

# Integration Agricultural Knowledge and Internet of Things for Multi-Agent Deficit Irrigation Control

Yi-Wei Ma<sup>a</sup>, Jin-Qiu Shi<sup>a</sup>, Jiann-Liang Chen<sup>a</sup>, Chia-Chi Hsu<sup>a</sup> and Chen-Hao Chuang<sup>a</sup>

<sup>a</sup> Department of Electrical Engineering, National Taiwan University of Science and Technology, Taiwan

Corresponding Author: a9605340@gmail.com

**Abstract**— Technology related to the Internet of Things and Big Data is developing rapidly, favoring agricultural management and cultivation. External environmental parameters affect crop growth. Irrigation operations involve multi-conditional decisions. Artificial intelligence and image processing technology are used to control watering, process environmental data, and use the processed data are then used to train models to predict soil moisture. The results thus obtained are used to divide soil into that with high, normal, and low moistures. A camera commonly used to capture images of soil, which are imported into a convolutional neural network for feature extraction. Next, the category of soil is predicted following deep learning. The results of the two predictions are sent to a fuzzy control system and the soil moisture interval is defined based on the category of crop that is being planted in it. The rule base is constructed using the defined parameters, and determines the judgment rule from the agricultural professional, And external conditions lead to the fuzzy controller. Defuzzified results are imported into controlled a control device. This work uses the IoT to serialize information from the fields in a farm and uses artificial intelligence techniques to analyze the state of plants. Image recognition technology is to provide more precise and comprehensive control to improve the accuracy of irrigation.

**Keywords**— Internet of Things, Agricultural Knowledge, Intelligent Agriculture

## I. INTRODUCTION

In Taiwan, agricultural technology is improving, and the Internet of Things and artificial intelligence are developing rapidly. The agricultural environment has changed with the global climate, and agricultural cultivation will change as a result. However, most agriculture depends on artificial judgment and the operation. and today's erroneous agricultural knowledge cannot be combined effectively with new knowledge. Today, old methods of agricultural cultivation are causing poor plant growth.

However, the Internet of Things has increased the rate at which information can be collected, processed, analyzed and applied. The collection of information is simpler today than ever before. After a large amount of information is collected, the state of the information is analyzed. The purpose of artificial intelligence is to derive results based on trends in data, and to correct results with reference to changes or offsets of the data. Using artificial intelligence in highly variable environments can help the consequences of external effects to be dealt with.

Therefore, the output can be varied such changes. Suitable for systems that cannot be judged directly.

## II. BACKGROUND KNOWLEDGE

### A. Fuzzy control

Fuzzy control is used when the control condition is not directly judgment, but the result that is obtained by scrutinizing various categories y states. The derivation of fuzzy logic requires the construction of an expert rule base, according to which each state must be defined.

Rodolfo Salazara et al. studied the state of soil using multiple sensors, and interpolated collected data to define values between collected values and to perform irrigation using fuzzy logic. This method of irrigation is comprehensive [1].

### B. Image recognition

Image recognition refers to analyzing images to obtain useful information. Images contain a large amount of important information and are easily obtained on a daily basis. In the past, images were captured manually. Today, techniques such as information capture, segmentation, filtering, and tracking can be performed using a computer, enabling faster identification of image.

Zhuoyi Rao et al. studied embedded image recognition system with MEC (Mobile Edge Computing) architecture, which can solve the problem of slow information transmission after cloud computing. Performing operation closer to the local end can reduce the time required for information transmission. Image recognition architectures are of two types – with mobile cameras and with non-mobile cameras. Static tracking is performed using fixed cameras and dynamic tracking is performed using mobile cameras [2].

Kaiming He et al. studied deep residual learning to solve the understand the phenomenon of gradient explosion or disappearance as a result of excessively deep CNN network architecture. This paper concerns the problem of the reduction of accuracy as a result of excessively deep network architecture, with reference to the function of the input layer. To evaluate the parameters of the next state, the system can be optimized. The ImageNet dataset is used to train samples. The experimental results indicate that the architecture is more accurate in deeper neural networks [3].

### C. Machine learning

The purpose of machine learning is to extract knowledge from complex and diverse information; to update and improve continually the architecture of algorithm using related algorithms. The core value of this method is that when the best solution is unavailable, it finds a reasonable answer based on previous data. Machine learning can be supervised or unsupervised.

Daniel Smith et al. identified types of soil by machine learning. They used the UNSODA database to provide research data, and training by the characteristics of the soil model. They used multiple machine learning calculations to achieve MLP (Multi-Layer Perceptron). The neural network accuracy was 85.11% [4].

#### D. Big data

Big data, also known as massive data, has been widely used by enterprises to provide business intelligence and for statistical purposes. However, big data is not just used for data processing; it is also used to model businesses. Since the volume of collected data is increasing rapidly, the cost of storage devices has dropped, software technology has evolved; the cloud environment has matured; and data analysis has evolved from gaining insights about the past to predicting the future. Big data can be used to detect business trends; determine the quality of research; prevent the spread of disease; combat crime; and measure complex conditions, such as traffic conditions in real time.

Ji-chun Zhao et al. studied researched the introduction of agricultural knowledge bases and the use of agricultural big data, and built a wheat cultivation system with big data as its core. The system analyzed on pests and diseases [5].

Wang Dongjie et al. used an agricultural big database to analyze the data and explore the impact of corn yield on the environment. The analytical methods included regression analysis, and the use of neural networks and tree models to extract knowledge from agricultural data. Evaluate the appropriate model using R-Square [6].

Peng Zhang et al. studied the construction of a big data-based watering system with the aim of reducing the wastage of irrigation resources and performing comprehensive management. Research architecture is divided into a data collection layer, a transmission layer, a big data database and a decision-making layer, and This architecture is applied to control the agricultural water resources in Binzhou City, Shandong Province, China. construct a watering model and monitoring system, and master and accurately implement watering [7].

### III. SYSTEM ARCHITECTURE AND ANALYSIS

#### A. Hardware architecture

This thesis concerns the implementation of an intelligent watering system at HappyFarm. The system comprises a control system and a sensing system. The sensing system senses temperature and humidity using an electronic sensing device. The temperature change of the environment is measured using a thermistor, and uses the trend of the resistance value to find temperature. The relative humidity is obtained from the

psychrometer. The soil sensing device monitors the conductivity of the soil, the change of the temperature and humidity of the soil. The light sensing device has a photo resistor that measures the change of the external ambient illuminance. Voltage difference is used to obtain the brightness LUX (luminous exitance) value. The outputs of the three sensing devices are input to the controller via a digital analog converter, and converted to a numerical value, and the calculated values are passed to the Wi-Fi module. ROUTER receives the information that is transmitted by Wi-Fi, and transfers it to a neural network, as schematically depicted in Fig.1.

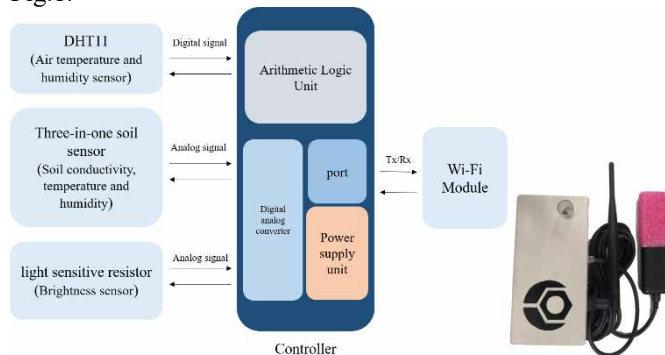


Figure 1. Sensor architecture

The control system includes a relay to control the water valve and a WIFI module to receive the control signal. A flow sensing device to collect information about the flow and to control it. While receiving the irrigation signal, the WIFI module also receives the ROUTER's ACK response and releases it to the controller. The controller digitizes the signal for use by the relay. The relay operates the water valve switch, and the flow sensor collects data and transmits them to the controller. When the flow reaches set threshold, the drive relay is turned off, and so irrigation stops.

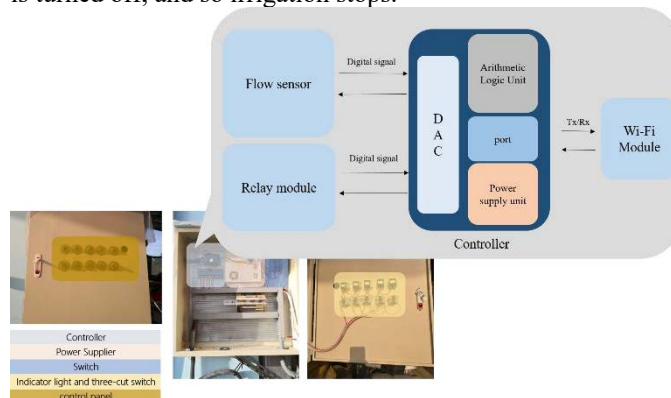


Figure 2. Water valve controller hardware architecture

#### B. Control method

This paper discusses the influence of the environment. The environment in which plants grow is affected by external factors. When weather conditions change, the state of the soil changes with them. The state of the soil affects plant growth. The system determines the state of the soil from the signal that is obtained from the corresponding sensor, and uses image information to identify the state of the plants. Based on the

states of the plants and the soil, a fuzzy control system controls watering.

### 1) Machine learning:

Machine learning involves classification and clustering rules. In this investigation, the tree-structured Random Forest algorithm in the machine learning is used. The Random Forest algorithm involves voting and multiple decision trees. IG (Information Gain) are used as standard to build the decision trees. IG convey the results of calculations of two variables : (1) entropy and (2) Gini impurity, which are expressed as follows.

$$I_H(t) = - \sum_{i=1}^c p(i|t) \log_2 p(i|t) \quad (1)$$

$$I_G(t) = \sum_{i=1}^c p(i|t)(1 - p(i|t)) = 1 - \sum_{i=1}^c p(i|t)^2 \quad (2)$$

The two formulas useful information, and capture important features, and establish a decision tree, as shown in Fig. 3.

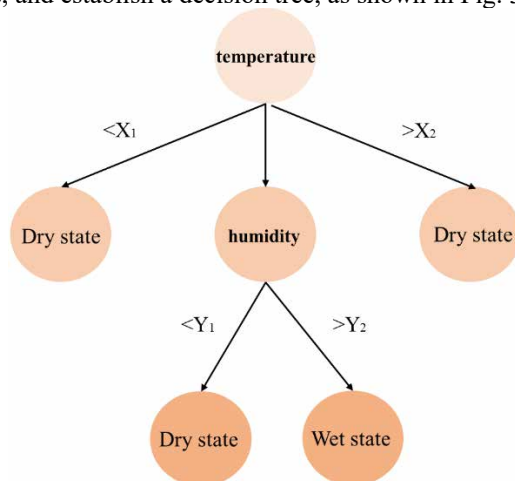


Figure 3. Decision tree

Random Forest is an extension of the decision tree. Since a single decision tree is likely to cause over-fitting during training model, it provides high accuracy during training, but performs less well on actual samples. Because multiple iteration will cause the model to be affected by a few noises, thus affecting accuracy. Random Forest is composed of multiple weak classifiers to solve the problem of over-fitting a single decision tree. Random samples and features are used to build each weak classifiers. Random Forest is the final result of reducing the part of the noise that causes over-fitting of the model during training.

The data set that was used herein was collected on the farm. It includes air temperature (TP), air humidity (AH), soil temperature (GT), electrical conductivity (EC) during the day and the night (LUM), and soil state (LAB). The soil state is specified as high humidity (H) and low humidity (L). The number of data is 61063, and the data distribution are plotted in Fig. 4.

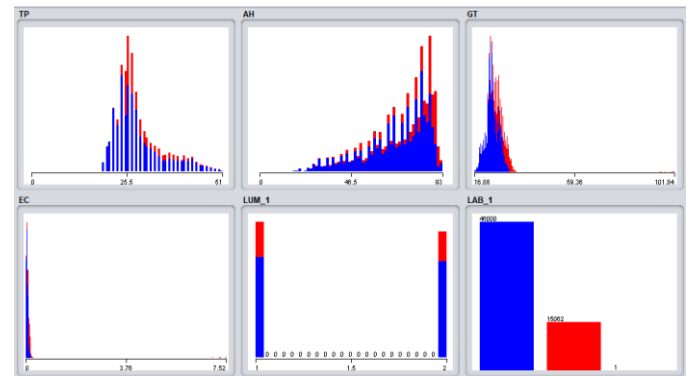


Figure 4. Data status map

The software WEKA (Waikato Environment for Knowledge Analysis) is used for data classification. It provides such functions as data processing, feature selection, classification, regression, clustering, application of association rules and visualization. The Random Forest algorithm for weak classification and 10-fold cross-validation in the test data set are used. Figure 5 shows the results thus obtained. In this training results, the overall accuracy of the model is 94.0422%.

```

=== Summary ===
Correctly Classified Instances      57425          94.0422 %
Incorrectly Classified Instances    3638           5.9578 %
Kappa statistic                    0.8388
Mean absolute error                 0.0775
Root mean squared error             0.2075
Relative absolute error             20.8532 %
Root relative squared error         48.1462 %
Total Number of Instances          61063

=== Detailed Accuracy By Class ===

```

|               | TP Rate | FP Rate | Precision | Recall | F-Measure | MCC   | ROC Area | PRC Area | Class |
|---------------|---------|---------|-----------|--------|-----------|-------|----------|----------|-------|
| Weighted Avg. | 0.963   | 0.129   | 0.958     | 0.963  | 0.961     | 0.839 | 0.982    | 0.993    | L     |
|               | 0.871   | 0.037   | 0.885     | 0.871  | 0.878     | 0.839 | 0.982    | 0.951    | H     |
|               | 0.940   | 0.106   | 0.940     | 0.940  | 0.940     | 0.839 | 0.982    | 0.983    |       |

```

=== Confusion Matrix ===
      a    b  <-- classified as
44304 1697 |    a = L
 1941 13121 |    b = H

```

Figure 5. RandomForest training results

Figure 6 shows the feature importance using attribute ranking. Following the analysis of feature importance, soil electrical conductivity (EC) and soil temperature (GT) are found to have the strongest influence in the model. value is strongly related to the soil state, and soil state is an important feature.

```

=== Attribute Selection on all input data ===

Search Method:
  Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 6 LAB_1):
  Information Gain Ranking Filter

Ranked attributes:
0.316459  4  EC
0.245388  3  GT
0.086819  1  TP
0.083182  2  AH
0.000512  5  LUM_1

Selected attributes: 4,3,1,2,5 : 5

```

Figure 6. Feature importance analysis

### 2) Image recognition:

The samples images that were collected by the study are photographs that were taken on the farm. The photographs were taken in three periods– the seedling stage, the growth stage and the maturity stage. Figure 7 shows the seedling stage. The scene in the seedling stage is relatively empty because the roots have not deepened, so the water demand is not high. Figure 8 shows the state at maturity, when the roots are deep and more water is required. Since the number and areas of leaves are larger, the evapotranspiration of the plants is faster and the water demand is larger.



Figure 7. Seedling stage



Figure 8. Mature period

Image analysis is performed using the architecture of Convolutional Neural Network (CNN), which includes an initial input layer, a convolutional layer and a pooling layer, which perform characteristic extractions and attribute classification.

The input layer is the starting layer of the CNN architecture. In the convolutional neural network, it is represented as a matrix of pixels with particular length, width, and depth. The convolutional layer is the core of the CNN architecture. The image that is input to the input layer is converted thereby into pixels and scan for features by filter. The scan size is specified manually, and the depth is determined by the number of filters. As indicated in Eq. (3),  $g(i)$  represents the value of the  $i$ -th pixel, and  $x_{j,k,l}$  is the value of pixel  $(j, k, l)$  in the filter;  $w_{j,k,l}^i$  represents the weight of the filter of the  $i$ -th pixel in the matrix of the unit pixel, and  $b^i$  represents the offset parameter of the  $i$ -th output.

$$g(i) = f \left( \sum_{j=1}^{x_j} \sum_{k=1}^{x_k} \sum_{l=1}^{x_l} x_{j,k,l} * w_{j,k,l}^i + b^i \right) \quad (3)$$

The pooling layer is usually located between convolutional layers. It reduces pixel points, and then reduces the size of the matrix, reducing the computational complexity of the model. In addition to speeding up the calculation, it prevents overfitting. After the convolutional layer and the pooled layer have processed, the image features can be processed by the data. The main purpose of the fully connected layer is to classify the images that have been characterized. The excitation function layer is mainly used to normalize the output.

Tensorflow in Python is used to implement the CNN architecture, which includes two layers – a convolutional layer and a pooling layer - to reduce the dimensionality and overall computational complexity. Use softmax to classify after the fully connected layer to predict soil category. The training includes three stages - seedling stage, growth stage and maturity stage.

### 3) Fuzzy control:

In the fuzzy control system, each parameter is defined in set interval, and the rule base is built according to the parameters. It establishes includes expert judgment rule, and the external environmental condition is in the fuzzy controller. Controller implement soil watering, as shown in Fig. 9. In this multi-condition system, fuzzy control of the watering provides accuracy.

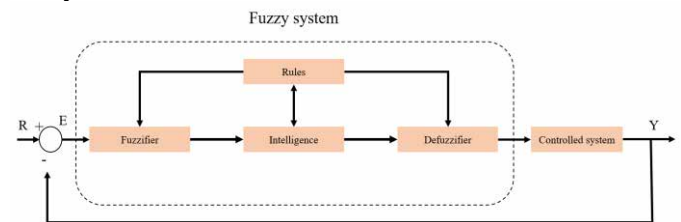


Figure 9. Fuzzy system

The machine learning and image recognition system herein predicts soil condition and plant growth status. The soil state is specified as high humidity (H) or low humidity (L). Plant growth status is three defined categories of seedling, growth and maturity, Table 1 presents the control rules based on agricultural knowledge.

Table 1. control rules table

| RULE | IF          |              | THEN   |
|------|-------------|--------------|--------|
|      | Soil status | Plant status | OUTPUT |
| 1    | H           | seedling     | OFF    |
| 2    | H           | Growth       | OFF    |
| 3    | H           | Maturity     | ON     |
| 4    | L           | seedling     | OFF    |
| 5    | L           | Growth       | ON     |
| 6    | L           | Maturity     | ON     |

After the rule table has been created and loading microprocessor, the trigger rule in the microprocessor is established. High humidity is represented as 1; low humidity is represented as 0. The seedling period is represented as 0; the growth period is 1/2, and the maturity period is 1. Define two sets and execute max, and use the maximum as the output, as shown in Table 2.

Table 2. rule triggering method

| Rule Table |                         |
|------------|-------------------------|
| Rule1:     | $\text{Max}\{1,0\} = 1$ |
| Rule2:     | $\text{Max}\{0,0\} = 0$ |
| Rule3:     | $\text{Max}\{0,1\} = 1$ |

After the trigger rules and conditions are established, and execute according to the rules and connected to the control system. In this system, Watering decision by multiple conditions. Calculation results after the judgment is made output to the system to realize watering, as shown in Fig.10.

| Soil status | Plant status |          |        |          |
|-------------|--------------|----------|--------|----------|
|             |              | seedling | Growth | Maturity |
|             | H            | 0        | 0      | 1        |
|             | L            | 0        | 1      | 1        |

Figure 10. Control state diagram (1: ON, 0: OFF)

### C. Multi-agent system integration and application

This system is developed by multi-many agents. The master agent manages the operation and selection of users. A user can choose a control mode according to the current situation. Modes include: scheduling control, threshold control and intelligent control. The current conditions are determined and the control message is sent to the control agent. The field agent is responsible for collecting various environmental data and network information. Sent to the master agent and the control agent as a basis for judgment. When the control agent receives the control signal, the control rules will be applied, and the most recent environmental change is stored in the database for reference by other agents. Effective division of labor with multi-many agents, as shown in Fig. 11.

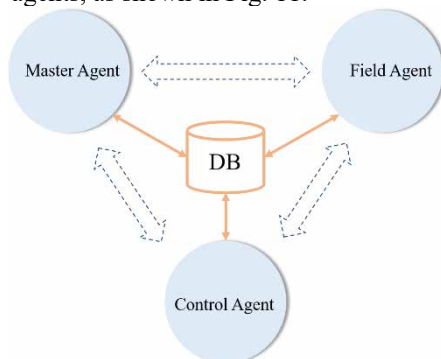


Figure 11. Multi-agent system architecture

## IV. CONCLUSIONS

This paper studies the analysis of useful knowledge from large amounts of diverse information about the environment, and converted to control signals. Machine learning and image recognition are used to analyze information from the field, to

extract useful knowledge from a large amount of environmental information and image information, and to analyze information. Analysis result imported into the fuzzy control system. fuzzy control system can effectively exploit the understanding of the environment thus obtained. The cost to agriculture of environmental changes is thus reduced, and cultivation is improved.

## ACKNOWLEDGMENT

Authors thank for financial supports of the Ministry of Science and Technology, Taiwan under contract MOST 107-2218-E-007-004. And the authors would like to thank the Happfarm for providing experimental fields and related agricultural knowledge.

## REFERENCES

- [1] R. Salazar, J.C. Rangel, C. Pinzón and A. Rodríguez, "Irrigation System through Intelligent Agents Implemented with Arduino Technology," *Advances in Distributed Computing and Artificial Intelligence Journal*, vol.2, no.3, pp. 29-36, 2013.
- [2] J. Ren, Y. Guo, D. Zhang, Q. Liua and Y. Zhang, "Distributed and Efficient Object Detection in Edge Computing: Challenges and Solutions," *Proceedings of IEEE Network*, pp. 1-7, 2018.
- [3] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770-778, 2016.
- [4] D. Smith and W. Peng, "Machine learning approaches for soil classification in a multi-agent deficit irrigation control system," *Proceedings of 2009 IEEE International Conference on Industrial Technology*, pp. 1-6, 2009.
- [5] J. Zhao and J. Guo, "Big data analysis technology application in agricultural intelligence decision system," *Proceedings of IEEE 3rd International Conference on Cloud Computing and Big Data Analysis*, pp. 209-212, 2018.
- [6] W. Dongjie, L. Zhemin and W. Shengwei, "Exploring the relationship between maize yield and climate big data on maize belt of northeast China," *Proceedings of IEEE 2nd International Conference on Big Data Analysis*, pp.513-516, 2017.
- [7] P. Zhang, Q. Zhang and F. Liu, "The Construction of the Integration of Water and Fertilizer Smart Water Saving Irrigation System Based on Big Data," *Proceedings of IEEE International Conference on Computational Science and Engineering and IEEE International Conference on Embedded and Ubiquitous Computing*, pp.392-397, 2017.



Yi-Wei Ma is an assistant professor in National Taiwan University of Science and Technology. He received the Ph.D. degree in Department of Engineering Science at National Cheng Kung University, Tainan, Taiwan in 2011. He received the M.S. degree in Computer Science and Information Engineering from National Dong Hwa University, Hualien, Taiwan in 2008. His research interests include internet of things, cloud computing, multimedia p2p streaming, digital home network, embedded system and ubiquitous computing.



Jin-Qiu Shi studying the M.S. degree in Electrical Engineering of National Taiwan University of Science and Technology, Taipei, Taiwan. His research interests include internet of things, and intelligent agriculture.



Jiann-Liang Chen was born in Taiwan on December 15, 1963. He received the Ph.D. degree in Electrical Engineering from National Taiwan University, Taipei, Taiwan in 1989. Since August 2008, he has been with the Department of Electrical Engineering of National Taiwan University of Science and Technology, where he is a professor now. His current research interests are directed at cellular mobility management and personal communication systems.



Chia-Chi Hsu studying the M.S. degree in Electrical Engineering of National Taiwan University of Science and Technology, Taipei, Taiwan. His research interests include internet of things, and intelligent agriculture.



Chen-Hao Chuang studying the M.S. degree in Electrical Engineering of National Taiwan University of Science and Technology, Taipei, Taiwan. His research interests include internet of things, and intelligent agriculture.