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PERFORMANCE EVALUATION OF CCD AND CMOS CAMERAS IN IMAGE TEXTURAL FEATURES EXTRACTION

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ABSTRACT: *The first stage of any vision system is the image acquisition stage. If the image has not been acquired satisfactorily, then the intended tasks for image processing and image classification may not be properly achievable. In this study, a machine vision system was developed to evaluate the performance of CCD and CMOS cameras for real-time monitoring of cucumber growth in a greenhouse by extracting image textural features. The leaf samples of cucumber crops were brought to the laboratory from the greenhouses to measure the textural features. Laboratory was consisted of a digital camera for taking the images, a LDR array for providing a uniform lightening and a computer for measuring the textural parameters from the obtained images. The objective of the current study was to select which type of camera is ideal for real-time plant health and growth monitoring systems. The effect of distance between camera and leaves for three values (30, 40 and 50cm) and the type of camera (CMOS and CCD) on the uniformity of resulted data were considered in this article. Results showed that data for 40cm distance between camera and leaves with a CCD camera had an acceptable trend for extracting image textural features.*

KEYWORDS: *CCD Camera, CMOS Camera, Image Processing, Pattern Recognition, Textural Features*

INTRODUCTION

The first stage of any vision system is the image acquisition stage [1]. After the image has been obtained, various methods of processing can be applied to the image to perform the many different vision tasks required today. However, if the image has not been acquired satisfactorily then the intended tasks may not be achievable, even with the aid of some form of image enhancement [5].

Cameras are usually used for image acquisition stage. Charge Coupled Device (CCD) and Complementary Metal Oxide Semiconductor (CMOS) image sensors are two different technologies for capturing images digitally. Each type has certain strengths and weaknesses giving advantages in different applications. The current situation and outlook for both technologies is vibrant, but a new framework exists for considering the relative strengths and opportunities of CCD and CMOS imagers [4].

Both types of imagers convert light into electric charge and process it into electronic signals. In a CCD sensor, every pixel's charge is transferred through a very limited number of output nodes (often just one) to be converted to voltage, buffered, and sent off-chip as an analogue signal.

All of the pixel can be devoted to light capture, and the output's uniformity (a key factor in image quality) is high. In a CMOS sensor, each pixel has its own charge-to-voltage conversion, and the sensor often also includes amplifiers, noise-correction, and digitization circuits, so that the chip outputs digital bits. These other functions increase the design complexity and reduce the area available for light capture. With each pixel doing its own conversion, uniformity is lower. But the chip can be built to require less off-chip circuitry for basic operation [13].

Developing high quality cameras based on CCD and CMOS sensors and image processing techniques have created a large number of machine vision applications in precision agriculture. Computer programs have increased the ability of image processing for sorting and grading fruits and other agricultural products. Calculating image textural parameters such as entropy, energy, homogeneity and contrast is one of the principle methods for determining the situation of image objects.

Some of the machine vision applications needed for non-contact monitoring of agricultural products conditions have already been developed. In a research, images of plants' leaves were taken digitally by a CCD camera. Then, spectral and morphological characteristics of these leaves were used to detect nutrient deficiency. This research also suggested the possibility of using machine vision systems that could determine plant status and indicate deficiencies [8].

In a research, a CCD camera was used to take the images from greenhouse grown grass and broadleaf plants. CO-OCCURRENCE MATRICES WERE utilized on a gray-scale image to compute texture features such as inertia and angular second moment to classify greenhouse plants [9].

By using a CMOS camera, co-occurrence matrices was made for the hue saturation and intensity colour space to obtain an overall classification accuracy of 91% on images of seven common cultivars of nursery stock. Computation time was an important factor and suggested using a smaller set of texture features [11].

A machine vision-guided plant sensing and monitoring system was used to detect calcium deficiency in lettuce crops grown in greenhouse conditions. Images were taken by a CCD colour camera and then, the machine vision system extracted plant features to determine overall plant growth and health status. The methodology developed was capable of identifying calcium-deficient lettuce plants one day prior to visual stress detection by human vision [12].

In a study, researchers designed an automatic robot with real time image processing system to detect nitrogen deficiency in greenhouse cucumber crops. Images were taken digitally by a CMOS camera and image textural features were extracted for calculating three textural parameters: entropy, energy and homogeneity [2]. They also used a CCD camera to take the images and measured entropy and homogeneity values for greenhouse crop leaves' image with a computer image processing method in an experiment. The objective of their study was growth modeling with a machine vision system for tomato, cucumber and eggplant crops [3].

The objective of the current study was to select which type of camera is ideal for real-time plant health and growth monitoring systems. This could be achieved by a multi-sensing systems (including CCD and CMOS cameras) equipped with an artificial light source for extracting image textural features.

MATERIALS AND METHODS – Experimental setup for growing greenhouse crop

The plant-production system was constructed in a research center located at the Controlled Environment Agricultural Center at the College of Abouraihan (University of Tehran, Iran). A hydroponic greenhouse of cucumber crop was chosen to collect data. Two rows were selected near the center of greenhouse in a time of one month after two-leaf stage. 100 leaves were picked randomly from each row every three days in 12:00 am and were brought to the laboratory. The greenhouses were covered with a double polycarbonate glazing and equipped with a Pad and Fan evaporative cooling system.

Desired climate set points were maintained by an automatic climate control system. Environmental parameters were collected by a data logger (Pardazesh Tamkar, Iran). Connected to the data logger, for each of two rows, four temperature sensors (LM35, National Semiconductor, Japan), two relative humidity sensors (083E, Met One Instruments, USA) and one carbon dioxide sensor (TGS4161, FIGARO, Japan) were hung from the greenhouse roof, 2m above the ground level. The distances between temperature sensors and relative humidity sensors in the rows were approximately 2m and 4m, respectively. During the experiment, the greenhouse temperature was set to 25°C for the day (14 h) and 20°C for the night (10 h). Root-zone environments were maintained at a pH of 6.2, EC of 2.0 dSm^{-1}, and a temperature of 20°C. Nutrient solutions were changed every 7 days to maintain proper nutrient levels in the root zone.

Image acquisition system

After picking the leaves, they were brought to a dark room for taking pictures. A CCD color camera (Canon, Powershot, G12, Japan) and a CMOS color camera (Canon, Powershot, SX40 HS, Japan) were used to take pictures from the leaves. Distance between Camera and the Leaves (DBCL) was set as a variable with three values of 30, 40 and 50 cm. A 200-LEDs array with view angle of 70° was used above the camera to increase the light uniformity for the region of interest. Distance between LDR and the leaves was set as a 20 cm (Figure 1).

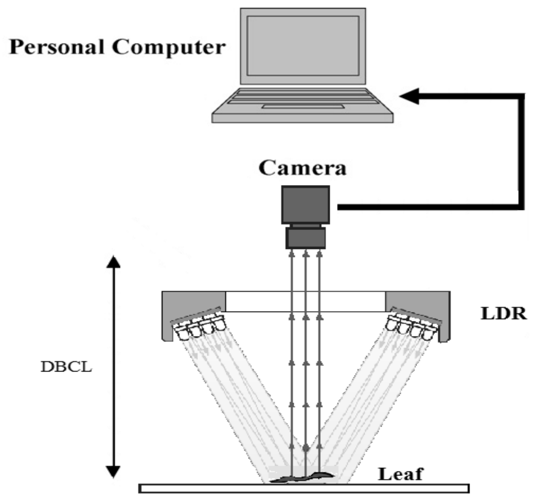

Figure1. Image acquisition system for plants' leaves

Two sequential images were taken by each camera from each plant leave with a certain DBCL. Images were transferred to the computer and then, image averaging was used for analysis to reduce the effect of random electronic noise and to reduce disturbances by factors that would cause the leaves to move. The captured images dimension was 1600 × 1200 pixels and was analyzed as a raw bitmap image. The program for the plant growth monitoring system was written with MathWorks MATLAB R2010b using Image Processing Toolbox.

Image processing and pattern recognition

From each retrieved image, the region of interest (the plant's leaf) was extracted through an image segmentation process [3,12]. This focused leaf image was used to calculate the colour features of the leaf. Gray-Level Co-occurrence Matrix (GLCM) was used to capture the spatial dependence of gray-level features of the image [6,7]. Each matrix was run through probability-density functions to calculate different textural parameters. After analyzing the colour features of the focused image, the textural features *were extracted. In one review, 21 textural parameters were identified [15]. However, another report indicated that only three textural parameters were useful in identifying plant health—entropy, energy, and homogeneity [12,14].*

In this research, two textural parameters were used in identifying plant quality—entropy and homogeneity. After calculating textural parameters from each image, the values of parameters were averaged to obtain a dimensionless number to expose a parameter in an interval.

RESULTS AND DISCUSSION

The experiment ran for a total of 90 days. Figure 2 and Figure 3 illustrate the timeline of the extracted entropy at 12:00 am as averaged values obtained from cucumber crops.

It was assumed that changes in the plant texture and surface structure are external symptoms of the plant's internal physiological status [10].

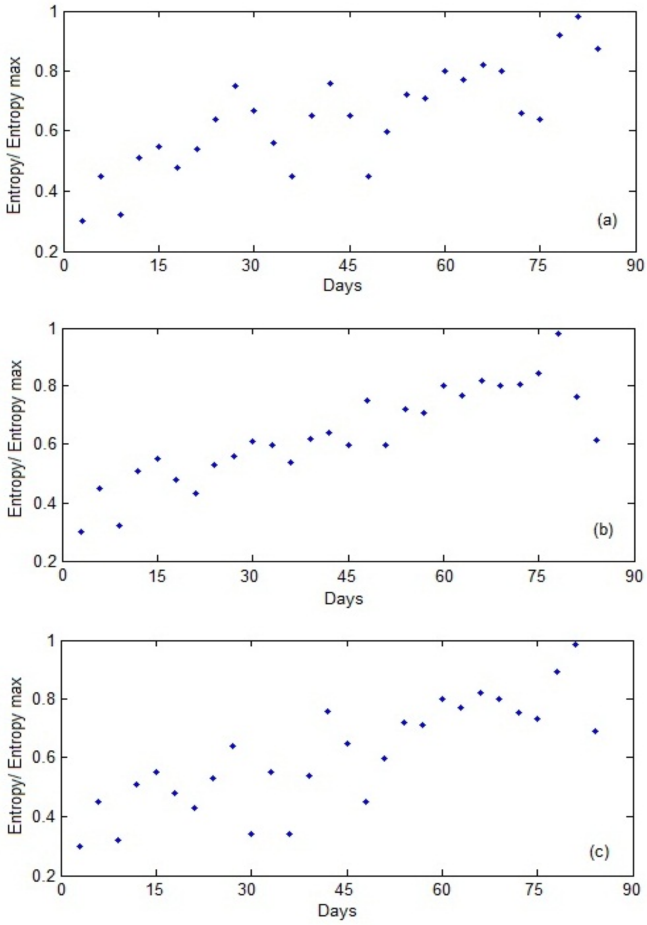

Figure 2. Timeline of the extracted entropy at 12:00 am as averaged values obtained from cucumber crops by CMOS camera when DBCL is: (a) 30cm, (b) 40cm, and (c) 50cm

In comparison with younger leaves, older plants' leaves are more colourful with different levels of green colour. This is usually detected by higher levels of entropy values from the images of older plants [3]. In this study, textural features were examined by probability-density functions on GLCM.

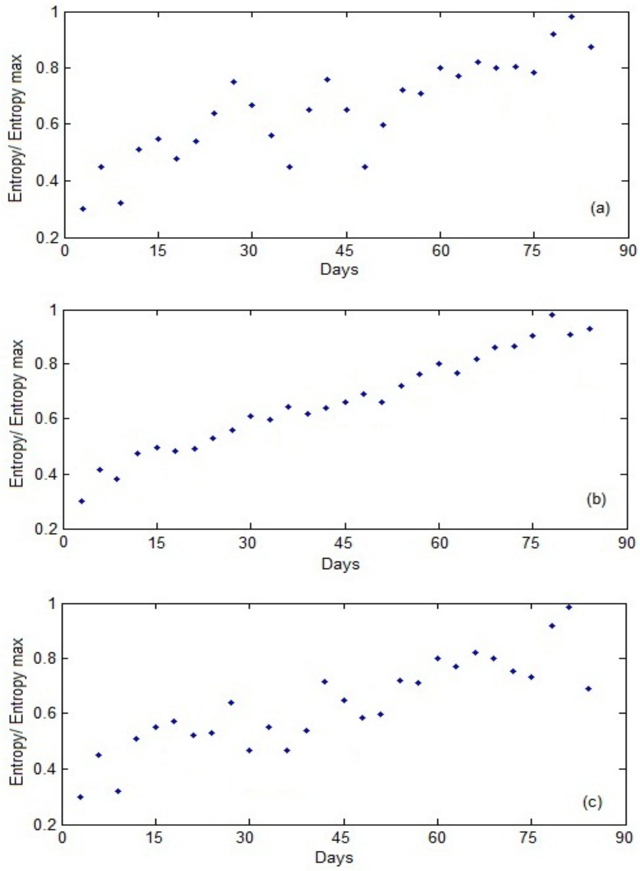

Figure 3. Timeline of the extracted entropy at 12:00 am as averaged values obtained from cucumber crops by CCD camera when DBCL is: (a) 30cm, (b) 40cm, and (c) 50cm

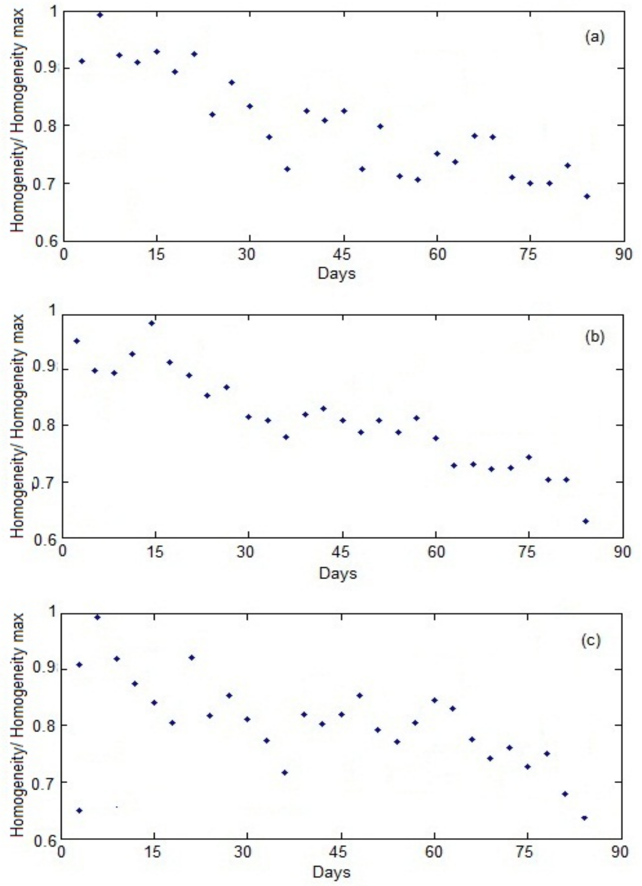

Figure 4. Timeline of the extracted homogeneity at 12:00 am as averaged values obtained from cucumber crops by CMOS camera when DBCL is: (a) 30cm, (b) 40cm, and (c) 50cm

During the experiment, non-uniform data with no certain trends was obtained by using CMOS camera in three values of DBCL to extract entropy.

Results of using CCD camera were also not reliable for DCBL 30cm and 50cm, but data for DCBL 40cm had an acceptable trend for extracting entropy feature.

Figure 4 and Figure 5 illustrate the timeline of the extracted homogeneity at 12:00 am as averaged values obtained from the cucumber crops.

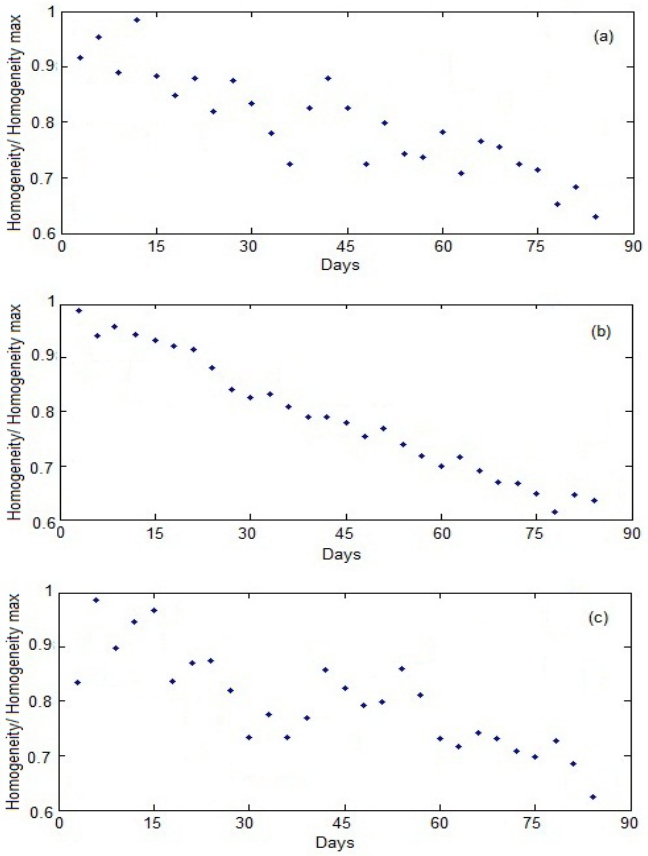

Figure 5. Timeline of the extracted homogeneity at 12:00 am as averaged values obtained from cucumber crops by CCD camera when DBCL is: (a) 30cm, (b) 40cm, and (c) 50cm

As older plants' leaves are more colourful with different shades of green, the related gray-level pixel distribution (homogeneity) decreases over time. Conversely, the younger plants, being more unified in colour, have higher homogeneity values [3]. During the experiment, non-uniform data with no certain trends was obtained by using CMOS camera in three values of DBCL to extract homogeneity. Results of using CCD camera were also not reliable for DCBL 30cm and 50cm, but data for DCBL 40cm had an acceptable trend for extracting homogeneity feature.

CONCLUSIONS

In this study, a machine vision system was developed to evaluate the performance of CCD and CMOS cameras for real-time monitoring of plant growth in a greenhouse. Entropy and homogeneity were measured as textural features for greenhouse plant leaves' image in an experiment for cucumber crops. The leaf samples were brought to the laboratory from the greenhouses to measure the textural features. The effect of Distance between Camera and Leaves (DBCL) for three values (30, 40 and 50cm) and the type of camera (CMOS and CCD) on the uniformity of resulted data were considered in this article.

Results showed that non-uniform data with no certain trends was obtained by using CMOS and CCD camera in two values of DBCL (30cm and 50cm) to extract entropy. Data for DCBL 40cm with a CCD camera had an acceptable trend for extracting both of entropy and homogeneity features.

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