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Monitoring Station for Agriculture Image Acquisition and Automatic Information about Plant

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ABSTRACT

The present work deals with Computer Vision precision in the agriculture domain designed to monitor the height variation of plants (h) and the percentage of Ground Cover (PGC). It brings together electronics and Computer Vision. the electronic part consists of two sensors: the first is the DHT11 sensor, which will monitor environmental parameters (temperature, humidity), and the second sensor is a camera (5 MP Raspberry Pi Camera Module Rev 1.3) which monitors the image acquisition to capture visual information about plants and Raspberry Pi 4 as the central processing unit for environmental data. For the Computer Vision part we have developed an algorithm able to do the acquisition and the segmentation of images acquired using Raspberry Pi 4 in real time.

keywords: Sensor DTH11, Raspberry Pi4, image segmentation.

Introduction

Nowadays, monitoring systems for agricultural image analysis have become a crucial area of research and a special task in precision agriculture, driven by the forthcoming human challenges, the need for enhanced crop management, precision farming, and early detection of diseases and pests to cope with achieving nutritional sufficiency and food security. Image analysis has been employed in agriculture since the early 1980s¹, integrating image analysis into an agricultural monitoring system is an interesting application such: a machine vision system designed to image acquisition and automated monitoring agriculture², an unmanned Aircraft Vehicle is currently used for precision and monitoring agriculture³, an application of a real-time field-programmable for crop monitoring in Precision Agriculture combined with remote sensors and real-time FPGA-based image processing⁴, a smart Agriculture Monitoring System to detect some parameters of plants⁵ and a system integrating a ground robot platform with a camera and object detector⁶.

The introduction of these technologies aims to solve several problems in the two phases:

During the crop growth: irrigation management, weeds, insects, diseases, temperature, humidity, and deficiency detection. During the harvesting: fruit grading, ripeness detection, fruit counting, and yield prediction.

The remainder of this paper is organized as follows. Section II presents the (Hardware + Software Pipeline). Section III contains our hardware design. Section IV presents a software conception. We then present experimental results in Section V, using real images. Finally, we conclude in Section VI with references.

1 System Overview

Generally, a given monitoring station is formed of a hardware and software parts. The hardware is all the sensors that collect the crop information. They are regrouped as:

- Weather sensors (ex. humidity, temperature, wind speed and direction ...);
- Irrigation system sensors (raindrop sensors);
- Crop sensors (ex. cameras on drone or on robots, leaf wetness sensors);
- Soil sensors (soil moisture).

And for the software part, Once the crop information are collected, it comes to give an automatic processing and analysis. This part consists of the development and implementation of algorithms able to deal with such information and answer some tasks.

The proposed station consists using DHT11 sensor, camera (5MP Raspberry Pi Camera Module Rev 1.3) and Raspberry Pi 4 for the hardware part. For the software part, we have developed an algorithm able to deal with the outdoor acquisition Data such images, Temperature and Humidity. The Raspberry Pi will process this data; Image processing techniques were employed on captured images to identify some information about the plant. The system designed to transmit the Data between the sensors and the Raspberry pi 4 module by a Wireless Module called Xbee; the collected data will save in a storage (SD card). The use of a Raspberry Pi 4 offers a cost-effective and versatile platform for this monitoring station. This approach promotes precision agriculture practices by providing real-time data and visual insights into crop health and environmental condition.

Hardware Design



Figure 1. The global flowchart of the proposed system.

The Fig.1 show a global flowchart of the proposed system with three principal operation:

Sensors acquisition and transmission: the sensor acquisition is presented for acquiring Data measurements from the installed sensors which assured by: DHT11 sensor, camera (5MP Raspberry Pi Camera Module Rev 1.3); The transmission is assured by a traditional wire transmission or a wireless communication like Module Xbee.

Data processing and saving: Data processing is the process of turning raw data into a readable format that can be analyzed, interpreted, which assured by a Developed Software installed on Raspberry Pi 4; The Data saving is keeping the data for later use which assured by a storage (SD card).

Application and Decision-making: according to the data analysis, we can make a suitable decision and apply in the real system which assured by: a Tablet or a Monitor.

Essentially, the hardware part is constructed of four modules. Each one ensure a function as it displayed on Table 1 in parenthesis.

The Fig. 2 shows a physical design of the monitoring station and the Fig. 3 shows a synoptic diagram of the proposed system installation with 1: Raspberry P4, 2: Battery 3: Monitor, 4: Humidity and temperature sensors, 5: Camera, 6: transmitter

Software Conception

A proposed image segmentation method based on Mumford-Shah Model In order to obtain a quantitative description of agronomic images and calculate the (*PGC*) parameter for images captured from a wheat field, digital image segmentation

Table 1. Hardware Conception

Energy	Power bank, solar panel (Ensures power supply to the monitoring system)	
Sensors	DHT11	Temperature (°C) (The DHT11 is used to measure Temperature and humidity)
		Humidity (%) (The DHT11 is used to measure Temperature and humidity)
	Camera	5MP Raspberry Pi Camera Module Rev 1.3 (It used to capture images with a resolution of 2592 x 1944 pixels)
Transmission	<1.2 km	Module Xbee (It is a popular wireless communication protocol used to transfer data)
	>1.2 km	Module Xbee (It is a popular wireless communication protocol used to transfer data)
Processes	Raspberry pi 4 (The Raspberry Pi 4 used as a central processing unit to gather environmental data, do the Data processing.)	
Display	Screen, Smart phone, Tablet (show the results)	

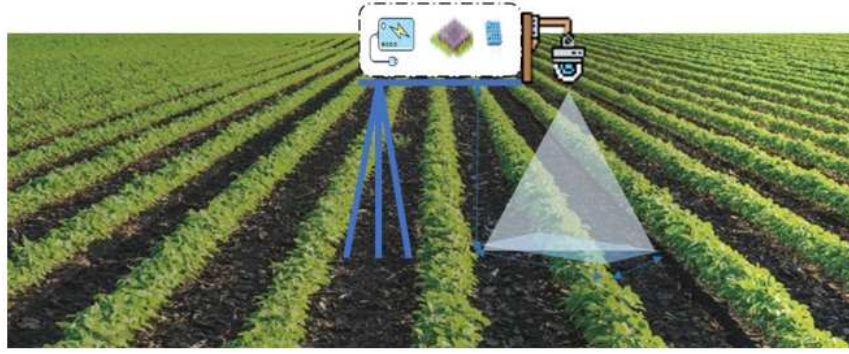


Figure 2. Physical design of the monitoring station.

is employed. This process involves extracting the different phases and their respective proportions present in the image. To achieve this, we propose an automated method that utilizes a Bayesian Mumford–Shah formulation. This approach allows for effective segmentation of the phases within the agronomic images.

Mumford Shah Model Problem

The Mumford-Shah model is based on the concept of minimizing an energy function, denoted as (E). This energy function aims to achieve a suitable representation of the segmented image. The minimization of the energy function can be mathematically expressed as follows⁷⁻¹¹

$$E(\Gamma_i, u_i) = \lambda \iint_{\Omega} (u_0 - u_i)^2 dx dy + \iint_{R_i} |\nabla u_i|^2 dx dy + \mu \int_{\Gamma_i} dl \quad (1)$$

Where u_0 represents the initial image of bounded value in Ω , $\Omega \subset R^2$, and Γ_i is composed by smooth arcs and creates boundaries for R_i ^{7,9}, the image u_0 is approached by a function u_i .

λ is a positive real for the quality control of the approximation, μ is a positive real represents the coarseness of the segment¹⁰. In the reduced simple case of the model where the functions u_i are constants, the second term of equation (1) is cancelled.

$$\iint_{R_i} |\nabla u_i|^2 dx dy = 0$$

The energy of equation (1) can be written as follows:

$$E(\Gamma_i, u) = \lambda \int_{\Omega} (u_0 - c_i)^2 dx dy + \mu \int_{\Gamma_i} dl \quad (2)$$

With c_i is given by

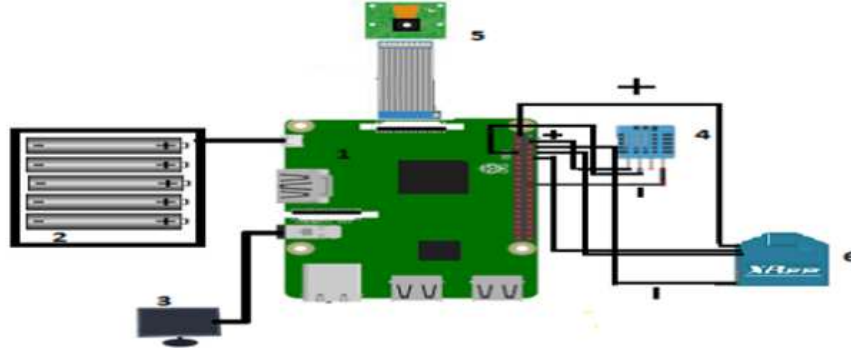


Figure 3. Synoptic diagram of the proposed system installation.

$$c_i = \lambda \iint_{\Omega} u_0 dx dy / \iint_{\Omega} dx dy \quad (3)$$

In the case where there are only two zones and therefore a curve $C \subset \Omega$. This curve delimits two zones, the interior of C and the exterior of C .

Bayesian Formulation

The Bayesian formulation for image segmentation is rooted in the assumption that the pixel intensities within each region follow a random process with a specific density function. This formulation incorporates statistical principles to estimate the probability distributions of the pixel intensities in different regions of the image. This approach draws inspiration from the work of Leventon and aims to capture the underlying probabilistic nature of image segmentation^{8,12}. The statistical parameters are introduced as unknowns. To make it simple, we start with the simple case of bipartition. The image assumed to be composed of two regions Ω_1 and Ω_2 . Let p_i be the normal probability distribution in the region Ω_i .

$$p_i(u|\mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(u-\mu_i)^2}{2\sigma_i^2}} \quad (4)$$

With μ_i and σ_i are respectively the mean and the variance of the probability distribution in the region Ω_i . A level set ϕ can represent the implicit interface between Ω_1 and Ω_2 , the corresponding energy equation (1) can be written as follows:

$$\begin{aligned} E(\mu_{1,2}, \sigma_{1,2}, \phi) &= \mu \int_{\Omega} \delta_0(\phi(x,y)) |\nabla(\phi(x,y))| dx dy \\ &+ \int_{\Omega} \log(2\pi\sigma_1^2) + \left(\frac{(\mu(x,y) - \mu_1)^2}{2\sigma_1^2} \right) H(\phi(x,y)) dx dy \\ &+ \int_{\Omega} (\log(2\pi\sigma_2^2)) + \left(\frac{(u(x,y) - \mu_2)^2}{2\sigma_2^2} \right) (1 - H(\phi(x,y))) dx dy \end{aligned} \quad (5)$$

This energy is minimized respect to ϕ by a minimization algorithm, the optimal statistical parameters are estimated (μ_i and σ_i of each region Ω_i). The two steps are repeated until convergence. For a fixed level set function, the form of the optimal statistical parameters can be easily obtained from the derivation:

$$\begin{aligned} \mu_1 &= \frac{\int_{\Omega} u(x,y) H(\phi(x,y)) dx dy}{\int_{\Omega} H(\phi(x,y)) dx dy}, \\ \mu_2 &= \frac{\int_{\Omega} u(x,y) (1 - H(\phi(x,y))) dx dy}{\int_{\Omega} (1 - H(\phi(x,y))) dx dy} \end{aligned} \quad (6)$$

$$\begin{aligned} \sigma_1 &= \frac{\int_{\Omega} (u(x,y) - \mu_1)^2 H(\phi(x,y)) dx dy}{\int_{\Omega} H(\phi(x,y)) dx dy}, \\ \sigma_2 &= \frac{\int_{\Omega} (u(x,y) - \mu_2)^2 (1 - H(\phi(x,y))) dx dy}{\int_{\Omega} (1 - H(\phi(x,y))) dx dy} \end{aligned} \quad (7)$$

Euler–Lagrange Equation

The Euler–Lagrange equation of ϕ is used to minimize $E(\phi)$ ^{13,14}. This amounts to cancel the differential of energy at ϕ to obtain:

$$\begin{aligned} \frac{\partial \phi}{\partial t} = & \delta_0(\phi) \left[\mu \operatorname{div} \left(\frac{\nabla \phi}{|\nabla \phi|} \right) - \frac{(u - \mu_1)^2}{2\sigma_1^2} \right. \\ & \left. + \frac{(u - \mu_2)^2}{2\sigma_2^2} - \log \frac{\sigma_1^2}{\sigma_2^2} \right] \end{aligned} \quad (8)$$

Percentage of Ground Cover

Percentage of Ground Cover (PGC) is a key parameter used to estimate several other parameters such as crop coefficient K_c and plant height h . The percentage of ground cover (PGC) reflects the ratio of plant compared to the soil in a given surface. The (PGC) is estimated directly from the segmented images using this formula^{15–17}:

$$PGC = \frac{V}{T} 100(\%) \quad (9)$$

Where V represents the area (number of pixels) occupied by vegetation and T is the total area.

Experiments and Results

Image acquisition

The experimental wheat field located at ITGC, FDPS Oued Smar, Algiers, Algeria was utilised in applying this technique. The images were captured using a 5MP Raspberry Pi Camera Module Rev 1.3, which offers a resolution of 1024×768 pixels. The camera was positioned at an adjustable height using the mobile part of its support. The images were taken at a height of 1.5 meters above the ground, and the height of the wheat plants (h) was measured each time. To calculate the percentage of soil cover (PGC) by wheat vegetation, multiple images were captured, and the best ones were selected^{18,19}. The height (h) was estimated based on (PGC) as illustrated in Fig. 5.

Results

Fig. 4 illustrates the results of multiple agricultural images segmentation steps employing the Mumford-Shah model, employing different values of N iterations for the multi-circle type. The figure presents three contours: the initial contour, the contour after 10 iterations ($N = 10$), and the final contour achieved after 100 iterations ($N = 100$). Additionally, thresholding is employed to differentiate between distinct phases throughout the image segmentation process.

Fig. 5 and table 2 demonstrate the height variation of plants (h) along with the outcomes of applying the Mumford-Shah model to agricultural images taken at different stages after germination (20, 75, 117 and 147) days.

This result allows us to see the parameters PGC and h for deferent Days ($N = 20, 75, 117, 160$) models, the proposed model can calculate the parameters. From these results, we can notice that the software adopted in this study does not need any preprocessing step.

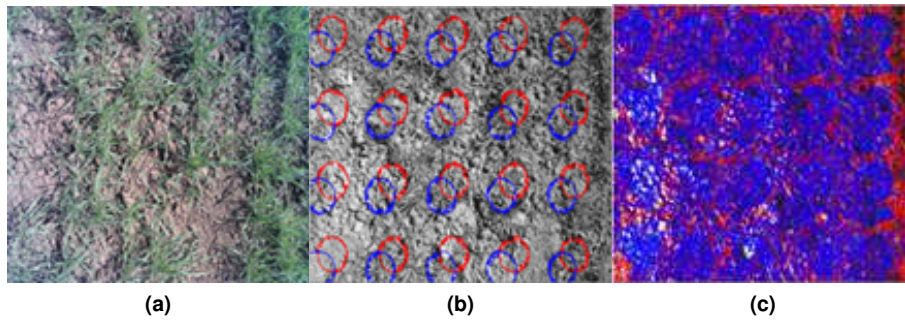


Figure 4. Segmentation steps of agricultural image: (a) Original image; (b) Initial contour; (c) Finale contour (100 iterations).

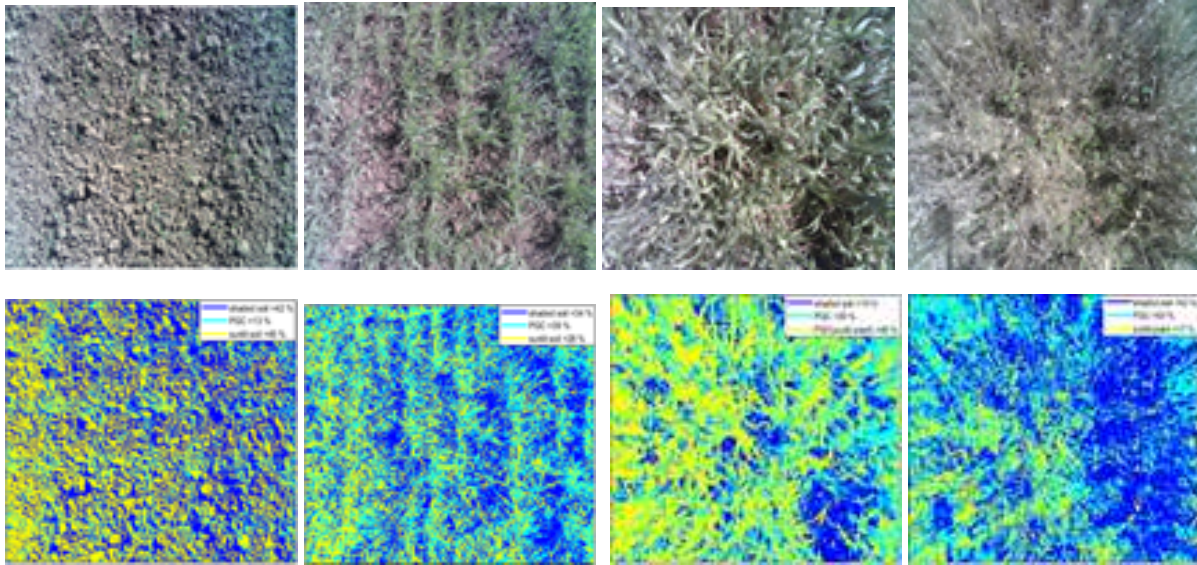


Figure 5. Some results obtained of plant height h and PGC extraction using Mumford Shah model in image segmentation, with $N = (20, 75, 117, 160)$ days; $h = (18, 40, 82, 90)$ cm; $PGC = 13, 42, 81, 40$ %.

Table 2. Plant height h and PGC in different days

N (Days)	20	75	117	160
h (cm)	10	40	82	90
PGC (%)	13	42	81	40

Conclusions

The idea of this paper addresses the problem of Monitoring Station for agriculture image Acquisition and Automatic information about plant. A hardware system composed to acquire parameters Temperature, Humidity, and images of Plant from a Field. In addition, a software developed for calculating the parameters Percentage of Ground Cover (PGC), crop coefficient and plant height h , the value of the parameters is deducted from the segmented image. The proposed system is characterized by its simplicity and efficacy, the system was tested in a real environment, the experience shows the robustness of our monitoring system.

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Author contributions statement

Propose a station consisting of using DHT11 sensor, camera (5MP Raspberry Pi Camera Module Rev 1.3), and Raspberry Pi 4 for the hardware part.

Developed an algorithm able to do the acquisition and segmentation of images acquired using Raspberry Pi 4 in real time.

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and material

Raw data was generated at "Research Centre in Industrial Technologies -CRTI-", and materials are available at the same centre. Derived data supporting the findings of this study are available from the corresponding author "Mohammed Khorchef" on request.

Competing interests

The authors of this work declare that they have no competing of interest.

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