied to infield cotton detection directly.

To the best of our knowledge, little research has been done to improve ground-based cotton detection in the field. Most researches are focused on implementing cotton detection on small path images captured by cameras equipped on picking cotton robot, which have uncomplicated background and single target. On the contrary, in view of the complicated environment in natural field, in-field cotton detection has been rendered to a challenging multi objective

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research issue. The challenges are summarized as follows: (1) various sizes and shapes, (2) changing illumination and leaf reflection, (3) plant occlusion and (4) sky or mulch interference.

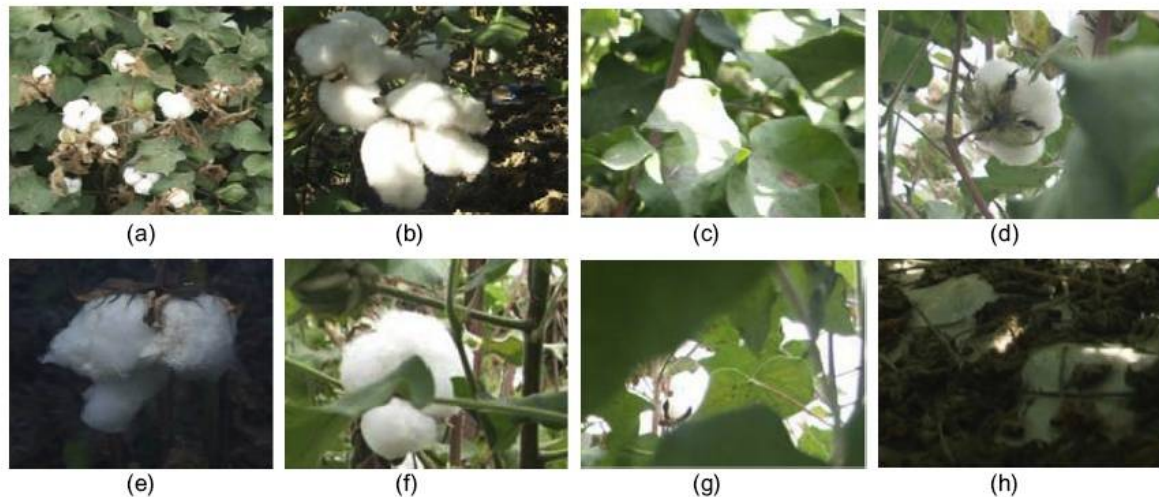


Fig.1 some typical challenges in the cotton detection. (a) Multiple cottons with various sizes; (b) shadow influence; (c) uneven distribution; (d) leaf specular reflection; (e) branch barrier; (f) leaf barrier; (g) sky interference; (h) mulch interference.[1]

For instance, owing to the different viewing angles and heights, sizes and shapes of cotton are various, as illustrated in Fig. 1(a) and 1(b) indicates that the color of cotton will get darker in the lower place of cotton plants or in cloudy days. Enough strong illumination in sunny days results in uneven distribution of cotton (Fig. 1(c)) and white regions in the leaf are produced by specular reflection (Fig. 1(d)). Because of the interlaced branches and large area leaf, cotton will be occluded by branch (Fig. 1(e)) and leaf (Fig. 1(f)), respectively. In addition, Fig. 1(g) and (h) shows the interferences by sky and mulch, which make it more challenging for cotton detection.

Yanan Li et al., developed novel in-field cotton detection via region-based semantic image segmentation with two perspectives of observation, including unsupervised region generation and supervised semantic labelling prediction. First, simple linear iterative clustering (SLIC) and density-based spatial clustering of applications with noise (DBSCAN) on Wasserstein distance are employed to generate regions, with superiority in edge-preserving and density contrast distribution. Then histogram-based color and texture features extracted from each region proposal are passed to random forest, achieving semantic labelling prediction on in-field cotton images. Finally, to evaluate the robustness and accuracy of the proposed method on cotton detection, 46 test images taken from the year 2012 to 2015 are utilized to compare the proposed method with other well-established methodologies based on four metrics. Experiments and comparisons demonstrate that the method can detect the boll opening stage automatically, which provides support for precision agriculture. [1]

II. LITERATURE REVIEW

The proposed work described the cotton identification using various techniques. This section is divided into three proposed methods. Some characteristics are shared by most methods presented in this section.

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Ycber color space:

Weixin Wang et al. worked on the development methods to identify cotton top features based on machine vision & image processing. They first extracted the cotton top in three different color spaces, and then they extracted the Area of the cotton top image as top's morphology feature. The result shows good accuracy in three different color space models. They also compared the results of images extracted in three different color space models, three different color spaces namely Ycber color space, HSI color space, and YIQ color space. In their experiments the comparison shows that Ycber color space is the best color space for extracting cotton top. Fig. 2 represents flowchart for identifying cotton in digital image. [2]

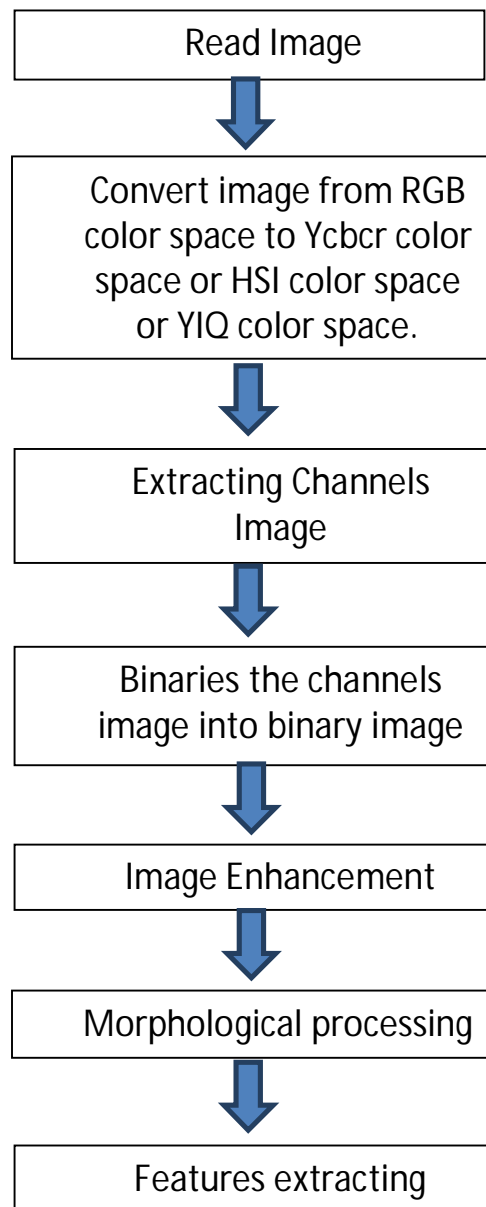


Fig. 2 Flowchart for Identify Cotton in Digital Images.

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The YCbCr color space has been characterized because of expanding requests for digital algorithms in handling video information, and has since become a widely used model in a digital video. It belongs to the family of television transmission color spaces. The family includes others such as YUV and YIQ. YCbCr is a digital color system, while YUV and YIQ are analog spaces for the individual PAL and NTSC frameworks. These color spaces separate RGB (Red-Green-Blue) into luminance and chrominance information and are useful in compression applications, however, the specification of colors is somewhat unintuitive. The Recommendation 601 specifies 8 bit (i.e. 0 to 255) coding of YCbCr, whereby the luminance component Y has an excursion of 219 and an offset of +16. This code places black at code 16 and white at code 235. In doing so, it reserves the extremes of the range for signal processing foot-room and headroom. On the other hand, the chrominance components Cb and Cr have excursions of +112 and offset of +128, producing a range from 16 to 240 inclusively.

The equations used for converting image from RGB color space to YCbCr color space are:

$$Y = 0.299R + 0.587G + 0.114B$$

$$Cb = -0.1687R - 0.3313G + 0.5B$$

$$Cr = 0.5R - 0.4187G - 0.0813B$$

In this paper they used Cr component segmentation cotton top and the other parts.

A.B. Payne et al. developed a system based on machine vision to count mango fruit from daytime images of individual trees for the purpose of a machine vision based estimation of mango crop yield. Images of mango trees were acquired over a three day period, 3 weeks before commercial harvest occurred. For these images, pixels were segmented into fruit and background pixels using colour segmentation in the RGB and YCbCr colour ranges and texture segmentation based on adjacent pixel variability. Resultant blobs were tallied to acquire a for every picture mango tally. Over an arrangement of 555 pictures (with mean \pm standard deviation of fruit per tree of 32.3 ± 14.3), a linear regression, ($y = 0.582x - 0.20$, $R^2 = 0.74$, bias adjusted root mean square error of prediction = 7.7) was achieved on the machine vision count relative to the image count. The algorithm decreased in effectiveness as the number of fruit on the tree increased, and when imaging conditions involved direct sunlight. The results presented here are encouraging that a machine vision based mango crop load estimator is possible. However, the development required is significant, particularly for application to less mature fruit, with less fruit colouration. [3]

Color Subtraction Module and Dynamic Freeman Chain Coding

USN Rao proposed an optimized method to identify cotton on the basis of Image processing techniques together with Microcontrollers. By structuring Automated Cotton Picking Robot (ACPR) based on machine vision new cotton recognition method is proposed using a single camera, which is based on color subtraction of different parts of cotton Plant. Dynamic Freeman chain coding is used to increase recognition accuracy. [4]

Color Subtraction Module used to correctly identify cotton fruits from the background in real time. In order to correctly identify cotton fruits from the background in real time, a new color module was developed. According to color Analysis, it can be seen that the color values of red, green and blue of cotton fruits are quite the same, whereas for Leaves and Stems are quite different. Hence, this characteristic can be used to differentiate cotton fruits from the other two.

When the subtraction value of red and blue is selected, the algorithm is as follows:

$$g(x, y) = 0 \text{ if } f(x, y) < T, \\ = 255, \text{ otherwise}$$

Where $f(x, y)$ is the gray value of pixel (x, y) , and T is the threshold.

As an example, Fig. 2 (b) is recognition result by color subtraction module.

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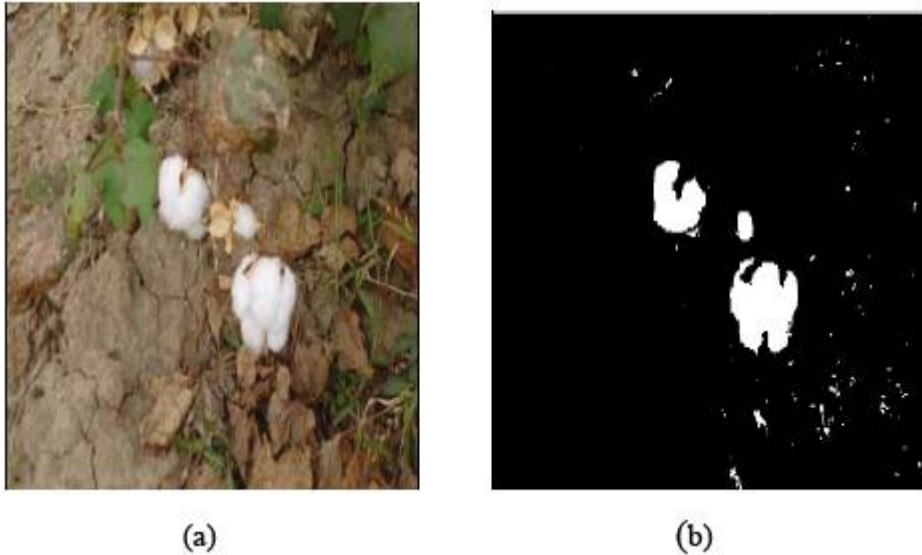


Fig. 3 original Image and Recognition Result

Dynamic Freeman chain coding technique used to increase recognition accuracy.

In order to solve the white points in Fig. 3(b), a new method of dynamic Freeman chain coding is proposed.

The algorithm of dynamic Freeman chain coding is as following:

- (1) Scan the binary image, if the pixel value is 255, then label, and use the rule of Freeman to trace anticlockwise.
- (2) Compute the perimeters of different regions.
- (3) Remove the region where perimeter is less than T which is calculated by the formula:

$$T = \mu_1 P_1 + \mu_2 P_2$$

$$\mu_1 = \frac{M_1}{\sum \text{Perimeter}}, \quad \mu_2 = 1 - \mu_1$$

Where P1 is the median value of perimeter, P2 is the maximum value of perimeter, μ_1 and μ_2 are weight indexes, M1 is the number whose perimeter is less than the median value. If perimeter is less than T, the value of the pixel in the region is 0, otherwise 255. Fig. 4 shows the recognition result by dynamic Freeman coding.

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Fig. 4 Recognition after Dynamic Freeman Coding

Yong Wang et al. proposed a new cotton recognition method which is based on color subtraction information of different parts of cotton. Furthermore, in order to increase accuracy rate of cotton recognition, dynamic Freeman chain coding is used to remove noise. It provides parameters for motion of the manipulator so that it can acquire precise location information of cotton, identify cotton from surroundings correctly, and accordingly pick up them automatically. Their Experimental results show that accuracy of recognition reaches above 85%. [5]

Machine Vision

Mulan Wang et al. proposed a new design of Intelligent Cotton Picking Robot (ICPR) based on machine vision including the motion control subsystem and machine vision subsystem. The former adopts the YASKAWA MP2100 as the core, which can control the robot of 4-DOF and X-axis. The latter based on the interface module of SEED-VPM642 with 2-CCD cameras, can get an efficient and precise recognition. The results demonstrate that the method for cotton recognition is well done and the recognition correctness rate is high up to 85%. [6]

Liu Zhen-yu et al. described sorting technology based on Industrial robot of machine vision, applies monocular vision technology in industrial robots. They also explained the characteristics of three main function model (image pre-processing, corner detection and contour recognition), and proposed algorithm of multi-objective center and a corner recognition. The simulated results show that the sorting system can effectively solve the sorting problem of regular geometric work piece, and accurately calculate center and edge of geometric work piece to achieve the sorting purpose. [7]

RemigiuszLabudzki et al. presented the possible applications of machine vision. The main aim is to show typical examples of the visions systems in the automated manufacturing systems. In the design and operation of a vision system, the image formation and visual process, computational methods and algorithms, depth information, image representation, and modelling and matching must be considered. On the other hand, the systematic consideration is important in the efficiency and the performance of the selected machine. The integration possibility, robustness, ease of operation, and adding intelligence into the system in order to make it a smart system are features of the advanced machine vision systems. [8]

Roland T. Chin et al. presented a comparative study and survey of model-based object-recognition algorithms for robot vision. The goal of these algorithms is to recognize the identity, position, and orientation of randomly oriented industrial parts. Recent trends indicate that multiple, disparate sensor types, including vision, range, and tactile sensors, will significantly improve the quality of the features that can be determined about a scene. The use of 3-D models is

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essential for reliably recognizing parts in the presence of significant uncertainty about their identities and positions in a robot's workspace. [9]

Identification

Image processing techniques are frequently used not only detecting the cotton, but also detecting crop, affected part of cotton disease and other object. The following methods focused only in the identification problem.

S. K. Pilli et al. designed a robot for crop disease detection using image processing. The ground based agricultural robot called eAGROBOT was presented for monitoring cotton and groundnut fields. The pictures of the plant were captured by the eAGROBOT. The captured image was pre-processed and transformed by artificial intelligence (AI) based embedded algorithms. Then the transformed images were clustered for detecting the cluster image of interest. Then the selective features were classified based on the neural network algorithm to identify the types of symptoms and differentiate early and late leaf diseases. However, the cost to end user and complexity of maintenance were high. [10]

P.Revathi et al. presented work carried out consists of two phases to identify the affected part of the disease. Initially Edge detection based Image segmentation is done, and at lastly image analysis and classification of diseases is carried out using our proposed Homogeneous Pixel Counting Technique for Cotton Diseases Detection (HPCCDD) Algorithm. The objective of this examination work is recognizing the disease affected part of cotton leaf sport by using the image analysis technique. [11]

Hironobu Sasaki et al. proposed a method which discussed intelligent robot vision in order to detect multiple object and human. There are many visual sensors and they use the range-imaging camera to detect distance and image data. They proposed a method for perceive moving target by using growing neural gas and Genetic algorithm. Their proposed method will be helpful for labelling the clusters, and utilize the information. [12]

III. CONCLUSION

In this paper, we have reviewed various papers and techniques for detecting cotton, and cotton plants using direct digital images. The work done in estimation and detection of cotton is mostly using satellite imagery, but not much has been done using digital images. Most of the algorithms rely on various colour spaces based recognition using density based clustering techniques, which is more faster and efficient than hierarchical based clustering techniques like k-means for detecting cotton. Shape based cotton detection forms second most prevalent choice in most of the papers. It is slow and can produce erroneous results, when multiple crops have been planted along with cotton. Both color based and shape based techniques together can form the most robust system possible.

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