Cloud of Things in Smart Agriculture: Intelligent Irrigation Monitoring by Thermal Imaging

Mehdi Roopaei, Paul Rad, and Kim-Kwang Raymond Choo,
The University of Texas at San Antonio

IRRIGATION IS CRUCIAL FOR AGRICULTURE PRODUCTION TO ENSURE THAT FARMERS ARE ABLE TO MEET CROP WATER DEMANDS EVEN IN SITUATIONS WHERE THERE IS INADEQUATE RAINFALL. However, poor irrigation scheduling and inefficient utilization of water resources are two of several ubiquitous parameters restricting production in many agricultural regions.[1]

Cultivators can use information such as light, humidity and temperature levels to modify irrigation schedules and avoid the risk of damaging crops.[2] For example, soil sensors can be used to collect information on how water flows through the land and can be used to track changes in soil moisture, temperature, and levels of nitrogen and carbon. These sensors can work in conjunction with drip irrigation methods and fertigation to avoid unnecessary waste of water and fertilizer, thus, increasing fruit and leaf quality. Real-time data of weather predictions, soil conditions, crop features, etc. can support farmers in making informed decisions on which crops to plant where and when as well as when to plough, etc. This allows the monitoring, optimization, and precise control of high-yielding (wheat, corn, etc.) and sensitive crops (vineyards, tropical fruits, etc.), whether cultivated outdoors or in greenhouses. This permits farmers to help reach maximum crop production with optimal quality.[3]

EDITOR:
KIM-KWANG RAYMOND CHOO
University of Texas at San Antonio
raymond.choo@fulbrightmail.org

Thermal Imaging in Smart Irrigation

While crops may be capable of dealing with water stress to some extent, it is important for farmers and irrigation administrators to monitor stress variations in order to avoid reaching a dangerously high level.

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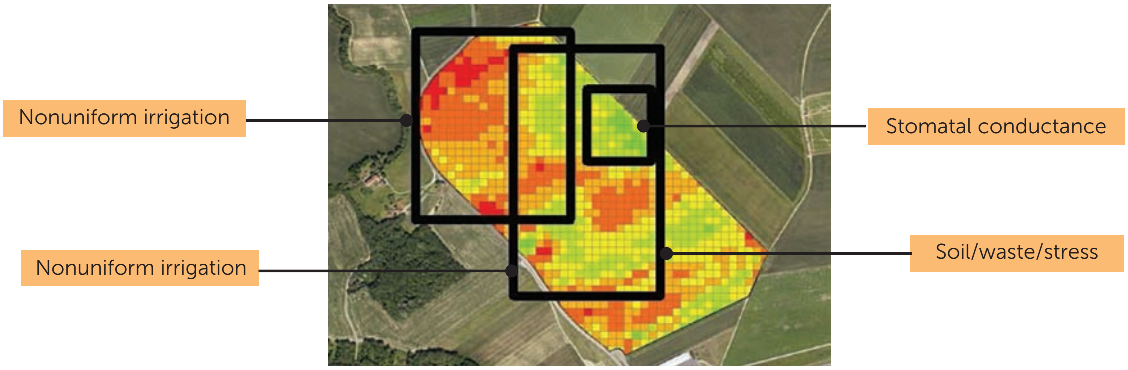

FIGURE 1. Examples of information from thermal imaging

Thermal imaging is a noncontact and nonintrusive technique, without the need for modifications in the surface temperature. It is also capable of displaying the temperature. This has been leveraged in many industrial and/or research fields when the temperature represents a key variable, including meteorology, environmental studies, medical diagnostics, and architecture.[4] Several studies have demonstrated that thermal imaging is an appropriate approach to identifying key parameters to schedule irrigation. There are several critical features for irrigation, such as water stress, gas-exchange rate, evapotranspiration rate, stomatal conductance, and closing of stomata. In water stress condition, stomata begin to close and cease to transpire, plant heats up, and the canopy temperature will rise.[5] Therefore, thermal remote sensing can potentially be used to measure plant temperature, stomatal conductance, and evapotranspiration rate by evaluating stomatal responses.[6–9] Thermal imaging has the advantage of providing a temperature value for all of the pixels within the sensor's field of view in comparison to thermometry, where the latter only provides an average value. Therefore, it is occasionally easier to discriminate between different components, such as sunlit versus covered plant portions and wet against dry soil surfaces. Recent thermal imaging in combination with other image processing and data analytic techniques attempt to decrease crop water stress and provide irrigation scheduling - see Figure 1. Taghvaeian et al. proposed a method that automatically measures canopy temperature by captioning a thermal image from the plant canopy using Gaussian mixture distribution extraction techniques.10 The algorithm successfully extracts the canopy temperature distribution and checks and controls all elements that are expected to improve irrigation management. The latter comprises automatic data collection, models, hardware, and software. Thermal remote sensing is based on the emitted temperature signals from the plant and has the advantage of not requiring signals from the soil. Therefore, thermal sensing reduces the number of sensors required in soil monitoring and measurement.

A good irrigation system must provide water to the whole field uniformly. In the absence of uniformity in irrigation, the quality of cultivated products will be reduced. For example, varying grape quality and rate of ripening affect wine quality. Smart agriculture can be used to improve water distribution in the farm, achieve uniform maturity, and accordingly, increase product quality. Thermal imaging could be used to determine the relation between water status of the plant/field and radiation emission, and therefore can be utilized as a measure for water stress and irrigation distribution.

Cloud of Things-Based Automated Irrigation

Deployment of a Cloud of Things (CoT) network, which can include Internet of Things and cyber-physical system, in smart agriculture can make energy use more efficient and less costly. For example, data analytics collected from the CoT network (e.g., weather situation, land condition, and type of soil) can provide practical information when used in combination with data captured by

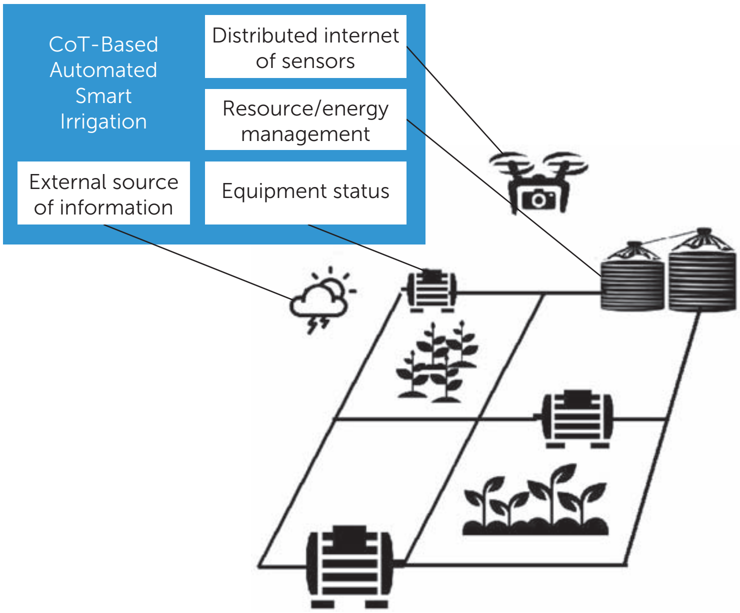

FIGURE 2. Overview of Deployment of a Cloud of Things (CoT)-based automated irrigation.

sensors measuring heat, moisture, chemicals, water stress, pump status, level of water resources, etc. This allows farmers to utilize water, fertilizer, and pesticides in more precise quantities and positions, and with better time scheduling to increase yields. Agriculture is very water and electricity intensive, and both water and electricity are two of the most important input parameters for agriculture. Water and electricity costs can also make or break agricultural commerce. Therefore, smarter water use (e.g., supervising and monitoring water capacity, location, timing, and period of flow based on data analytics) helps to improve irrigation efficiency and leads to lower costs. CoT can also provide more effective energy uses for pumps, lighting, boosters, and other purposes and remotely control the status, working conditions, and performance of equipment. For example, data analytics and CoT can be used to determine equipment status, e.g., whether a gate or a valve is opened or closed, an irrigation pump is turned on or off as well as other indicators that signal the need for maintenance or replacement (see Figure 2).

Why the Cloud?

CoT, such as the cloud-based smart irrigation system discussed in this article, can provide a number of advantages. However, to create a tool of maximum effectiveness, we need more than just sensors and Internet connection. Indeed, this infrastructure must be supported by a system capable of collecting, storing, analyzing, processing, and managing the vast amount of intelligent data generated (the big data challenge). The structure depicted in Figure 3 enables task automation through processes based on the data received by the interconnected sensors and devices. Furthermore, it generates performance reports and statistics to provide the farmer with real-time information on the activity of the business and to enable the farmer to make well-informed and timely decisions. Everyday farming applications are starting to move into the cloud, with the aim of delivering benefits in terms of data access, synchronization, storage, and even cost to the farmer. The rising use of smart mobile and embedded devices, e.g., Android and the Unix-like operating system (iOS) devices as well as mobile sensors, on farms means that apps can be used to cache data offline until it can be synchronized. Thus, data need not be tied to a single computer in a single location.

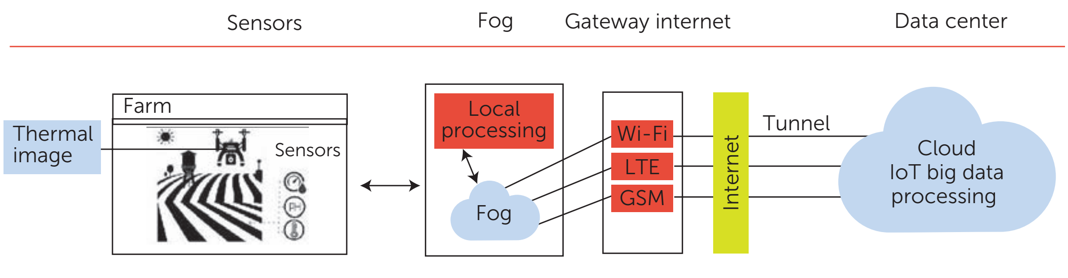

FIGURE 3. Overview of the real time cloud-fog based automated irrigation system.

Irrigation Temperature Distribution Measurement by Thermal Imaging

Irrigation temperature distribution measurement (ITDM) by thermal imaging is based on input from the human visual system and a density-based measure. Let the captured thermal image I is decomposed into Ω blocks. Consider the ω^{th} block, and sorting the density values and intensity of the mentioned blocks, we have the following:

$$P^{\omega}_{min} \leq \cdots \leq P^{\omega}_{[T_\omega]} \leq \cdots \leq P^{\omega}_{max},$$

and

$$I^{\omega}_{min} \leq \cdots \leq I^{\omega}_{[T_\omega]} \leq \cdots \leq I^{\omega}_{max}$$

where I^{ω}_{min} and I^{ω}_{max} represent the minimum and maximum image intensity values of the considered blocks, respectively, and P^{ω}_{min} and P^{ω}_{max} stand for minimum and maximum mass values, which are defined as $P_k = n_k$ Here k is the k^{th} gray level, and n_k is the total number of pixels in the image with gray level k. T_ω is the threshold notation, which is determined as high/low temperature cross-entropy.

The high and low temperature are defined as high-density temperature

$$T^{\omega}_{H} = \sum_{[T_\omega]+1}^{max} P^{\omega}_{i} \Big/ \sum_{min}^{max} P^{\omega}_{i}$$

and low-density temperature

$$T^{\omega}_{L} = \sum_{min}^{[T_\omega]} P^{\omega}_{i} \Big/ \sum_{min}^{max} P^{\omega}_{i},$$

respectively, where T_ω is a threshold that is determined based on minimization of the cross-entropy between the low T^{ω}_{L} and high T^{ω}_{H} temperature of the considered block. To calculate the threshold, an optimization algorithm could be used, such as the genetic algorithm and recursive algorithm. The new temperature distribution measurement is represented as:

$$\mathrm{ITDM} = \frac{1}{k_1 k_2} \sum_{\omega=1}^{\Omega} \frac{T^{\omega}_{L}}{T^{\omega}_{H}} \log \frac{T^{\omega}_{L}}{T^{\omega}_{H}}$$

The schematic diagram of the proposed thermal distribution of irrigation monitoring system is illustrated in Figure 4.[11–14] The mentioned measurements calculate the low- and high-temperature segments of the thermal image. In a practical irrigation system, a thermal image with both low- and high-temperature values for the ITDM will result in a better irrigation system. However the introduced measure could also determine the location of the area that needs water and uniform irrigation (see Figure 5). Therefore, the introduced temperature distribution could be utilized in a smart agricultural COT as a quality measure for automated intelligent CoT-based irrigation systems.

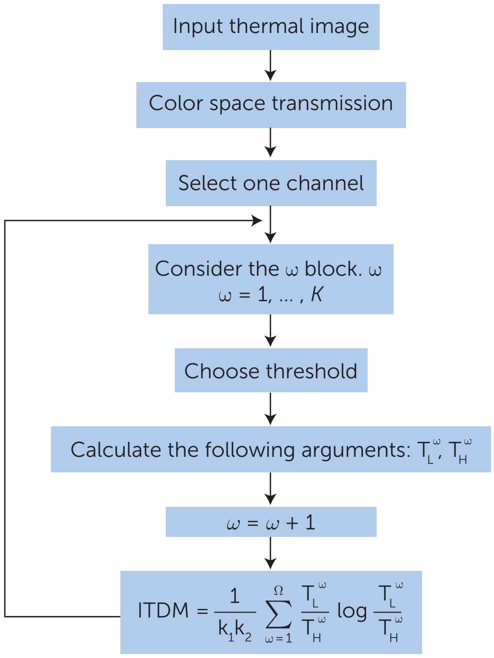

FIGURE 4. Irrigation temperature distribution measurement (ITDM) block diagram irrigation system.

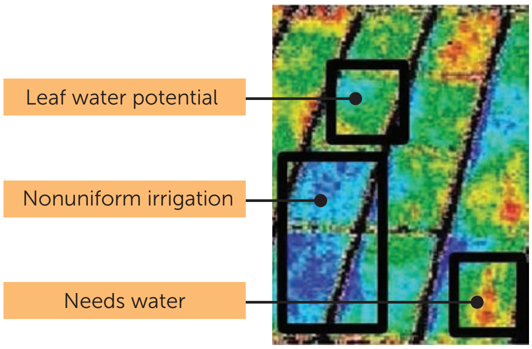

FIGURE 5. ITDM block diagram irrigation system (e.g. location requiring water and communication with CoT for irrigation scheduling).

Security and Regulatory Challenges

CoT-based systems are likely to play an increasingly important role in a number of real-world applications, such as smart agriculture. As with any new consumer and industrial technologies, CoT-based systems, including CoT-based irrigation systems, will go through various phases before such systems eventually becomes mainstream. Unfortunately, these systems potentially have more attack vectors (e.g., hardware, firmware, and applications running on CoT devices) that can be (remotely) exploited by attackers, particularly during early stages and in comparison to traditional, isolated, irrigation systems. The nature of resource-constrained devices or nodes in CoT-based systems and the interdependency of such systems require us to rethink how we design security solutions for CoT systems. For example, limitations in the computational capability of the underlying hardware (e.g., short battery life and less powerful computing capabilities) mean that existing security solutions (that generally require complex cryptography computations such as modular-exponentiation operation) may not be fit-for-purpose. An ongoing challenge in designing lightweight security solutions for CoT-based systems is to strike the right balance between having an optimal security assurance without incurring excessive computational overhead and energy consumption particularly on resource-constrained devices or nodes.[15,16] In addition, it can be an expensive exercise for CoT software and system developers to subject their products to extensive testing prior to release to market. Therefore, there is a need for ongoing research on the building of a security testbed or environment that allows CoT software and system developers to evaluate the security of the systems and the components in a simulated, yet realistic, environment.

The regulatory environment (e.g., data protection and the Internet governance) concerning the deployment of CoT (including Internet of Things (IoT) and Cyber Physical Systems) has also attracted the interest of legal and privacy scholars as well as policymakers. In 2012, for example, the European Union held a public consultation on the need for an IoT-specific legislation. Views from more than 600 individuals, associations, and various groups ranging from academics and civil society as well as industry sectors were voiced. While a large majority of interested citizens and consumer organizations claimed that the current data protection framework is not sufficient and a greater focus on privacy and data protection in the context of IoT is needed,[17] others cautioned of overregulation and unnecessary regulatory burdens in a complex and fast-evolving technological landscape. Such concerns are not surprising because legislation and regulation are generally slower in dealing with technological developments. Also, the time required to develop an appropriate legal and regulatory framework is significantly longer than the time it takes to develop the next-generation CoT systems (or any technologies). More recently in 2015, the European Commission's Alliance for Internet of Things Innovation concluded that regulatory proposal targeting the IoT should address only well-defined market failures that cannot be addressed through existing law and self-regulatory measures as well as the need to be mindful of regulatory error in the complex and fast-evolving technological landscape.[18] In addition to these (generic) legal issues, there could be other industry / sector-specific issues that need to be addressed. For example, in the context of this article, it is important to ensure that the high resolution images collected and processed by CoT-based automated irrigation system are secured and do not violate existing privacy and national security requirements. There is no doubt that one of the ongoing challenges is to draft legislation and regulatory frameworks that are sufficiently flexible and innovative that will keep pace with the complex and constantly evolving technological and threat landscape.

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MEHDI ROOPAEI *(mehdi.roopaei@utsa.edu) is the chief research scientist of Open Cloud Institute at the University of Texas at San Antonio. His research interests include intelligent control systems, artificial intelligence, image processing, vision detection/recognition systems, and deep machine learning. He has a PhD in artificial intelligence from Shiraz University, Iran, and is a senior member of IEEE, AIAA, and ISA.*

PAUL RAD *(paul.rad@utsa.edu) is a cofounder and assistant director of Open Cloud Institute at the University of Texas at San Antonio. His research interests include deep learning, cybersecurity, and cloud computing with applications to cyber-physical, machine vision, and machine to machine decentralized decision making and security. He holds fifteen patents for cyber infrastructure and related solution sets. He has a PhD in electrical and computer engineering with a concentration in big data analytics from the University of Texas at San Antonio.*

KIM-KWANG RAYMOND CHOO *(raymond.choo@fulbrightmail.org) holds the Cloud Technology Endowed Professorship at the University of Texas at San Antonio. His research interests include cyber and information security and digital forensics. He has a PhD in information security from Queensland University of Technology, Australia, and is a fellow of the Australian Computer Society and a senior member of IEEE.*