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The Smart Agriculture based on Reconstructed Thermal Image

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A B S T R A C T

The utilization of thermal image in supporting precision agriculture is tremendous nowadays. There are many applications of thermal images in agricultural fields, such as detecting crop water stress, monitoring of free-range rabbits, measuring of crop canopy temperature and so on. Furthermore, the importance of thermal camera became the urgent need of perform the smart agriculture. Otherwise, the price of thermal camera is very expensive todays. Then, this kind of camera is not easy to find in the market. Therefore, it makes the utilization of implementation thermal images difficult. In order to handle this problem, the proposed method intends to generate thermal image from visible images. Further, the thermal information concerning with the agriculture, especially the fertility of leaves in paddy fields and the water stress can be monitored. The proposed method uses deep learning architecture to learn the thermal and visible image dataset. It applies Generative Adversarial Network architecture. This GAN pre-trained model trained using 150 images of training dataset and tested using many images of testset. The obtained model is used for generating thermal images from visible images. The results show the constructed thermal image has high accuracy. The assessment metric uses SSIM and PSNR methods. Their indexes show that the results have the high accuracy. The visual assessment shows the reconstructed thermal images also have high precision. Finally, the constructed thermal images can be implemented in smart agriculture purposes.

INTRODUCTION

World's need of agricultural product is predicted to rise by 50% in 30 years. Further, the agricultural production should increase as high as 2.4 % per year[1]. On the other side, the expansion of land used for agriculture is very little. In addition, the impact of extreme climate might give the disreputable output of agricultural product in many countries in the world. As the threatening of agricultural yields impact is very clear, it is needed an effort to ensure the availability of food security for the future. There are many methods used to ensure the security of food, such as improvement of soil-crop management practices, so it can escalade production to reach the optimum yields[2]. The useful strategy to increase the quality of the yields is through monitoring leaf temperature[3]. The leaf temperature is a standard indicator of plant water stress[4]. The stomatal closure is known as a sensor of root signaling. The stomata close under water deficit, leaf temperature rise. In order to determine the stressed and unstressed plant, it is needed thermal information. The complete and efficient method to obtain thermal information of the canopy temperature, it is needed thermal camera. This thermal camera is able to deliver the information of canopy temperature completely. Moreover, this information makes the understanding of canopy temperature becomes easier to read and faster to comprehend. The visible image of leaves is as shown in Figure 1 below.

Figure 1. The area of interest on thermal image of digital image[4]

Based on Figure 1 region of interest, the thermal information of the canopy is as shown in Figure 2 below. The high and low temperature scores of canopy are according to temperature bar at right side of thermal image. The red color is higher than yellow and green colors. The white is the highest score of temperature. As the temperature is high, the stomata is close, it means the leaf keeps the water inside because of deficit of water stress.

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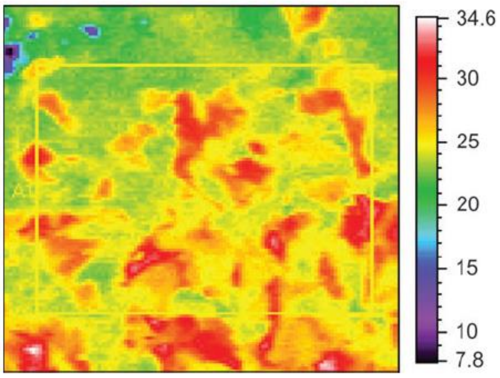

Figure 2. The thermal image of region of interest of Figure 1 [4]

Since, the use of thermal image is very important to understand the leave temperature in smart agriculture, that the need of thermal camera is very urgent and inevitable. Otherwise, the availability of thermal camera is only at certain places and difficult to find in common market. Thus, the price of thermal camera is very expensive. As a result, to possess the thermal camera is very difficult for everyone. In order to handle this problem, the proposed method is generating the thermal image from visible image using deep learning model. This proposed method produce the thermal information in the form of image is obtained with affordable price and easier.

METHOD

The application of image processing in many field and in various image forms are ubiquitous todays. The advancement of hardware and software of computer computation makes development of artificial intelligent runs faster. One of the famous artificial intelligent computation todays is deep learning[5]. One of the popular purpose of deep learning is to perform prediction task[6]. The prediction task is very important in changes of environment and behavior of object. It is applied in many applications such as surveillance and monitoring, autonomous driving and scene understanding.

Besides using visible images or RGB images, the thermal images also are implemented in agricultural fields. The very common purpose is for monitoring agricultural fields. The thermal camera is used for detecting free-range rabbits[7], assessing crop water stress[8], measuring crop canopy temperature[9] and detection of stress response in grapevine[4]. The high price of thermal cameras, make them difficult to obtain by the common farmers.

Meanwhile, the use of deep learning is very common in visible image. As it is mentioned previously on the above paragraph. This task aims to show the visual appearance of the predicted object and the scene to other form of image[6]. The predicting projected image from input or original image in image processing field is called image translation[10]. This method can be implemented in many applications such as image stylist, cartoon generation and so on. The image translation can be formulated as in Equation (1) as follow:

$$x_{AB} \in B : x_{AB} = G_{A \to B}(x_A) \quad (1)$$

Where $G_{A\to B}$ is a mapping of input image x_A to target image x_B. There were many methods of image translation available. Nevertheless, the vary famous are the method uses Variational Auto Encoder[11] and Generative Adversarial Network[12]. The others methods in general are the generative of those methods. Otherwise, the proposed method perform the implementation of RGB image to generate IR image. The method uses a Generative Adversarial Network architecture to predict the IR image from RGB image.

The Generative Adversarial Network is a modelling framework that contains two multilayer perceptrons. The first is determine the prior on input noise variable p_z (Z). Then, denote the mapping of data space as $G(z;\ \theta_g)$, where G is a function represented by a multilayer perseptron with parameter θ_g. The second multilayers perceptron $D(x;\ \theta_d)$. $D(x)$ indicates the probability of x came from the data rather than p_g. The p_g is generator's distribution over data x. Then, the training of D to maximize the probability of assigning the correct label to both training example and sample from G. The training of G to minimize log(1-D(G(z))). In addition, D and G play the following two-player minimax game with value function V(G,D). The process of training is formulated as in Equation (2).

$$\underset{G}{min}\,\underset{D}{max}\, V(D,G) = E_{x\sim pdata}[\log D(x)] + E_{z\sim pz(z)}[\log(1 - D(G(z)))] \quad (2)$$

The above equation can be drawn as in Figure 3, below.

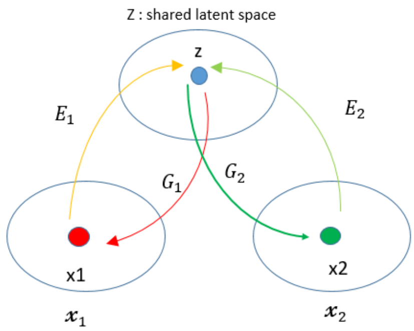

Figure 3. The shared latent assumption

The pair of corresponding images (x_1,x_2) in two different domains, X_1 and X_2. . They can be mapped into a same latent code z in a share latent space Z. Otherwise, E_1 and E_2 are two encoding functions. These function mapped images into latent codes. Furthermore, G_1 and G_2 are two generation functions. These functions mapped the latent codes into images[13]. The network architecture is as shown in Figure 4 below.

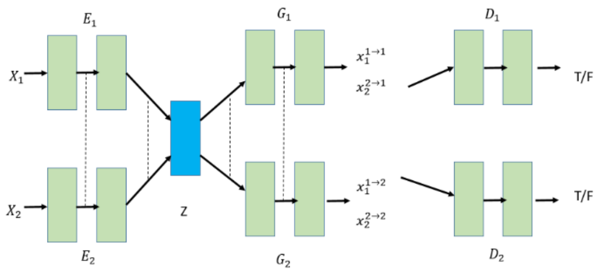

Figure 4. The network architecture

The architecture contains multilayer perceptron. The implementation of CNN model is used for encoding and generation functions, E_1, E_2, G_1 and G_2 respectively. The dashes lines show the weight sharing constraint. The shared-weight is placed at the end of few layers in encoding functions, nevertheless the few beginning layers of generation functions are tied with shared weight. Then, the $x_1^{1\to1}$ and $x_2^{2\to2}$ are self-reconstructed images, and $x_1^{1\to2}$ and $x_2^{2\to1}$ are the domain-translated images. In addition, the $D_1$and D_2 are the adversarial discriminators for respective domain.

Training Process

Training Dataset

The training dataset contains the infrared (IR) images and RGB images. The number of IR image is 75 and the same as RGB images. The sample of RGB images for training process are as shown in Figure 5 below.

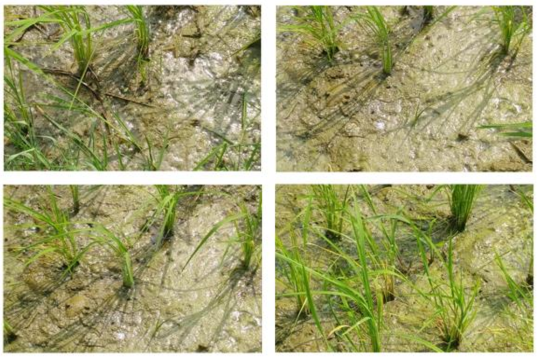

Figure 5. The sample of RGB images

The training process involves generating of discriminator network for visible image and IR image. The parameters for this network include number of sampling blocks, filter size, initialization of conv weight and normalization layers.

The RGB images are taken through RGB camera. They are registered with the IR images. The size and orientation of those images dataset are the same. Further, the training process obtained the dataset from the datastore. It is indexed and separated with the IR dataset. Otherwise, training parameters are adjusted to find the accurate model. The learning rate is given by 0.0001. This makes the learning work slowly but gives accurate response. The other parameters are mini batch and number of epoch. They are 1 and 6 respectively. These parameters work faster to complete the learning process. The generator network is as shown in Figure 6 below.

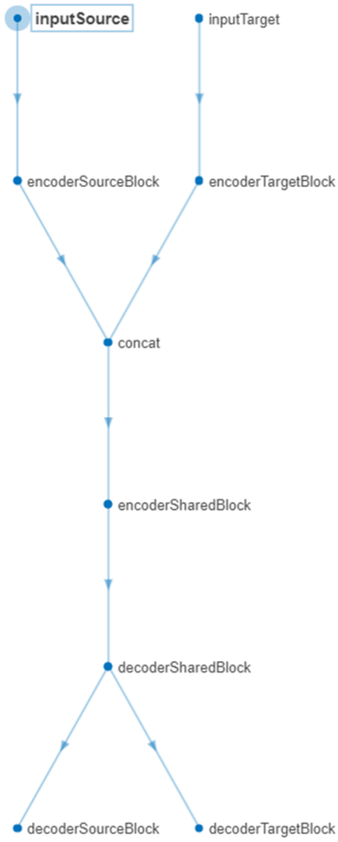

Figure 6. Generator Network to perform image translation

The unit generator network contains two inputs (source and target images) and four outputs (two self-reconstructed image and two translated images) created to perform image to image translation operation. The IR image dataset for training the model is as shown in Figure 7 below.

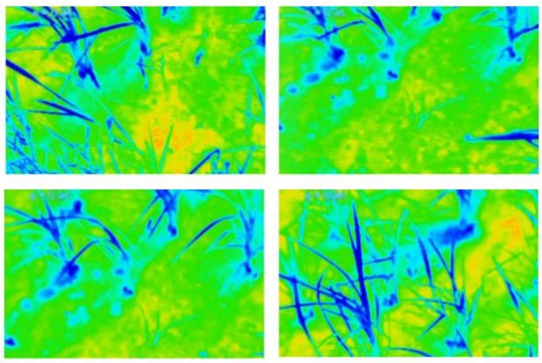

Figure 7. The sample of IR images for training dataset

Otherwise, the discriminators of visible images and IR images are generated through pathGAN discriminator network. The visible image of discriminator networks contains convolution layers and ReLu layers. The final layer is convolution layers. The input image has image size 256 x 256 x 3. The last layers has 16 x 16 x 1 image size. The whole network of this discriminator consists of 6 layers of conv and 5 layers of ReLu.

The architecture of discriminator network of IR image has the same architecture and parameter with visible image. The detail of discriminator network is as shown in Figure 8 below.
The output of this processing is model network.

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The training process involves parameters such as number of epoch, it is 6. Input size, dataset, learning rate, gradient decay, mini batch size and loss weights.

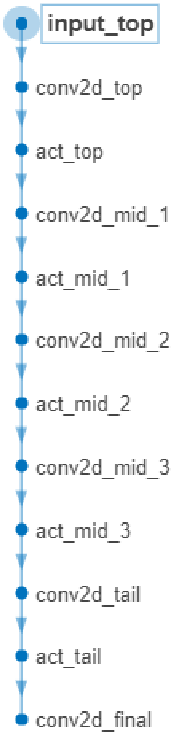

Figure 8. Discriminator network architecture

Testing Process

The testing process is involves testing visible images set, the pre-trained network model and translation operation prediction process function. The RGB test dataset is as shown in Figure 9 below.

1

2

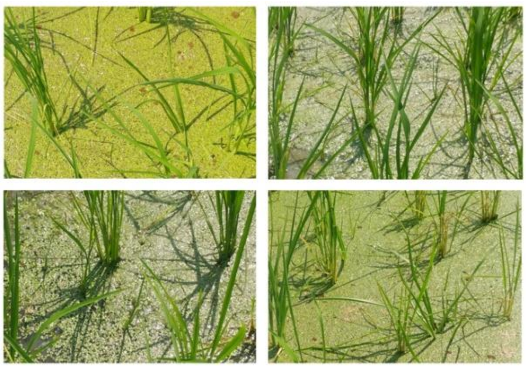

Figure 9. RGB images for testing the network

The input images of the network are RGB images only. These images become the input of the network model to generate reconstructed IR images. Then, these RGB images are absolutely different with the training dataset. The RGB images have been registered, that they have the same size and scene with the IR images.

3

4

5

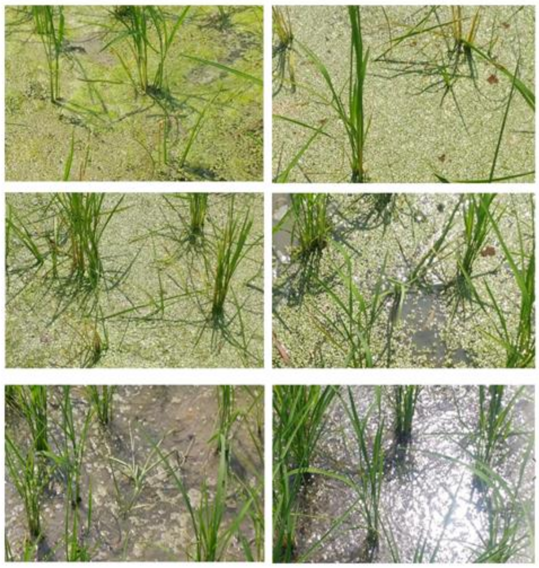

Figure 10 Testing images (continuity)

The time needed for testing the image is fast, only for several minutes.

RESULTS AND DISCUSSION

The result of the predicting thermal images from RGB images are as shown in Figure 10 below.

1

2

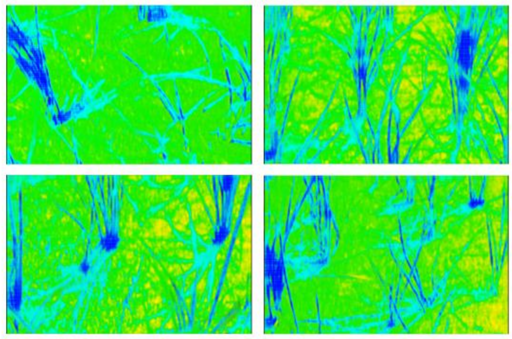

Figure 10 The reconstructed thermal image of RGB image

Figure 10 is the first two rows of reconstructed thermal images. These reconstructed IR images are output of the input visual images as shown in Figure 9. The first and the second rows of the Figure 10 are generated based on the visual images as shown in Figure 9. The reconstructed IR images can represent clearly the information of canopy temperature on the paddy's leaves. The darker of the reconstructed IR images show that the canopy temperature is high. Otherwise, the brighter color map of reconstructed IR images show the canopy temperature is lower. In the Figure 10, the blue color map is mapped as a leaf of the paddy. Since, the leaf contains water inside or because of water stress of the plant.

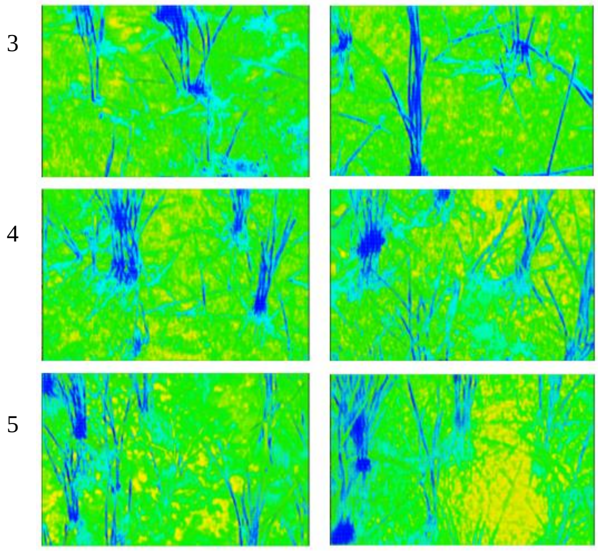

Figure 11. The reconstructed thermal images (continuity)

Figure 11 is the continuity of the Figure 10. The number of row IR image, reconstructed IR images is as according to the number of RGB images.

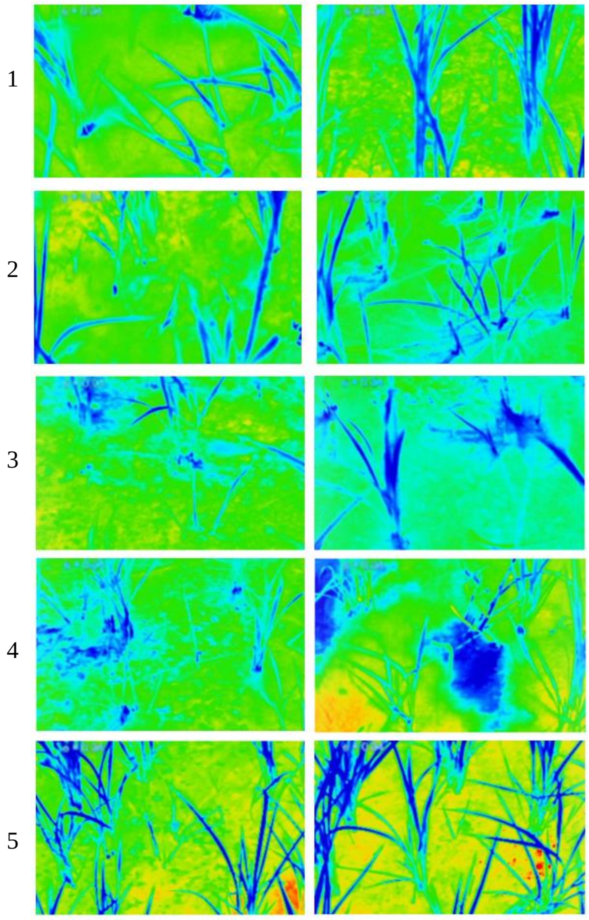

Figure 12 The ground truth of thermal image

The ground truth image is the target image. Based on each this image, the quality of reconstructed IR image can be measured. The first column of the reconstructed IR images can be compared to the first column of the ground truth IR images. The second column of reconstructed IR image also can be compared with the second column of ground truth IR images.

Based on the comparison, it can be stated that the reconstructed IR images have high quality, since they are look like very similar each other. Visually, the performance of reconstructed IR images have been able to present the high of low temperature of paddy's leaf. The canopy temperature can be understand well through read or see the reconstructed IR images. Furthermore, these reconstructed IR images.

CONCLUSIONS

The IR images is very important to measure the fertility and plant water stress in agricultural process. The IR image is able to deliver the information clearly and accurately about canopy temperature. Further, the agricultural management can increase and develop the production rate rapidly. Otherwise, the thermal camera price is very high and rare in the common market. The generating of reconstructed IR images is the best and efficient solution to handle the problem. The results show that the reconstructed IR image have the high accuracy. Further, they can be a reference to analyze the fertility of the leaf, especially paddy. The visual assessment is done through comparison with target IR images. They show that the difference between reconstructed IR image and ground truth (target) IR images have high similarity. Based on the above result, it can be stated that reconstructed IR image can be applied well to measure the fertility and water stress of the paddy's leaf.

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