Remote Monitoring of Plant Water Stress with RGB Imaging

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***Abstract*—Precision irrigation in greenhouses necessitates remote monitoring of soil moisture. Traditional methods often rely on point measurements, making comprehensive water stress assessment across all crop plants impractical. As an alternative, machine vision has emerged as a promising solution. This study presents a novel approach to soil moisture monitoring using plant images, implementable with low-cost devices and minimal computational resources. The method is based on the hypothesis that leaf discoloration serves as an early indicator of water stress, detectable through RGB imaging. We detail the development and installation of a monitoring system within a grow tent, designed to test irrigation automation based on leaf color across various crops in a controlled environment.**

***Index Terms*—Machine vision in agriculture, Remote soil moisture monitoring, RGB imaging, Precision irrigation, Water stress detection**

I. Introduction

Automated irrigation systems in greenhouses optimize water use [1], save labor [2], promote plant health, and enable stress physiology studies [3]. Moreover, data collected by environmental sensors allow to maintain a favorable microclimate within the greenhouse. Sensor-based precision agriculture minimizes human intervention and promotes real-time monitoring, allowing for immediate response based on prevailing soil and environmental conditions. Irrigation automation and crop telemetry benefit both producers and scientific research.

Traditional grower-based irrigation typically employs timers [4]. A monitoring system for soil moisture can be constructed with low-cost components such as microcontrollers, soil moisture sensors, and solenoid valves [5]. Conventional low-cost sensors are typically inserted into the soil and are based on resistive or capacitive measurements [6]. These sensors monitor the electrical resistance or the dielectric permittivity of the soil, providing insights into variations in soil moisture. However, these sensors are susceptible to short-term deterioration. For example, the chemical reaction between the electrodes of resistive sensors and the soil, known as electrolysis, degrades their measurements. Similarly, capacitive sensors, due to their poor impermeability, undergo changes in the structure of the terminals and infiltration compromises their electronic circuits. Such issues, observed both in this study and in other research [7], highlight the limitations of these sensors leading to gradual erroneous measurements.

In recent years, diverse machine vision techniques have been applied for phenotyping, i.e., determining structural and physiological traits of plants [8], [9]. A promising approach is to use phenotypic traits extracted from images to estimate water stress. Various traits have been explored for this purpose: root zone water status has been classified based on 37 phenotypic traits of Pakchoi plants [10]; water and nitrogen deficit stress in tomato plants has been detected using multispectral indices [11]; substrate water status has been forecasted using 9 morphological traits, 6 color traits, and 14 near-infrared feature traits for netted muskmelon crops [12]. This work also discusses which color traits are significant for predicting substrate water content at different growth stages; water stress in tomato crops has been predicted based on leaf wilting estimated from plant images combined with environmental data [13]; and leaf chlorophyll content of pomegranate trees has been estimated using RGB imaging [14].

The simplest trait that can be extracted from plant images is leaf color. Interestingly, a correlation between soil moisture and leaf color has been identified, at least for tomato plants [15]. If such a relationship can be established for a wider range of crops, RGB imaging of cultivated plants could serve as a low-cost, non-invasive humidity sensor. In other words, machine vision might enable plants to "communicate" their water needs through the color of their leaves. A similar idea was followed when detecting anomalies in the emission of volatile organic compounds of crops [16].

II. Sensing Architecture

The irrigation water uptake time for tomato plants has been estimated from changes in leaf color [7], demonstrating the sensitivity of this approach for certain crops. However, the required measurements were carried out manually using a colorimeter, which is an expensive piece of equipment. In this study, the automation of a similar experiment is proposed using lower-cost components and data storage in the cloud. The system is depicted in Fig. 2(a). To better analyze the color and opacity of the crop leaf in response to hydric stress and to

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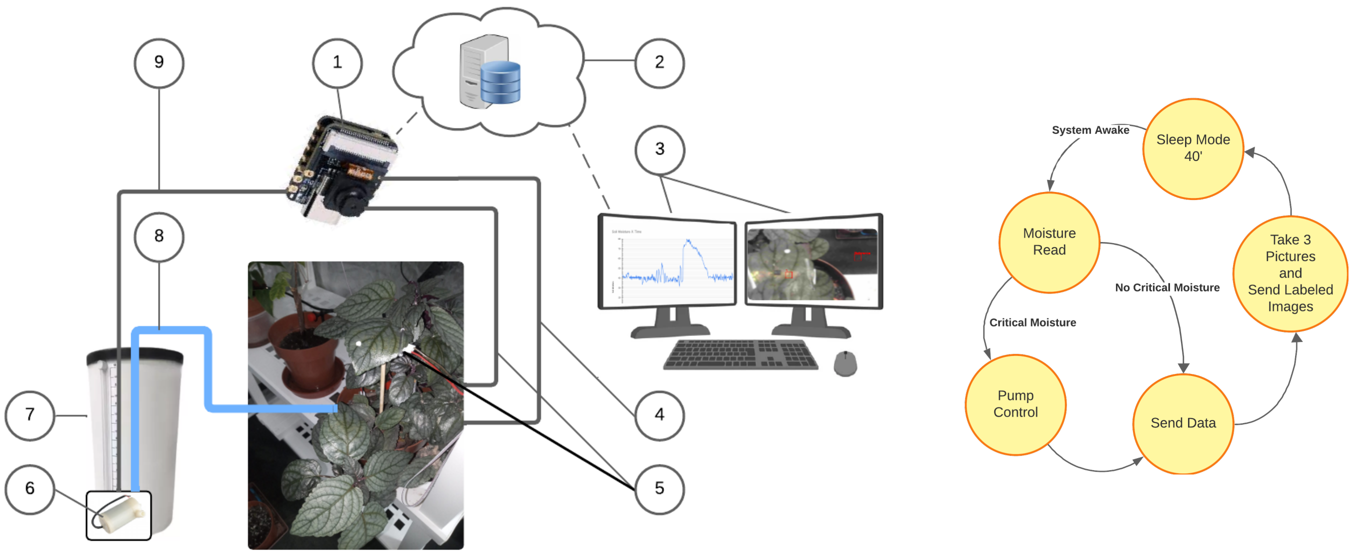


(a) Phenotyping system

(b) State diagram of controller

Fig. 1. The developed phenotyping system (a) includes a controller module, the Seeed Studio XIAO ESP32S3 Sense, featuring a CMOS camera (1280×1024 pixels) connected to the Internet by Wi-Fi (1); A cloud server storing data and snapshots (2); A remote computer for data inspection, irrigation specification (user-defined humidity thresholds), image analysis, and processing (Python program) (3); A capacitive moisture sensor connected to the module (4); A flash lamp positioned under the plant's leaf connected to the same module (5); A mini water pump (6) inserted in a PVC reservoir (7) and also connected to the development board (9); and a drip irrigation conduct (8). Two power drivers were used to control the mini water pump and the flash lamp. The controller cycles through five states (b) to control the irrigation and periodically capture images for the extraction of phenotype traits.

increase the versatility of the suggested phenotyping system, a flash lamp was positioned at the back of the leaf. This mode of imaging helps monitor a novel "opacity color" trait. Moreover, to mitigate the impact of the natural movement of the plant over time, which could result in the capture of highly variable images, the leaf under the camera's focus was fixated.

As depicted in Fig. 1(b), the controller of the phenotyping system is a finite state machine cycling through five states. In the first state, the controller monitors soil moisture. Depending on the results, the water pump may be activated. Subsequently, the controller sends the moisture data and pump status to the cloud. In the fourth state, the controller captures and transmits images of the plant. In the final state, the controller enters sleep mode, waking up after $40\,\mathrm{min}$, and restarts the cycle with new readings followed by the same sequence of states.

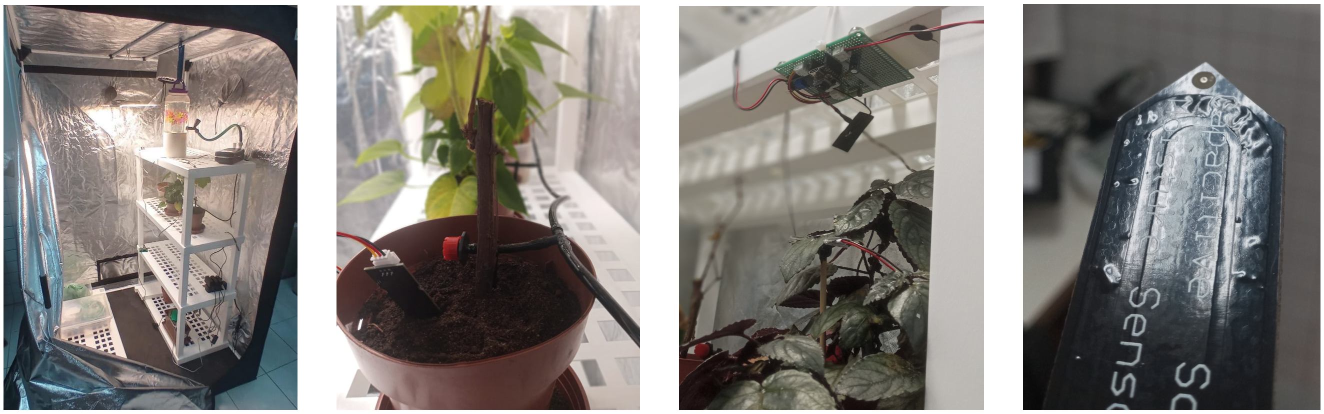
Each transmitted humidity value represents the mean of 256 readings to reduce noise. The obtained mean is mapped to a scale between 0 and 100, corresponding to 0% and 100% relative soil humidity. The system uses two critical soil moisture thresholds for irrigation control: a lower value to activate the water pump and an upper value to deactivate it. These thresholds are either pre-defined at startup or set remotely by the user. In the "pump control" state, when triggered, the irrigation circuit is activated for $4\,\mathrm{s}$. After the "send data" state, the controller captures six images in total: three with the flash lamp activated and three without. The captured images are sent to the repository and named according to the current soil moisture value and the storage timestamp.

III. Methods and Experimental Design

The developed phenotyping system was installed in a grow tent to evaluate the relationship between the RGB color of plant leaves and the corresponding soil moisture (Fig. 2). The grow tent provided controlled artificial lighting, alternating between $12\,\mathrm{h}$ of LED lighting (representing "day") and $12\,\mathrm{h}$ of no LED lighting (representing "night") controlled by a programmable timer switch. Fig. 2(d) illustrates that the capacitive soil moisture sensor is susceptible to infiltration. To prevent this and extend the sensor's lifespan, another replacement sensor was wrapped with a thin layer of impermeable adhesive plastic. This protective layer effectively prevented water absorption into the sensor's circuitry. After this modification, the sensor was adjusted to ensure accurate measurements.

Fig. 3(a) shows the two extreme soil conditions used to adjust the moisture readings. Two small pots were filled with $500\,\mathrm{g}$ of dry gardening soil. One pot was left dry, while the other was watered until water drained through the bottom opening. The soil moisture sensor was inserted sequentially into both pots. Dry soil was defined as 0% relative moisture, while saturated soil represented 100% relative humidity. Soil moisture is measured with 9-bit resolution (0 to 511, corresponding to $0\,\mathrm{V}$ to $3.3\,\mathrm{V}$). The two soil conditions lead to readings of 241 (0%) and 164 (100%), i.e., a one percent change in relative humidity changes the voltage by $5\,\mathrm{mV}$.

In a pilot experiment, Red Ivy, *Hemigraphis alternata*, a plant sensitive to irrigation conditions [17], was monitored over several weeks. Image processing included blurring and the extraction of RGB indices from two regions: a section



(a) Grow tent (b) Drip irrigation (c) SoC with camera (d) Moisture sensor

Fig. 2. Installation of the phenotyping system in a grow tent (a). The drip irrigation conduct supplied water to the grow pots and was controlled by a small water pump (b). The camera module was positioned at a distance of 10 cm above the leaf under monitoring (c). Capacitive sensors inserted into the soil monitored moisture but were vulnerable to infiltration (d).

(a) Sensor Regulation (b) RGB Reference

Fig. 3. Dry (left) and wet (right) soil used to regulate the two extreme values of the moisture sensor (a). To mitigate the effect of noise present in the captured leaf images, images were blurred and RGB indices extracted from two regions (b). The leaf color is obtained from region one and normalized by the values obtained from region two, which is not expected to change color.

of the leaf (primary region) and a section of the tent floor (secondary reference region), see Fig. 3(b). The average RGB values obtained for the reference region were subtracted from the average RGB indices extracted from the leaf section for normalization and noise reduction mainly caused by the artificial LED illumination due to the alternating power supply at 60 Hz. Mean values were computed from the three consecutive images captured at the same instance. The pilot experiment aimed to demonstrate the full functionality of the developed low-cost phenotyping system, including verifying the irrigation automation, acquiring a phenotype image database over several weeks, and analyzing the images, specifically extracting the red (R), green (G), and blue (B) color indices.

IV. Results

Fig. 4 demonstrates the automatic control of soil moisture over time. The graph combines two distinct periods. In the first period, approximately 6 d, the system was remotely configured to maintain a moisture level around 80%. In a second moment, the user-defined irrigation specification was modified, and the soil moisture was kept close to 40% for approximately 10 d. The readings from the moisture sensor show that the automated irrigation system successfully maintained the humidity at the desired levels, demonstrating the correct operation of the system. Other humidity levels between 0% and 100% were also achieved through remote configuration of the hysteresis thresholds. For illustrative purposes, soil moisture transitions have been omitted from Fig. 4.

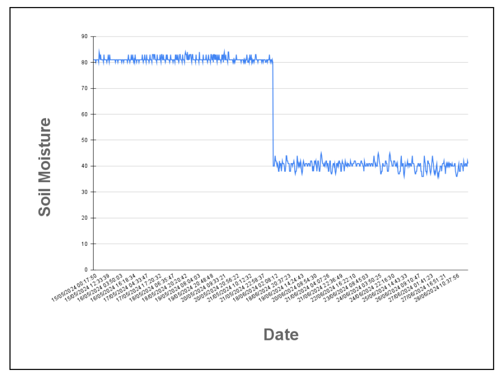
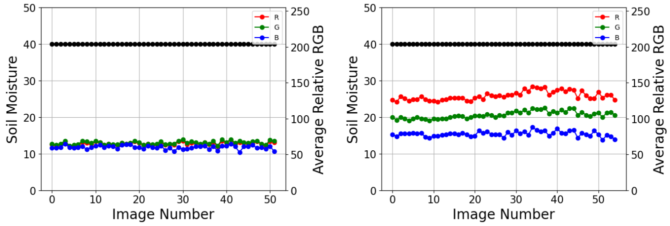


Fig. 4. The automated irrigation system succeeded in maintaining the soil moisture at constant levels as remotely specified by the user. For the two shown periods the targeted moisture levels amount to 80% and 40%, respectively. The control parameters are the lower and upper limits to activate and deactivate the water pump. The user-provided limits equalled 80% and 81% during the first period and 40% and 41% for the second period. The shown graph is a slight adaptation (to improve readability) of the user view of the remote moisture monitoring as depicted in Fig. 1.

The soil moisture level of 40% is lower than optimal, and the plant experienced drought stress. The developed system proved capable of acquiring a phenotype image dataset. In total, 156 snapshots without back flash illumination and 165 images with back flash illumination were captured for color trait extraction. An example is given in Fig. 3(b). The extraction of the leaf color followed the procedure outlined in Sec. III. Fig. 5 shows the evolution of the obtained leaf color during the course of the stress experiment.

The obtained results indicate an increase in the average RGB values for both capture modes. Interestingly, the back flash illumination seems to help resolve slight color changes.



(a) No flash (b) Flash

Fig. 5. Leaf color evolution of a Red Ivy plant during water stress. The soil moisture was kept during a period of 10 d at a low value of 40%. In response, the mean red (R), green (G) and blue (B) indices increased slightly, both without back flash illumination (a) and with back flash illumination (b). Even more significant is an increase in variability of the RGB indices. In total 52 and 55 instances are shown for the two illumination modes, respectively.

Fig. 5(b) shows a significant variation in the normalized R, G, and B indices, with the red component showing the most considerable variability, followed by the green and the blue component. Conversely, in Fig. 5(a), which depicts the experiment without back flash illumination, a smaller variation in all components is noted. However, the B component exhibits the greatest variability compared to the other components. In conclusion, for the Red Ivy plant under investigation, the variance and not the mean values of the RGB indices, especially with back flash illumination, seems to be a better indicator of water stress.

V. Conclusion

The developed phenotyping system required minimal maintenance during the study, with the primary challenges being occasional power and network failures.

The irrigation system successfully maintained the soil moisture at user-defined target levels by utilizing lower and upper threshold values to control the activation and deactivation of the water pump. Notably, absolute calibration of the soil moisture sensor was not necessary; instead, the user defined the extreme soil moisture conditions framing the desired target state for the growing environment.

In this study, the phenotyping system was used to extract color traits of an ornamental plant, Red Ivy, during drought stress. Over an extended period, soil moisture was maintained at a low level. Surprisingly, the mean RGB indices did not change significantly during the stress test, contrasting with several reports in the literature for other plants, such as tomato crops. However, the variance of the RGB indices, especially with back flash illumination, might be a good indicator of water stress. Our findings emphasize that the concept of a ”plant as a humidity sensor” is crop-dependent.

The described prototype phenotyping system can be easily adapted by other research teams to enable stress physiology studies related to substrate-plant-water relations.

An interesting addition to the proposed system would be machine learning-based tracking of the natural movement of the plants. This would improve precision in the extraction of color traits compared to the leaf fixation method used in this study, as a larger extraction region with more pixels could be employed. Additionally, detecting anomalies in natural movement could serve as an additional indicator of water stress.

VI. Online Resources

The source code of the microcontroller configuration and software artefacts (Python) for color treat extraction are available in our GitHub repository.

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