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A farmer-assistant robot for nitrogen fertilizing management of greenhouse crops

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ABSTRACT

In this study, an autonomous machine vision-based system was developed for precise nitrogen fertilizing management to improve nitrogen use efficiency in greenhouse crops. Two scenarios were considered: in the first scenario, nitrogen fertilization was done based on available instructions and protocols provided by the seed producer. The second scenario was nitrogen fertilization using a machine vision-based robot which was moving between the crop rows to monitor plants' needs and requirements. The scenarios were examined in a hydroponic greenhouse for four varieties of cucumber. The extracted plant image features, namely entropy, energy, and local homogeneity were the markers for precise timing of nitrogen fertilization in the cucumber crops. In scenario 2, nitrogen fertilizing was based on a signal transmitted from the robot to a wireless receiver when at least one of the mean values of normalized image textural features of cucumber crops had a difference more than a (a = 10, 15, and 20%) with the same feature in scenario 1. Experimental results showed that scenario 2 for a = 15% decreased the nitrogen fertilizer consumption about 18% without lowering the fruit yield or fruit quality parameters including firmness, total soluble solids, chlorophyll and ascorbic acid contents. This scenario can be considered as an efficient nitrogen fertilizing management method in commercial greenhouses using a low-cost machine vision-based robotic system.

1. Introduction

Integrated nutrient management is an important concept majorly dealing with the maintenance of plant nutrient supply at an optimum level through optimization of all possible nutritive sources (Zhang et al., 2012; Mondal et al., 2016). Since either nutrition deficiency or nutrition accumulation can result in undesired changes of plant physiological characteristics, integrated nutrient management has become a key solution in sustainable agriculture (Wu and Ma, 2015).

Integrated nutrient management can be implemented by fertilizing management in controlled agricultural environments such as greenhouses (Grizzetti et al., 2015). Greenhouses are usually equipped with several autonomous or farmer-controlled systems including a closed system for water and nutrient supply, heating and cooling systems, fogging system, CO_2 generator, forced air ventilation, air circulation fans, artificial lighting system, and natural air ventilation system (Bozchalui et al., 2015).

Recently, several studies have revealed the application of closed systems for water and nutrient supply to enhance nutrient use efficiency in greenhouses (Dwivedi et al., 2016; Oliveira et al., 2017). This is usually done by recycling the drainage water and monitoring its ion concentration (Kudo et al., 2014). Electro Conductivity (EC) and pH sensors are useful devices which are extensively used in commercial modern greenhouses to compare the irrigation water (clean water of basin + nutritive solution) with drainage water. The results of this comparison indicate an overall status of nutrient uptake by plants in controlled agricultural environments (Neocleous and Savvas, 2016). These results along with visual inspection of plants' status can be utilized by experienced farmers to provide precise fertilizing and dosing control of the nutritive solution. In modern greenhouses, the raw data of EC and pH sensors together with temperature, relative humidity, and CO_2 concentration sensors are firstly processed to obtain reliable results about the condition of greenhouse and growing plants. Then, these results are used for autonomous control of hydraulically or mechanically driven valves which determine the dosage of

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nutritive solution in irrigation water (Gieling et al., 2004; Matos et al., 2015).

Nitrogen as a macro nutrition plays an important role in the plant growth since it is a component of nucleic acids, amino acids, and chlorophyll (Mengel et al., 2001). Proper nitrogen fertilizing management is important because it is usually the most limiting nutrient in crop production and can be easily lost from the soil system (Fageria et al., 2010). Since ammonium and nitrate are the forms of nitrogen available for plant uptake, several ion-specific sensors such as ion selective electrodes and ion selective field effect transistors have been developed to measure nitrate concentration in irrigation and drainage water as a part of nitrogen use efficiency enhancement programs (Gieling et al., 2005).

To date, dozens of instructions and protocols have been introduced for nitrogen fertilization of all kinds of agricultural crops which farmers can use as trusted information sources in their agricultural farms. However, the trends of nitrogen uptake by plants and their nitrogen requirements may be changed according to the environmental conditions, fertilizing management, diseases, stresses, and so on. Thus, the real-time monitoring of plant status seems to be necessary to avoid the possibilities of nitrogen deficiency or nitrogen accumulation.

As mentioned, visual inspection and analysis of drain-water of greenhouse are applicable real-time monitoring techniques in nitrogen fertilizing management. However, there are some limitations which lower the reliability of these methods. Nitrogen deficiency of plants is very difficult to detect by naked eye at the early stage (Blackmer et al., 1996). Furthermore, low-experienced farmers are not able to identify the nitrogen deficiency from visual symptoms. On the other hand, analysis of drainage needs costly sensors which may not be affordable for all farmers. Besides, calibration of these sensors and analysis of their data are not easy and need some expertise.

During the last three decades, with the advent of low-cost image acquisition systems, digital image processing and machine vision techniques have been developed in greenhouse engineering. Studies have shown that non-contact phytomonitoring using machine vision can be considered as an appropriate technique in determination of health status of plants (Arefi et al., 2011; Asefpour Vakilian and Massah, 2013). Image processing has been used to detect some plants' potential problems such as nitrogen and calcium deficiencies in greenhouse crops which has resulted in an improvement in plant production efficiency and plant overall quality (Story et al., 2010; Asefpour Vakilian and Massah, 2012a). Furthermore, it has been used for determination of plants' viral and fungal disease in controlled environments (Corkidi et al. 2006; Qin et al. 2009; Schor et al., 2016).

It is desirable to develop a real-time plant health/growth and quality monitoring system with no need to move the sample plants to the laboratory. This could be achieved by an autonomous robot equipped with a digital camera which moves in the commercial greenhouses between the plants rows. Such a system could be used to detect deviations of plants from normal growth/development due to different plant stresses (e.g., nutrient deficiencies or other diseases). The objective of this study was to develop a machine vision-based robotic system using textural features of plants' images for the management of nitrogen fertilization in greenhouse crops.

The rest of this paper is structured as follows: In Section 2, related works including offline and online vision-based plant health monitoring methods are briefly reviewed. Section 3 introduces some basic concepts of image textural features and the necessary background of using these features in plant health monitoring. Materials and methods are explained in Section 4, which itself is divided in four subsections. Section 4.1 provides the robotic-based framework for machine vision module, and presents a general scheme for navigation and control of the robot in greenhouse environment. Section 4.2 provides the experimental setup for determination of precise time of nitrogen fertilization. Proposed image processing method for accurate timing of nitrogen fertilization is brought in Section 4.3. Section 4.4 deals with performance parameters of introduced nitrogen fertilizing management method. Section 5 gives results of proposed system in managing nitrogen fertilization in comparison with standard programs and fertilizing protocols. Finally, conclusions and future perspectives are presented in Section 6.

2. Related work

2.1. Offline vision-based plant health monitoring methods

Some of image processing-based plant health monitoring methods need to transfer a part of unhealthy plant (for example, a leaf) as a sample to an image processing module for image acquisition. This module is usually a chamber where a lighting LED array provides sufficient and uniform brightness to take a picture from the sample using a suitable digital CCD or CMOS camera (Kruse et al., 2014). Furthermore, images can be acquired in field and later processed in a laboratory (Borges et al., 2016).

Digital cameras can acquire data from the region of interest in three visible bands: red, green and blue (RGB). In addition to visible range cameras, thermography (Wang et al., 2010), chlorophyll fluorescence (Jeong et al., 2017) and multi and hyper-spectral sensors (Römer et al., 2011; Bareth et al., 2015; Yeh et al., 2016) are extensively used in plant health monitoring systems. However, to limit the length of this section, only RGB cameras are considered for review. In this method, the obtained image is later transferred to a computer for image processing and decision making about the health status of the plant. Since there is time interval between sampling and decision making, this technique can be categorized in plants' offline health monitoring methods.

As a pioneering work, Camargo and Smith (2009) introduced a machine vision system for identification of diseases of cotton crops from color images. They extracted several features including shape, texture, fractal dimension, lacunarity, dispersion, gray level, and histogram of frequencies from the obtained images of plants' leaves. The features were then used for training a support vector machine (SVM) to classify the possible diseases of cotton crops. Experimental results showed that texture-related features were useful in plant disease detection especially where the color quality of training images was not uniform. Artificial neural network-based classifiers are also used in vision-based plant disease identification (Al-Hiary et al., 2011; Al-Bashish et al., 2011).

Asefpour Vakilian and Massah (2012b) developed a machine vision system for offline monitoring of plant health and growth in greenhouses. By surveying the trends of changing image textural features of crops, a power equation was presented as the growth model of greenhouse crops in conventional conditions. Pertot et al. (2012) designed a simple and efficient web-based tool for visual identification of strawberry diseases using a computer and an image captured from infected plants. Performance evaluation of their system showed that it enables non-expert farmers and growers to identify more than 30 strawberry viral and fungal diseases.

Arivazhagan et al. (2013) developed a software solution for automatic detection and classification of plant leaf diseases. The proposed system was able to extract useful image textural features from input RGB images. Using extracted features, the trained classifier was able to identify several plants' bacterial and viral diseases such as early and late scorch and fungal diseases in beans with an accuracy of 94%.

Romualdo et al. (2014) introduced an artificial vision system based on volumetric fractal dimension (VFD) and Gabor wavelet (GW) features to identify nutrient deficiencies at different stages of plant development, especially in the early stages of growth in plant leaves. The presented system was able to identify levels of nitrogen deficiency in the early stages of development of maize, with an accuracy higher than 85%.

In a similar research, Silva et al. (2014) have proposed a combined artificial vision and pattern recognition system to identify magnesium concentration in maize plants grown in the greenhouse using VFD, GW, and VFD with canonical analysis (VFDCA) methods. They showed that VFDCA method was able to identify all levels of nutrient deficiency, with approximately 75% classification accuracy using the images of the middle section of leaves.

Pujari et al. (2013, 2015) have reviewed the image processing based detection methods of fungal diseases in plants. They have investigated available machine vision methods in detection of fungal diseases in fruit, vegetable, commercial, and cereal crops. Most of the reviewed methods are able to detect common fungal disease symptoms including anthracnose, powdery mildew, downy mildew, gray mildew, rust, blights, fruit rot, alternaria leaf spot, fusarium wilt, red rot, and smut.

Kruse et al. (2014) compared several approaches for classifying individual image pixels as healthy or injured from RGB images of clover leaves with different degrees of ozone-induced visible injuries. They showed that a feature vector of single pixel color channel intensities was able to capture the information relevant for pixel identification. They also reported that linear discriminative classifier has acceptable performance in individual pixel classification.

Zhou et al. (2014) used orientation code matching (OCM) for robust, continuous, and site-specific observations of disease development in sugar beet plants. They introduced a robust template matching method of OCM the improve the performance of the digital image processing using a SVM classifier for robust detection and precise quantization of Cercospora Leaf Spot development in sugar beet.

Pethybridge and Nelson (2015) developed a free, simple, and interactive smartphone application for quantitative assessment of plant disease intensity using image processing. The application is called: "Leaf Doctor" and it is developed for iOS platform. They showed that the application was able to identify severity of several fungal diseases with acceptable performance.

Borges et al. (2016) introduced an autonomous method to detect and classify bacterial spot disease in tomato fields. They used a handheld commercial camera to acquire color images of the plants and then, CIELab color space was used to group regions of interest in the images to healthy and unhealthy areas.

Barbedo (2013) and Mutka and Bart (2015) have reviewed digital image processing techniques for detecting, quantifying and classifying plant diseases with their symptoms on leaves, fruits, and stems.

2.2. Online vision-based plant health monitoring methods

Online monitoring methods do not need to transfer the plant samples to the image processing chamber. They usually consist of a moving module which can take pictures from the plants and process them at the same time. The module is a tracking chassis which sometimes equipped with a navigation system, an end-effector, a camera and an image processing unit (Malneršič et al., 2016; Oberti et al., 2016; Bechar and Vigneault, 2017). Not only there is an increased attention to use online robotic systems for weed spraying (Montalvo et al., 2013; Peña et al., 2013; Gonzalez-de-Soto et al., 2016), yield estimation (Annamalai, 2004; Payne et al., 2013; Maldonado and Barbosa, 2016), and harvesting purposes (De-An et al., 2011; Ji et al., 2012; Qiang et al., 2014; Kondo, 2014), but these systems are becoming popular in unmanned plant health monitoring applications.

Story et al. (2010) used an online machine vision-guided phytomonitoring system to detect calcium deficiency in greenhouse lettuce crops. The machine vision system was able to extract plant features using the images captured from the canopy of the plants to determine the overall plant growth and health status. The methodology developed in their study was able to identify nutrient-deficient plants one day prior to visual stress detection by human vision.

In another study, Asefpour Vakilian and Massah (2012a) examined a real-time machine vision-guided plant monitoring system for early detection of nitrogen deficiency in cucumber crops grown in greenhouse conditions using stem and leaves' color changes of the cucumber plants. The proposed system consisted of a remote-controlled moving robot and a machine vision module. They showed that the processing of the plants' image textural features was able to determine nitrogen deficiency in early stages.

Tewari et al. (2013) introduced a manually operated four-wheel trolley for outdoor color image acquisition from paddy plants under controlled illumination to predict crop nitrogen content. Various image color features such as R, G, B, normalized 'R' and normalized 'G' were analyzed to present appropriate regression models for prediction of plant nitrogen content. Performance of the proposed method was compared with commercial SPAD meters and the chemical analysis of plant leaf which are used to measure the chlorophyll content of the crops. Results showed that the plant nitrogen content can be successfully estimated by its image color features with acceptable accuracy.

Schor et al. (2015) investigated the detection of two common diseases of pepper plants by a robotic monitoring system. They used a dual-camera system (an RGB color camera for plant location determination and a multispectral camera for disease detection) for image acquisition. Schor et al. (2016) have also designed a robotic combined viral and fungal disease detection system based on a manipulator which facilitates reaching multiple detection poses. The robotic manipulator enabled the digital camera to capture required images from the canopy and along the sides of the plant. Several image features including principal component analysis (PCA) and the coefficient of variation (CV) were used for disease detection.

Wspanialy and Moussa (2016) studied an automated system for early detection of powdery mildew in greenhouses. Their system applied the Hough forest machine learning technique to learn powdery mildew image features under various clutter and background conditions. Experimental results of this study showed that the true detection rate of their system was approximately 85%.

A comparison between offline and online methods in plant health monitoring reveals that researchers show more attention to offline methods. In general, online methods require more complicated image processing and decision making techniques compared with offline methods. Furthermore, uncontrolled illumination of environment in online methods adds some complexities in image pre-processing stages including color transform and image segmentation.

3. Preliminaries: Basic concepts of image texture analysis for plant monitoring

Most of image processing techniques which are developed for plant monitoring systems are based on morphological operations, image segmentation, shape analysis, color transform methods, and image texture analysis. Agricultural engineers can implement these image processing algorithms using available toolboxes and libraries in programming languages such as MATLAB, Microsoft Visual Studio, OpenCV, Java, and Python.

Image textural features provide information about the spatial arrangement of color or intensities in an image or region of interest in an image. Several textural features can be extracted from digital images: statistical, structural, model-based, and transform-based textures (Zheng et al., 2006). Among these features, statistical texture obtained from gray-level co-occurrence matrix (GLCM) has been used extensively in plant monitoring systems (Story et al., 2010; Arivazhagan et al., 2013; Mao et al., 2015).

GLCM is usually used to capture the spatial dependence of gray-level values for different angles of pixel relativity (Gonzalez and Woods, 2008). This matrix is run through probability-density functions to calculate different textural parameters which are useful in agricultural engineering. According to Zheng et al. (2006), there are 21 image textural parameters which can be useful in agricultural applications. Several toolboxes and libraries developed for programming languages are now available to calculate some of these features.

Some researchers have revealed that only a few of these parameters can be sufficient in identifying plant health status: entropy, energy, and local homogeneity (Ushada et al., 2007; Story et al., 2010; Asefpour Vakilian and Massah (2012a)). Other features, somehow, can be extracted from these features and share similar information with them (Howarth and Rüger, 2004).

Entropy is usually defined as the randomness of gray-level distribution in a gray-scale image. Images containing objects with higher surface structure complexity result in higher entropy values. Story et al. (2010) have shown that healthy plant leaves are colorful and the entropy of their images is higher than entropy of images of leaves belonging to nutrient deficient plants. Although this is relatively true for nitrogen deficient plants, this is not always applicable and it depends on the kind of plant and its nutrition deficiency.

Energy is another textural feature which represents the level of grayscale brightness. In other words, energy level of an image is a singular value which represents overall brightness or darkness of the image. Among plants with similar growing stage, healthier plants are usually darker green in color, compared with nutrient deficient plants. Furthermore, energy level of plant images decreases over time (Story et al., 2010). Yellowish appearance in the leaves of nitrogen deficient plants results in a lighter color and raises the energy levels in their images.

Local homogeneity is defined as related gray-level pixel distribution amongst the surrounding pixels in a color image. Different shades of red, green, and blue in a color image can result in lower local homogeneity values. Nitrogen deficiency which makes plant leaves unified in color increase the local homogeneity of their images.

To calculate these features for a grayscale image, it is necessary to find the GLCM of the image in the first place. GLCM is a square matrix which its dimension equals to the highest gray value in the grayscale image. Each element (i,j) in GLCM specifies the number of times that the pixel with value i occurred horizontally adjacent to a pixel with value j.

Although several toolboxes have been developed to calculate textural features of an image, they can be easily calculated using Eqs. (1)–(3) (Haralick and Shanmugam, 1973).

$$\text{Entropy} = -\sum_i \sum_j p(i,j)\log(p(i,j)) \tag{1}$$

$$\text{Energy} = \sum_i \sum_j p(i,j)^2 \tag{2}$$

$$\text{Local homogeneity} = \sum_i \sum_j \frac{p(i,j)}{1+(i-j)^2} \tag{3}$$

where $p(i,j)$ is the (i,j)-th element of the GLCM.

4. Materials and methods

4.1. Development of the robotic-based framework for machine vision module

In this study, a machine vision-equipped robotic system was developed for online plant health and growth monitoring in greenhouses (Fig. 1). The robotic-based framework consisted of a robotic tracking chassis, an image acquisition unit and a data analysis/storage/transfer module. The robotic moving module was a tracked vehicle system driven by two DC motor-gearboxes (mod. 1.61.068.501, Buehler, Germany). For image acquisition, a CCD color camera (mod. DF-7107, Sony, Japan) was attached to the chassis at the height of approximately 1 m from ground (Fig. 1).

Although the robot was developed for operating in hydroponic commercial greenhouses and it was moving on a concrete platform between the rows, the tracked vehicle system made the robot able for moving on uneven surfaces such as sandy grounds which are usually found in traditional greenhouses (Fig. 2).

The moving path of the robot between the crop rows in the greenhouse was uploaded on a computer (MD101, Apple Inc., United States) according to the geometry of the plant rows and the area of the greenhouse. Fig. 3 shows the algorithm which was used to control the robot trajectory in the greenhouse based on the uploaded path. The algorithm was implemented on the computer using a code written in MATLAB R2016b programming language (Mathworks, Massachusetts, United States). During the operation, the information about current location of the robot gathered by a GPS Module (MAX-7Q, U-BLOX, Switzerland) was being transferred

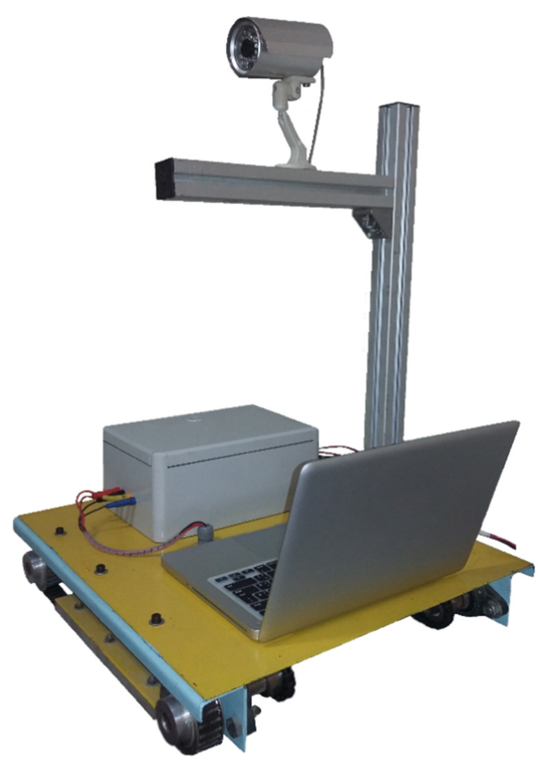

Fig. 1. The machine vision-equipped robotic system for online plant health and growth monitoring.

Fig. 2. The tracked vehicle system enabled the robot for appropriate operating even in rough conditions.

to the computer through a data acquisition kit (Mega 2560, Arduino, Italy).

According to the algorithm, when the robot was moving forward between two adjacent rows, with two seconds intervals, it stopped for two seconds to take an image from the plants by the camera. Distance between the camera and the plants in the rows was 25 ± 5 cm. Captured images were then transferred to the computer using a USB 2.0 docking station DVI video card (capture card adapter, i-Tek, Germany) for image processing.

4.2. Experimental setup for nitrogen fertilizing management

To manage the nitrogen fertilization of greenhouse crops, two main scenarios were considered:

Scenario 1: using available instructions and protocols for nitrogen fertilization provided by the seed producers;
Scenario 2: nitrogen fertilization based on image textural features which reflects the plant needs and requirements.

Since the changes of nitrogen requirements by the plants according to the environmental conditions, fertilizing management, diseases, and various stresses are not considered in the scenario 1, this study aims to proper managing of nitrogen fertilization using changes of image textural features of plants during the growth period.

To do this, four varieties of cucumber (*Cucumis sativus*) including: "Marketmore 76", "Green Fingers F1", "Diva F1", and "Manny F1" were considered for experiments and their seeds were purchased from Harris Seeds (New York, United States).

The cucumbers grew for eight weeks from seed stage to maturity in two adjacent hydroponic greenhouses in a research center located at the controlled-environment agricultural center (College of Abouraihan, University of Tehran, Iran) (35°41′N, 51°25′E). The greenhouses were covered with double polycarbonate glazing and were equipped with Pad and Fan evaporative cooling systems. Desired climate set points were maintained by an automatic climate control system. Environmental parameters of each greenhouse was collected by a data logger (Pardazesh Tamkar, Iran). Connected to each data logger, several temperature sensors (LM35, National Semiconductor, Japan), relative humidity sensors (083E, Met One Instruments, United States) and carbon dioxide sensors (TGS4161, FIGARO, Japan) were hung from the greenhouse roof, 2 m above the ground level at different locations of the greenhouses. The distances between temperature sensors and relative humidity sensors above the rows were approximately 2 m and 4 m, respectively.

Nitrogen fertilizing in greenhouse No. 1 and greenhouse No. 2 were according to scenario 1 and scenario 2, respectively. Each greenhouse consisted of four crop rows, each of which considered for one cucumber variety. In scenario 1, similar to other nutrients, nitrogen fertilizing was applied according to the instructions provided by the seed producer. There was a timer for accurate timing of nutrient injection into the irrigation water. In contrast, the robotic-based machine vision module was used in scenario 2 to enhance the nitrogen use efficiency in greenhouse No. 2. In both

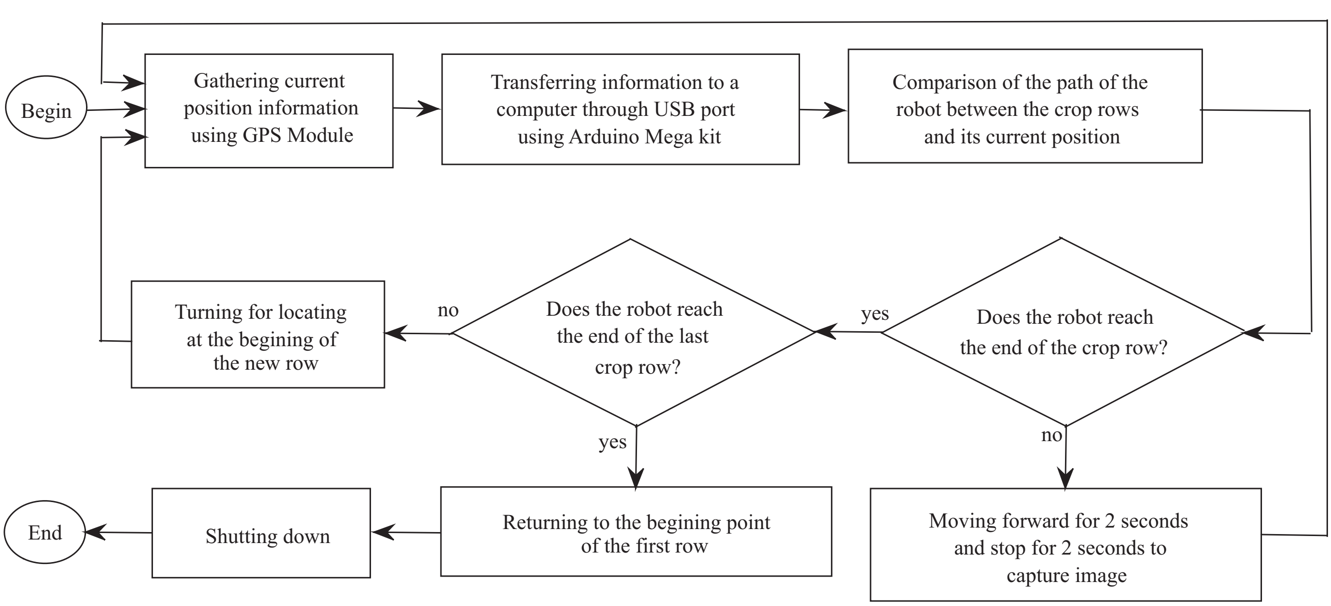

Fig. 3. The algorithm used to control the robot trajectory in the greenhouse based on the uploaded path.

scenarios, the fertilizing was done once per day during the experiments.

Since it has been tried to lower the costs of construction of the proposed robotic system, artificial lighting module was not installed on the robot. Therefore, the robotic solution was implemented in daytime applications. The robot started moving between the plant rows from the beginning point of the first row on 12:00 P.M. and 1:00 P.M. in greenhouse No. 1 and greenhouse No. 2, respectively every day during the eight weeks. Since the length of each plant row was about 45 m and the velocity of the robot was 10 cm s^{-1}, the time required for monitoring each row was about 8 min. As shown in Fig. 3, when the robot was reaching the end of the last row in each greenhouse, it returned to the beginning point and was shut down.

There was a wireless transmitter on the robot to transmit the results of the image processing unit of the robot to a wireless receiver which actuated the solenoids to control the amount of nitrogen source fertilizing for each crop row (Fig. 4).

Management of nitrogen fertilizing for each plant in a greenhouse can result in better nitrogen use efficiency. But in this situation, a solenoid is required for each plant which is practically impossible in commercial greenhouses. The method presented here is an applicable technique which determines the precise time of nitrogen fertilizing based on the average condition of the whole greenhouse which is obtained by the robotic machine-vision. As shown in Fig. 4, a solenoid is considered for nitrogen fertilizing of each row. It is because that four cucumber varieties are considered in this study. In commercial purposes where just one variety of cucumber is breeding in a greenhouse, just one solenoid would be enough for the entire greenhouse.

The source of nitrogen macronutrient included: urea (CH_4N_2O, 46% total N) and ammonium nitrate (NH_4NO_3, 34% total N). Granular or liquid urea and ammonium nitrate fertilizers are the most common sources of nitrogen injected into irrigation water. They maintain a constant concentration without agitation and are easy to transport and store. The control of other nutrient fertilizers was done with a timer similar to scenario 1.

4.3. Image processing method

To find the optimum time of nitrogen fertilization using machine vision in scenario 2, it was necessary to take into account some considerations:

Since the robot was operating in the daytime, the reflectance of sunlight by the leaves should be considered as an issue in the image processing algorithm. Furthermore, the background and cucumber fruits may result in some undesirable changes in textural features of the images obtained by the image acquisition module. Asefpour Vakilian and Massah (2012) used a white curtain behind each crop row in the greenhouse to reduce the effects of background. Besides, they harvested the cucumber fruits before image acquisition to reduce the undesirable phenomena. However, these actions limit the applicability of the autonomous robotic systems in commercial greenhouses.

To untie this knot, after converting the raw RGB image obtained by the image acquisition module to grayscale image, a high-pass filter was applied to the grayscale image to remove background and fruits in the images. This filter was able to keep the pixels whose brightness was higher than a threshold value. As can be seen in Fig. 5(b), the filter could remove background and cucumber fruits from the original image shown in Fig. 5(a). In the next step, a

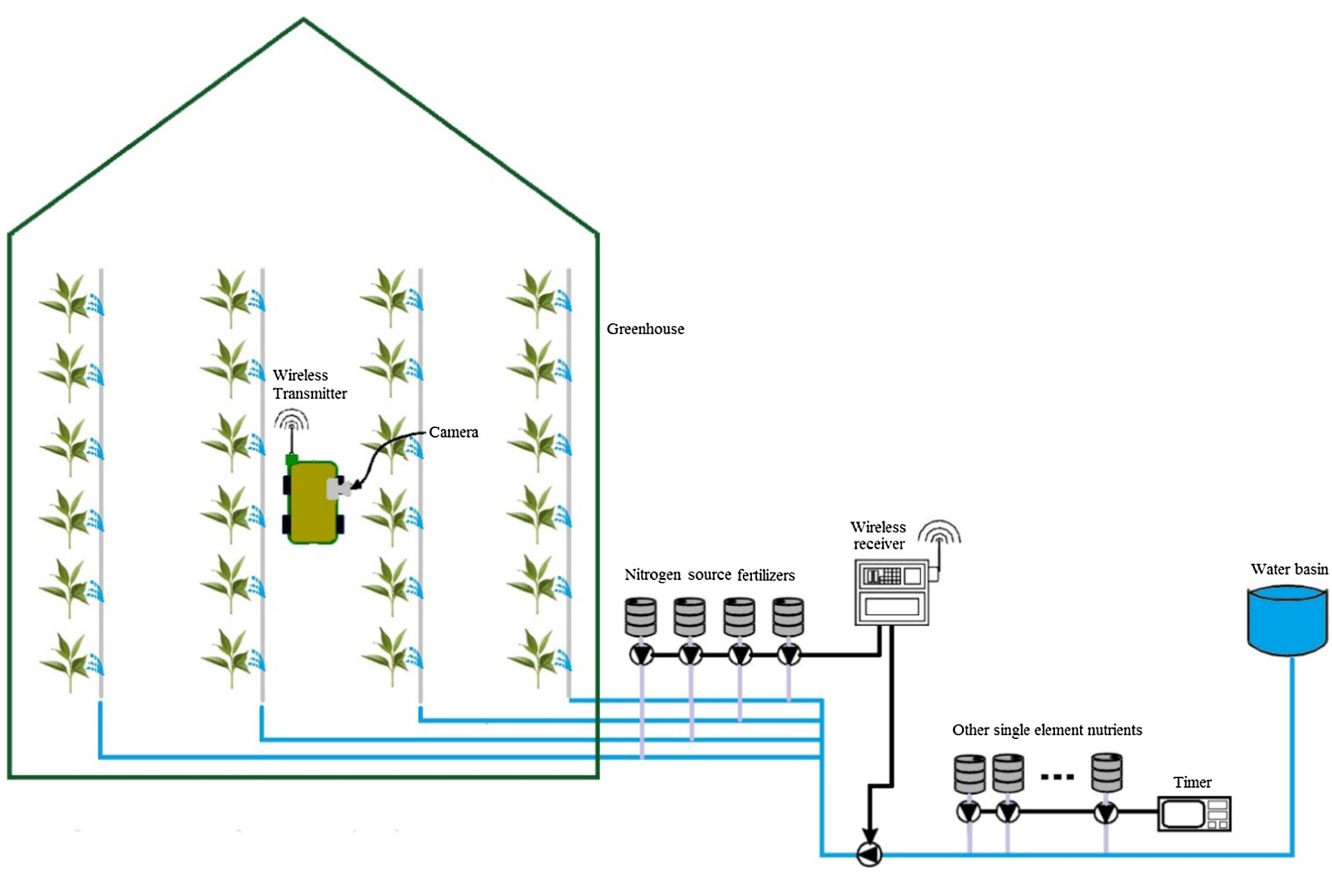

Fig. 4. Schematic view of the proposed robotic system for nitrogen fertilizing management (scenario 2).

Fig. 5. (a) An arbitrary RGB color image of cucumber plants in a commercial greenhouse, (b) image after applying a high-pass filter to remove background and fruits, (c) image after applying a low-pass filter to remove leaves areas which directly reflect the sunlight.

low-pass filter was applied to the obtained image to remove leaves areas which directly reflect the sunlight. Since the brightness of image regions which reflect the sunlight was higher than the brightness of other regions, the filter kept the pixels whose brightness was lower than a defined threshold. The threshold values of the filters depended on environment illumination and the type of robot's camera. The illumination itself depends on the geographical location of the greenhouse, time of image acquisition and so on. The selection of appropriate values for the thresholds was done by the system operator in the first run.

In the next step, the remained pixel gray-level values were used to calculate image textural features including: entropy, energy and local homogeneity. It should be noted that since image textural features are scale invariant, the differences in distance of the camera and the plant rows did not affect the performance of machine-vision module. Furthermore, since the camera was capturing image with two seconds intervals, there were possibilities that captured areas of plant rows by the camera have some significant overlaps. This issue also did not undesirably affect the results because textural features extracted from images of each plant row were averaged to determine the overall growth condition of each row.

Image processing was done using a code written in MATLAB R2016b programming language (Mathworks, Massachusetts, United States) ran on the computer located on the robot. Although each image had different textural features, these differences were not significant because in a controlled environment (in this study, a hydroponic greenhouse), all plants have similar growing conditions. Their growth is similar to each other and when a stress is emerging in a hydroponic greenhouse, almost all plants show similar symptoms due to that stress.

A signal was transmitted from the robot to the wireless receiver if the mean value of at least one of normalized textural features of the captured images in scenario 2 had a difference equal to or higher than a (in percentage) of the same feature in scenario 1 for the same variety in that particular time.

After receiving the signal, the wireless receiver actuated the solenoid belonging to that variety to inject nitrogen fertilizers into the irrigation water. The a value was changed at three levels of 10%, 15%, and 20% during the experiments to find out how much image textural features of plants in scenario 2 can take distance from ones belonging to the plants in scenario 1. Higher values of a mean significant difference of image textural features of plants belonging to scenarios 1 and 2 and can result in meaningful quality decrement of plants of scenario 2.

The hypothesis here is that at the onset of nitrogen deficiency stress in scenario 2, there are low differences between the image textural features of the plants in the two scenarios. With the increment of this difference, plants show the symptoms of nitrogen deficiencies and nitrogen fertilizing should be done before the yield quality and quantity decrease significantly.

4.4. Performance evaluation of nitrogen fertilizing management

To evaluate the performance of the proposed method for nitrogen fertilizing management (scenario 2), the nitrogen fertilizer consumption for each variety of cucumber plant was reported for the two scenarios. Furthermore, the fruit yield of each plant was measured in the scenarios. Beside performance evaluation of the two scenarios from the viewpoint of nitrogen use efficiency in nutrient fertilizing management, several quality parameters of obtained fruits were also investigated in each scenario. Fruit firmness, the total soluble solids (TSS), chlorophyll, and ascorbic acid content of the fruits were measured and reported for quality analysis of the cucumber fruits obtained in each scenario. The protocols to carry out these quality tests were according to Zhang et al. (2015).

Values of quality parameters were expressed as means ± standard deviation. Data was analyzed using SPSS (SPSS Inc., Illinois, United States). Analysis of variance (ANOVA) and Duncan's multiple range tests were used to compare significance of the difference between the samples. Differences at $p < 0.05$ were considered significant.

5. Results and discussion

The experiment ran for a total of eight weeks from April to June in 2013. The average day temperature, night temperature, and day time/night time relative humidity values in the research greenhouses were 30.1 ± 2.1 °C, 22.1 ± 2.9 °C, 60.9 ± 8.1%, and 63.0 ± 8.5%, respectively, during the experimental period. The average CO_2 concentration was 420 ± 18.0 ppm.

During the study, general yellowing of older leaves which is the most common symptom due to the nitrogen deficiency was not detected by human naked eye in scenario 2 for lower values of a. However, for higher values of a, the yellowish color of some varieties was recognizable by the farmers.

Table 1 shows the performance evaluation of each scenario in nitrogen use efficiency for different cucumber varieties. The key assumption in the scenarios was that changes in the plant texture and surface structure are external symptoms of the plant's internal physiological status (Peñuelas and Filella, 1998). As it can be seen in this table, the nitrogen fertilizer consumption in scenario 1 was higher than the nitrogen fertilizer consumption in scenario 2 for all values of a. This result was predictable, because in the scenario 2, nitrogen fertilizing was done only when a signal from the robot

Table 1
Performance evaluation of each scenario in nitrogen use efficiency for different cucumber varieties.[a]

Scenario	Cucumber variety	Nitrogen fertilizer consumption (g plant^{-1})
Scenario 1	Marketmore 76	4.91 ± 0.00a
	Green Fingers F1	4.91 ± 0.00a
	Diva F1	4.91 ± 0.00a
	Manny F1	4.91 ± 0.00a
Scenario 2, a = 10%	Marketmore 76	4.29 ± 0.15b
	Green Fingers F1	4.21 ± 0.11b
	Diva F1	4.22 ± 0.03b
	Manny F1	4.28 ± 0.14b
Scenario 2, a = 15%	Marketmore 76	3.96 ± 0.12c
	Green Fingers F1	3.91 ± 0.04c
	Diva F1	4.01 ± 0.15c
	Manny F1	4.13 ± 0.12c
Scenario 2, a = 20%	Marketmore 76	3.78 ± 0.15d
	Green Fingers F1	3.60 ± 0.11e
	Diva F1	3.72 ± 0.16d
	Manny F1	3.84 ± 0.19d

[a] The data is expressed as the mean ± SD (n = 3). Means in same column with different letters are significantly different (p < 0.05) according to Duncan's multiple range tests.

was transmitted to the wireless receiver which controlled the solenoids.

Results show that according to the changes of plant's image textural features, each variety needs a specific nitrogen source fertilizing. This means that some commercial fertilizing management computer and cell-phone applications which just recommend the nutrient fertilizing based in crop species are not completely reliable and the cultivar of the crop should be considered in fertilizing process. With increasing the a, the nitrogen fertilizer consumption was decreased. This is because higher values of a allowed crops for more color changing prior to fertilizing. This color changing postponed the nitrogen fertilizing and reduced the nitrogen consumption. It should be noticed that in this study, a is changed from 10% to 20%. Higher values of a (for example, 30%) can result in the occurrence of serious nitrogen deficiencies which reduces the quality and quantity of the produced fruits. In this situation, even non-expert farmers can detect the changes in general appearance of the plants with their naked eyes.

In comparison with scenario 1, the mean of nitrogen fertilizer consumption is decreased about 12%, 18%, and 24% for a values equal to 10%, 15%, and 20% in scenario 2, respectively. This amount of decrement in nitrogen fertilizing can be investigated from two important aspects. First, lower consumptions of inorganic fertilizers result in lower toxic nutrient accumulation in various parts of the plants which can threaten the health of the consumers. Second, in large commercial greenhouses, lowering nitrogen fertilization for about 20% can somehow reduce the cost of crop production.

Investigating scientific sources shows that reduction of nitrogen fertilizing in greenhouse crops decreases the fruit yield significantly (Warner et al., 2004; Jasso-Chaverria et al., 2005). As shown in Table 1, the scenario 2 reduced the amount of nitrogen source fertilizing. Therefore, it seems that this scenario lowers the fruit yield. Fig. 6 shows the fruit yield of each cucumber variety for the scenarios 1 and 2. As can be seen in this figure, the fruit yield was not significantly different for scenario 1, and scenario 2 for a = 10% and 15%. However, in scenario 2 with a = 20%, the fruit yield decreased significantly for all varieties. If the nitrogen fertilizing reduces according to Table 1 without consideration of precise timing of fertilization which is obtained by the robot in the greenhouse, the yield will certainly decrease, as reported by former studies. But in this study, according to findings expressed in Fig. 6, the robot can provide the precise timing of nitrogen fertilization to reduce the nitrogen fertilizing about 18% without significant decrease of fruit yield when the a = 15%. Although the reduction in fertilizing will be 24% for a = 20%, the mean of fruit yield will be decreased significantly. Fig. 7 shows the spider graph of mean of fruit yield (in kg plant^{-1}) for each scenario.

Nitrogen is a major component of chlorophyll, the compound by which plants use sunlight energy to produce sugars from water and carbon dioxide. Nitrogen is also a significant component of nucleic acids such as DNA, the genetic material that allows cells (and eventually whole plants) to grow and reproduce. So the growing ability of nitrogen deficient plants will be reduced (Rahimizadeh et al., 2010). Since the consumption of nitrogen fertilizing decreased in scenario 2, the quality parameters of obtained fruits were analyzed for each scenario. Performance evaluation of each scenario in quality analysis for different cucumber varieties is show in Table 2.

Firmness is an important quality parameter in cucumber fruits. Costumers prefer a firm, crisp, and crunchy cucumber fruit (Thompson et al., 1982). Table 2 shows that produced fruits in scenario 2 had higher values of firmness. This value increased by increasing the parameter a. this result was along with several studies which have reported that firmness of cucumber fruits decreases by increasing nitrogen fertilizing levels. Jasso-Chaverria et al. (2005) reported that cucumber fruit firmness decreased as solution of nitrogen in irrigation water increased with a linear trend. It should be noted that their studied varieties (Sarig and Bologna) were not similar to cucumber varieties used in this research. It has also been reported that the proportion of poorly developed cucumber fruit increased with increasing concentrations of nitrogen in the feed (Adams et al., 1992; Kotsiras et al., 2005), while in another study high application rates of nitrogen fertilizing to cucumbers resulted in low commercial production and low quality due to high nitrate and low calcium content, which decreased fruit firmness (Ruiz and Romero, 1998). Since the storage time have a significant effect on firmness of agricultural products, in this study firmness of the cucumber fruits was measured immediately after harvest.

Total soluble solids (TSS) is a quality parameter of agricultural products and represents the fraction of solid contents which are dissolved within a substance (in the fruit flesh). Although researches have reported that higher nitrogen fertilization levels result in higher values of TSS (Ruiz and Romero, 1998), Table 2 shows that TSS value does not change significantly in scenario 2 (for a = 10 and 15%) because of precise timing of nitrogen fertilizing. According to Table 2, higher values of a in scenario 2 decreased TSS value of cucumber fruits which is not desirable. Various varieties of cucumber had different TSS values. Results of refractometry shows that varieties with higher water contents have lower TSS values on the Brix scale.

Chlorophyll and ascorbic acid are two important fruit quality parameters in food chemical analysis. Nutritional values of vegetables and other agricultural crops have a positive correlation with these parameters. Several results have shown that the amount of chlorophyll and ascorbic acid in fresh cucumber fruits is affected by the nitrogen fertilizing level (Hunt and McNeil, 1998). Table 2 shows that scenario 2 for a values equal to 10 and 15% does not affect the amounts of these quality parameters significantly compared with scenario 1. However, with increasing of the parameter a, this effect was meaningful and lowered the chlorophyll and ascorbic acid contents.

Overall, a comparison between scenarios 1 and 2 according to their performance in nitrogen use efficiency and quality analysis shows that scenario 2 for a = 15% has decreased the nitrogen fertilizer consumption about 18% without lowering the fruit yield or fruit quality parameters.

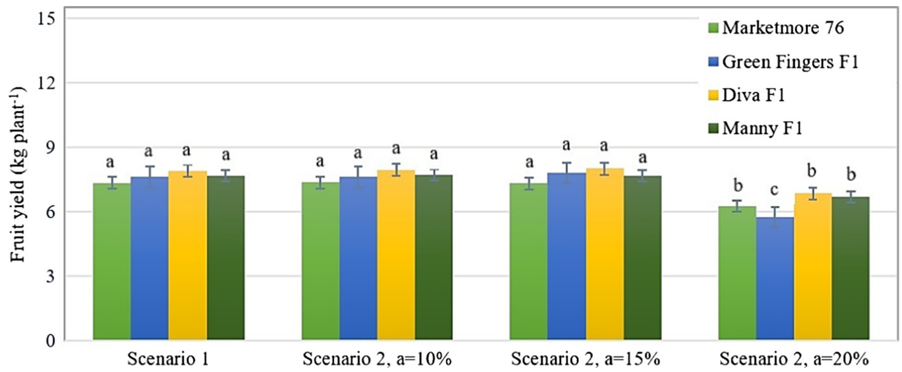

Fig. 6. Fruit yield of each cucumber variety for two scenarios.

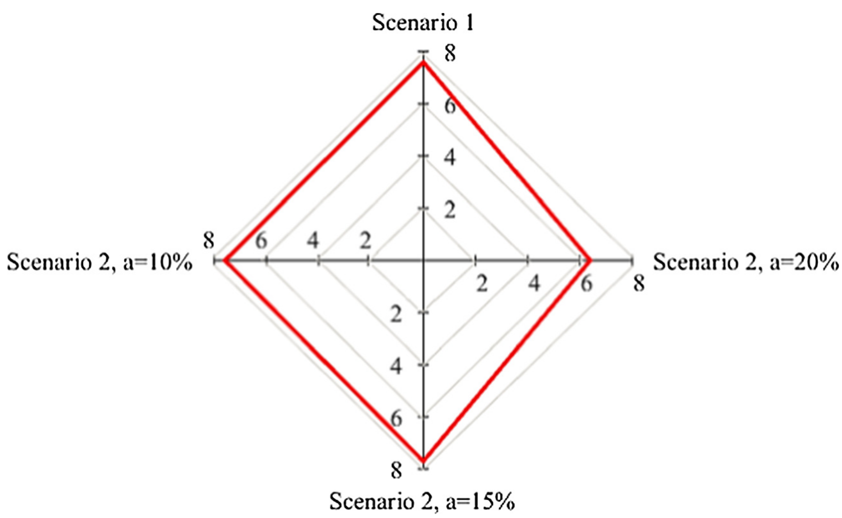

Fig. 7. Spider graph of mean of fruit yield (in kg plant^{-1}) for the scenarios.

Table 2
Performance evaluation of each scenario in quality analysis for different cucumber varieties.[a]

Scenario	Cucumber variety	Firmness (N)	TSS (%)	Chlorophyll (mg kg^{-1} FW)	Ascorbic acid (mg kg^{-1} FW)
Scenario 1	Marketmore 76	20.21 ± 2.20d	4.01 ± 0.22a	48.39 ± 1.78a	25.54 ± 1.53b
	Green Fingers F1	27.84 ± 2.33a	3.89 ± 0.07b	50.23 ± 2.11a	29.43 ± 1.15a
	Diva F1	22.91 ± 2.46c	3.76 ± 0.20b	39.10 ± 1.91b	22.78 ± 1.74b
	Manny F1	20.18 ± 2.39d	3.81 ± 0.23b	47.45 ± 1.96a	30.23 ± 2.01a
Scenario 2, a = 10%	Marketmore 76	21.52 ± 2.15c	3.96 ± 0.27a	47.54 ± 1.68a	23.19 ± 1.34b
	Green Fingers F1	26.24 ± 2.34b	3.73 ± 0.19b	48.27 ± 1.94a	28.64 ± 1.22a
	Diva F1	21.53 ± 2.73c	3.52 ± 0.18b	39.84 ± 2.03b	21.83 ± 1.09b
	Manny F1	23.67 ± 2.92c	3.64 ± 0.30b	46.54 ± 1.66a	29.58 ± 1.21a
Scenario 2, a = 15%	Marketmore 76	22.84 ± 2.12c	3.87 ± 0.23a	48.33 ± 1.89a	22.93 ± 1.25b
	Green Fingers F1	31.21 ± 3.09a	3.61 ± 0.09b	49.72 ± 2.22a	27.42 ± 1.11a
	Diva F1	28.53 ± 2.79a	3.59 ± 0.30b	38.82 ± 1.78b	21.51 ± 1.14b
	Manny F1	24.30 ± 2.85c	3.65 ± 0.15b	45.31 ± 1.83a	28.00 ± 1.20a
Scenario 2, a = 20%	Marketmore 76	28.32 ± 1.99a	3.13 ± 0.16c	41.13 ± 1.89b	17.42 ± 1.02c
	Green Fingers F1	32.54 ± 2.39a	3.22 ± 0.21c	38.75 ± 2.22b	18.61 ± 1.17c
	Diva F1	29.32 ± 2.84a	3.23 ± 0.19c	35.93 ± 1.78c	17.02 ± 0.98c
	Manny F1	25.55 ± 2.17b	3.16 ± 0.22c	39.54 ± 1.83b	18.98 ± 1.13c

[a] The data is expressed as the mean ± SD (n = 3). Means in same column with different letters are significantly different ($p < 0.05$) according to Duncan's multiple range tests.

6. Conclusions and future perspectives

Enhancement of nutrient use efficiency in greenhouse crops is a challenging task. Inefficient reduction of nutrient fertilizing can result in lower production yield or a decrement in quality parameters of obtained products. Since previous studies have indicated that lower nitrogen fertilizing consumption reduces the fruit yield, total soluble solids, and chlorophyll and ascorbic acid contents, a machine vision-based system is introduced in this study to determine precise timing of nitrogen fertilization in greenhouse cucumber.

Results showed that using a robotic machine vision system which analyses the captured images from crop rows based on image textural features including: entropy, energy, and local homogeneity resulted in reduction of nitrogen fertilizer consumption in hydroponic greenhouses.

The nitrogen fertilizing of four commercial varieties of cucumber: ''Marketmore 76'', ''Green Fingers F1'', ''Diva F1'', and ''Manny F1'' grown in a hydroponic greenhouse was done according to two different scenarios. Nitrogen fertilizing was according to protocols provided by the seed producer in scenario 1, where, in scenario 2, nitrogen fertilizing was based on the difference equal to a between image textural features of cucumber crops with the features in the routine fertilized crops.

Experimental results showed that fertilizing according to scenario 2 for $a = 15\%$ was able to decrease the nitrogen fertilizer consumption about 18% without lowering the fruit yield. Quality parameters of obtained fruits from each scenario were analyzed to investigate the effects of nitrogen fertilizing managements on the produced cucumber fruits. Firmness, TSS, chlorophyll, and ascorbic acid contents were measured for the obtained fruits. Results showed that scenario 2 for a equal to 10 and 15% did not affect quality parameters of the fruits significantly in comparison with fruits obtained in scenario 1.

In conclusion, scenario 2 for $a = 15\%$ can be recommended for cucumber hydroponic greenhouses to enhance nitrogen use efficiency. This scenario can be implemented for other greenhouse crops such as pepper, tomato, and eggplant to determine proper value of a for each crop. Furthermore, this scenario can be implemented to enhance the efficiency of usage of other nutrients especially those which have certain visual symptoms such as calcium. One of the most noticeable visual signs due to the deficiency of calcium and some other nutrients is leaf tip burn which should be considered in image processing stage (Barta and Tibbitts, 2000).

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