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Soil Moisture Retrieval from Airborne Multispectral and Infrared Images using Convolutional Neural Network ⋆

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Abstract: This paper deals with the modeling of soil moisture retrieval from multispectral and infrared (IR) images using convolutional neural network (CNN). Since it is difficult to measure the soil moisture level of large fields, it is essential to retrieve soil moisture level from remotely sensed data. Quadrotor unmanned aerial vehicle (UAV) is considered as sensing platform in order to acquire data with high spatial resolution at anytime by non-experts. With considerations both on the availability of sensors for the platform and the information needed to overcome the effects of the canopies covering soil, IR and multispectral images are selected to be used for soil moisture retrieval. In order to prevent information loss by the calculation of parameters from measurements and enhance the applicabiliy for online operations, CNN is applied for the construction of soil moisture retrieval model to use the sensor measurement images directly as input data. Training and testing are conducted for the proposed CNN-based soil moisture retrieval model using the data from actual quadrotor flight over an agricultural field.

Keywords: Remote Sensing, Sensor Fusion, Convolutional Neural Network, Soil Moisture Retrieval

1. INTRODUCTION

Soil moisture is obviously one of the most crucial factor to be monitored in agricultural fields. The stress level and health of crops are highly dependent on the moisture contained in them, which is directly related with the soil moisture level. Thus, it is essential to observe the moisture content of soil and conduct proper irrigation. However, for large areas of agricultural fields, it is difficult and expensive to construct static sensor systems for soil moisture level measurement to cover all the areas. Measuring the soil moisture level with mobile sensors require a lot of time and manpower. This means that an algorithm or a model to estimate the soil moisture level from the remotely sensed data of the agricultural field is required.

Several points are required to be considered for the design of soil moisture retrieval system. The first point is which platform to utilize for the remote sensing. Satellites are commonly utilized remote sensing platforms for the soil moisture retrieval of the previous studies in Sandholt et al. (2002); Ahmad et al. (2010); Younis and Iqbal (2015); Paloscia et al. (2008). The sensors are able to be mounted on an aircraft, as proposed in Notarnicola et al. (2006). However, the spatial resolution of the images acquired from satellites or large agricultural aircrafts are too low. This implies that the precise investigation on the soil moisture level for each point of the agricultural field is difficult. Also, these platforms are difficult and expensive to operate. More importantly, the availability of the platforms are highly limited. A satellite can observe a certain agricultural field only when it passes over that area. Aircrafts require trained and experienced pilots, who are not always available. In this study, a small quadrotor unmanned aerial vehicle (UAV) is utilized as a remote sensing platform. Since it fly over the fields at extremely lower altitude than satellites or aircrafts, the spatial resolutions of the data measured with UAV are much higher. Also, this platform obviously requires much less cost, and it can be operated easily by non-experts. Moreover, UAV can conduct data acquisition at anytime required by users.

The next consideration is the selection of sensors to be utilized for soil moisture retrieval. Since remote sensings are usually conducted from the above of the agricultural field, when the field is covered by crops or grass, the measurements on soil are affected by the canopy. Thus, it is important to decide a sensor or a combination of

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sensors to obtain the soil moisture information and exclude the effects of the canopy. Radiometer has been utilized for the soil moisture retrieval of canopied soil in previous studies. Microwave radiometers are applied in Liou et al. (2001); Del Frate et al. (2003). Sandholt et al. (2002) used multiple-channel radiometer (Advanced Very High Resolution Radiometer, AVHRR). Synthetic aperture radar (SAR) (ENVIronmental SATellite, ENVISAT/Advanced Systhetic Aperture Radar, ASAR) is considered in Paloscia et al. (2008). Also, combinations of radar with an additional sensor have been suggested in the previous literature. Ahmad et al. (2010) introduced radar with AVHRR, and radar and optical camera are utilized together in Notarnicola et al. (2006). However, radiometers and radar are usually too heavy to be equipped on small agricultural UAVs. Also, to the best of the authors' knowledges, there is no appropriate commercial radiometer or radar for small UAVs. The combination of infrared(IR) sensor with Fourier-transform infrared spectroscopy (FTIR) and multispectral sensor is proposed in Younis and Iqbal (2015). IR image sensors and multispectral cameras for UAVs are available and easy to be integrated with UAV systems. This means that the utilization of those sensors is practical and cost-effective with UAVs. Thus, the soil moisture retrieval model proposed in this paper is designed with IR and multispectral images selected as the remotely sensed data.

The last point to be considered is the methodology to construct a soil moisture retrieval algorithm or model. In Sandholt et al. (2002), a dryness index for land surface, Temperature-Vegetation Dryness Index (TVDI), is designed from the empirical parameterization of the relationship between land surface temperature and Normalized Difference Vegetation Index (NDVI). Younis and Iqbal (2015) conducted correlation and regression analysis to discuss on the relationship between TVDI and soil moisture measurement. The Bayesian approaches using backscattering coefficients in Notarnicola et al. (2006) or backscattering coefficients with emissivities in Notarnicola et al. (2008) are proposed. A regression technique, support vector machine (SVM), is used to estimate soil moisture level from radar backscatter, incidence angle, and NDVI. The algorithms discussed so far require to calculate the parameters, which have been studied to be related to the soil moisture level, like NDVI or backscattering coefficients, from the sensor measurements using the models proposed in the previous studies. This implies that there are possibilities of information loss during these procedures, and the modeling can be restricted by the previous knowledges between the parameters and soil moisture level. Neural network-based approaches have been proposed by several studies in Del Frate et al. (2003); Liou et al. (2001); Notarnicola et al. (2008); Paloscia et al. (2008). However, the input data of those neural network-based algorithms are parameters, like backscattering coefficients, emissivities or brightness temperature, which are still needed to be calculated from the sensor measurements using existing models. In this paper, a convolutional neural network (CNN) in Krizhevsky et al. (2012) is introduced to design a soil moisture retrieval model. CNN is used in various applications on image classifications and regressions. Since CNN takes images as input data directly, by constructing soil moisture retrieval model using this technique and define input as images from IR and multispectral sensors, the procedures to figure out parameters are not required. This means that the information possessed in the images are not lost while calculation of input parameters for previous neural network-based algorithms from sensor data can result in the loss of information. The trained CNN-based model is free from the previous knowledges, implying the possibility of figuring out hidden correlations between input images and soil moisture level. Also, since the trained CNN-based model conduct soil moisture retrival directly from the image measurements within a short time, it can be implemented for the online operations. Another important feature of the CNN is that the input image is not required to be flattened; it can be a 2-dimensional image with multiple layers form different channels. Thus, the spatial information of pixels are remained and it could be reflected to the trained CNN-based model.

This paper is organized as follows. The descriptions on the procedures of data collection are provided in Section 2. Section 3 deals with the development of the soil moisture retrieval model using CNN. The training and testing results are addressed in Section 4. The overall concluding remarks of the paper are discussed in Section 5.

2. DATA COLLECTION

2.1 Trial Site

Fig. 1. Trial Site

The aerial remote data and soil moisture level data acquisition took place on September 2018. The trial site is near Claxton, York, United Kingdom. The overall image of trial site is provided in Fig. 1. It is shown in Fig. 1 that most of the trial site is covered with plants. This implies that it is difficult to remotely obtain images of bare soil. Thus, an algorithm or model to estimate the moisture level of the soil beneath the canopy from the airborne images acquired from the UAVs is required to be designed.

2.2 Remote Sensing Platform

The drone system for remote data collection is constituted as shown in Fig. 2. Inpire 1 from DJI is selected as a

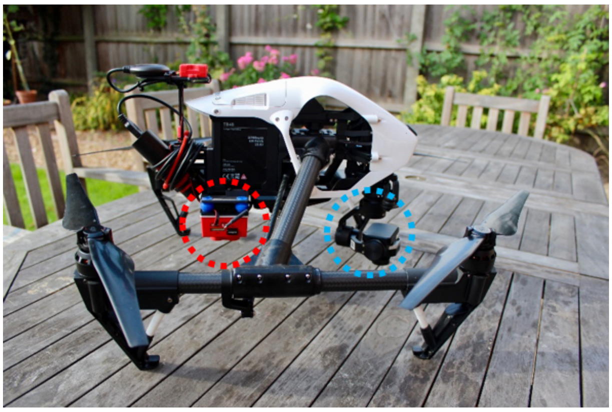

Fig. 2. Drone and Sensor Equipment for Data Collection

sensing platform. The sensor marked with a red circle is the multi-spectral sensor, RedEdge-M by MicaSense. It acquires images of 5 different frequencies, which are blue, green, red, red edge and near-IR, at the same time. The infra-red sensor, ZENMUSE XT of FLIR, is highlighted with a blue circle in Fig. 2. Since the two types of images, multi-spectral and infra-red, are required to be obtained simultaneously, multi-spectral and infra-red sensors are equipped on the platform at the same time.

In order to maintain the spatial resolutions of the images, the altitude of the platform is maintained to be constant during the data acquisition. When the altitude is higher, the spatial resolution becomes lower. If the platform flies at a lower altitude, the spatial resolution of the image could get higher. However, the crops could move due to the vortex from the platform, resulting in the distortions on the images. Thus, the flight altitude should be selected with these points in considerations. The airborne data utilized in this paper are obtained at the altitude of 50 m.

2.3 Ground Truth Measurement

(a) SM200 Soil Moisture Sensor

(b) HH2 Moisture Meter

Fig. 3. Soil Moisture Sensor System

The ground truth data of soil moisture level is measured with the sensor system composed of the devices in Fig. 3. The figures of the equipments in Fig. 3 are available at Delta-T (2019). SM200 in Fig. 3(a) is a soil moisture sensor by Delta-T devised to measure soil moisture content level at a single position. It consists of a plastic body with two stainless steel rods for sensing. The moisture meter in Fig. 3(b) is HH2 by Delta-T to show the measured soil moisture level on the display. The overall soil moisture measurement system is constructed by conneting the soil moisture sensor with the moisture meter. In order to measure the moisture content of soil at a certain point, the first step is to drive both of the stainless steel rods of the soil moisture sensor into soil at the point to conduct a measurement. A waveform is generated and applied to the stainless steel rods when power is connected to the sensor. This drives the stainless steel rods to generate electromagnetic field into surrounding soil. The permittivity of soil is dominated by the water content, and this permittivity affects the electromagnetic field from the sensor. This influence from the permittivity of moisture in soil is measured by the sensor as a voltage signal. The soil moisture level is derived from this voltage signal, and displayed on the moisture meter. The result can be displayed in either of mV or %Vol unit. The unit for the soil moisture level is selected to be %Vol in this paper.

2.4 Data Collection Procedures

The most important requirement for the data is that the remotely sensed data and ground truth data should be acquired for the same points on the ground. In other words, a certain point where each soil moisture measurement is conducted has to be identified as a pixel on the airborne images. Thus, before starting data collection, two reference positions are defined and marked with white pannels on the trial site. The points for soil moisture level measurement are defined as a relative positions from the reference positions. The ground truth data acquisitions are conducted for those points. After the soil moisture level measurement, airborne multispectral and IR images are obtained with the remote sensing platform. On the airborne images, the reference positions are clearly marked. Since the distance between the reference points is known and the relative position of the soil moisture level measurement points are given, the soil moisture level measurement points are identified on the images as pixels.

3. CONVOLUTIONAL NEURAL NETWORK FOR SOIL MOISTURE RETRIEVAL

3.1 Input Image Data Processing

The objective of the soil moisture retrieval modeling is to estimate the soil moisture level at a certain point from the remotely sensed image data. Also, as will be discussed in the next subsection, the CNN-based models get multi-layered images as input data. This means that the images for each soil moisture measurement point are needed to be defined and identified from the measurements on the whole agricultural field obtained by both IR and multispectral image sensors. The whole procedures of cropping and stacking images for input data definition are addressed in Fig. 4.

Since the multispectral image sensor utilizes 5 different frequencies, the sensor combination of this paper acquires

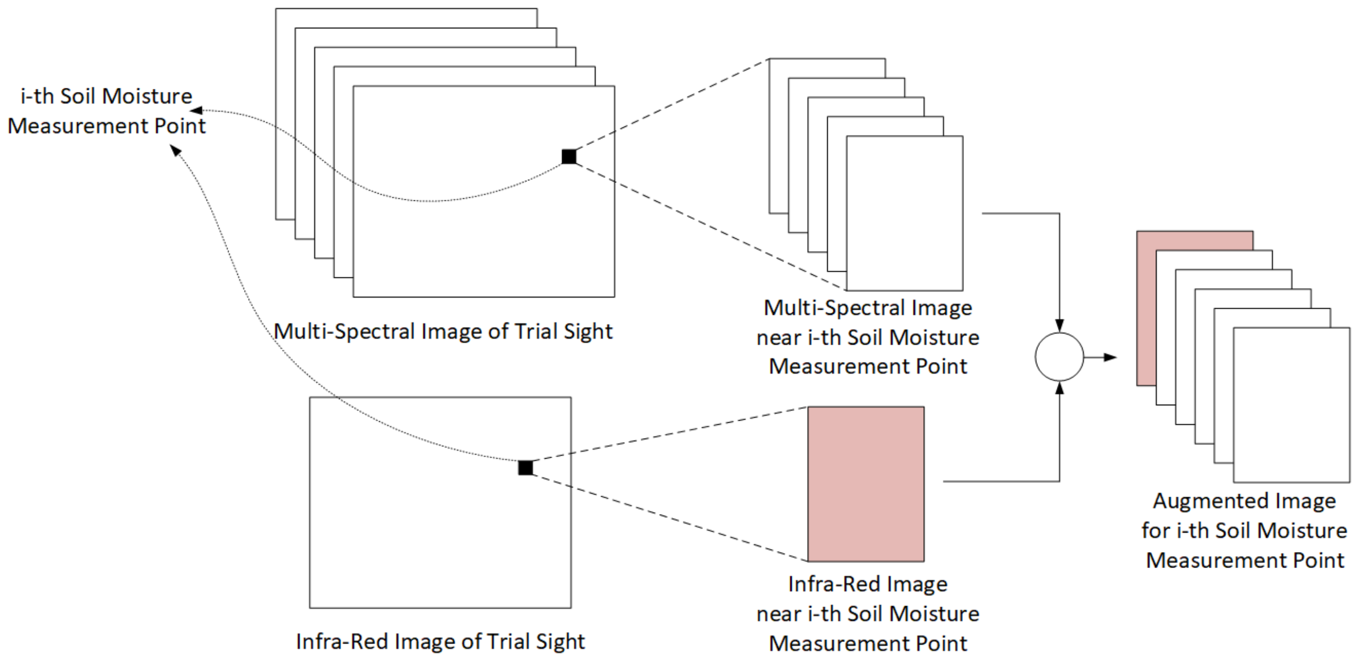

Fig. 4. Cropping and Stacking Images for Soil Moisture Measurement Point

total 6 different frequencies of images. For an arbitrary i-th soil moisture measurement point, the first step to construct input image is to identify the point on each image. The reference points of the trial sites are marked with white pannels, so they are easily found on the measurement images. Since the position of the i-th point is defined relatively from the reference points, from the relationship between the coordinates on the ground and those on the images, the pixel which represents the i-th point on each image is identified. The next step is to define and crop input image of each frequency for the i-th point. The size of input image is defined as a constant odd-number parameter, p. For each image, the input image for the i-th point is defined to be a $(p \times p)$-image with the pixel of i-th point on the center. Note that the information of the surrounding area of the i-th point, such as the gradient of pixel values, can be included and considered in the input image by increasing p. However, the increase of p means that the ratio of the data on the i-th point to the input data decreases. Thus, the size of the input images p is needed to be designed carefully to enhance the performance of the overall model. The last step is to stacking the images of 6 frequencies for the i-th point. Those 6 images for the i-th point are stacked up into a single image with 6 layers. This makes the pixels representing the same point on the ground to be stacked up and corrlated within the obtained input image. This spatial data of the pixels could be utilized by the CNN-based model.

Note that those procedures for input image construction do not include any parameter calculation from the image data. Complex image processings are not conducted and only the cropping of the images around the pixels of the soil moisture measurement points into a desired size is introduced. Thus, there is no data loss during the input image construction, and the proposed CNN-based model utilizes the constructed images directly as input data.

3.2 Convolutional Neural Network Design

CNN is applied for designing the soil moisture estimation model in this paper. The CNN-based models intake an image with multiple layers from various channels as input data and perform classification or regression. The overall structure of the proposed CNN-based soil moisture retrieval model is addressed in 5.

The proposed CNN-based model consists of 2 convolution layers with activation functions and 1 fully connected layer. At the first step of estimation, a stacked IR and multispectral image is given as an input image, and the first convolution layer is applied to this image. In the first convolution layer, a set of weighting parameters, called filter, is slided over the input image. A filter is a 2-dimensional array of weights and its size is a design parameter. Also, the number of filters can be defined to be equal to or more than 1 for each convolution layer. The training of the CNN-based model is performed to optimize those weights on all the filters to minimize regression errors. Dot products are conducted between the weights in the filter and the values of the pixels on the image overlapped by the filter. The results obtained from the dot products for all the pixels covered by the filter are summed up to be a single number. These procedures are defined to be a convolution operation. The convolution operations are conducted for all the possible partial areas of the input image with the size of the filter. The results from all the parts of input image with all the filters are accumulated while keeping their relative positions in the original image, resulting in feature maps. The second convolution layer takes these feature maps as input data and returns another feature maps by conducting the similar operations. Note that the filters of the second convolution layer are different from those of the first layer. The activation functions are introduced after each of convolution layer. They induce nonlinearities on the model and enable the model to con-

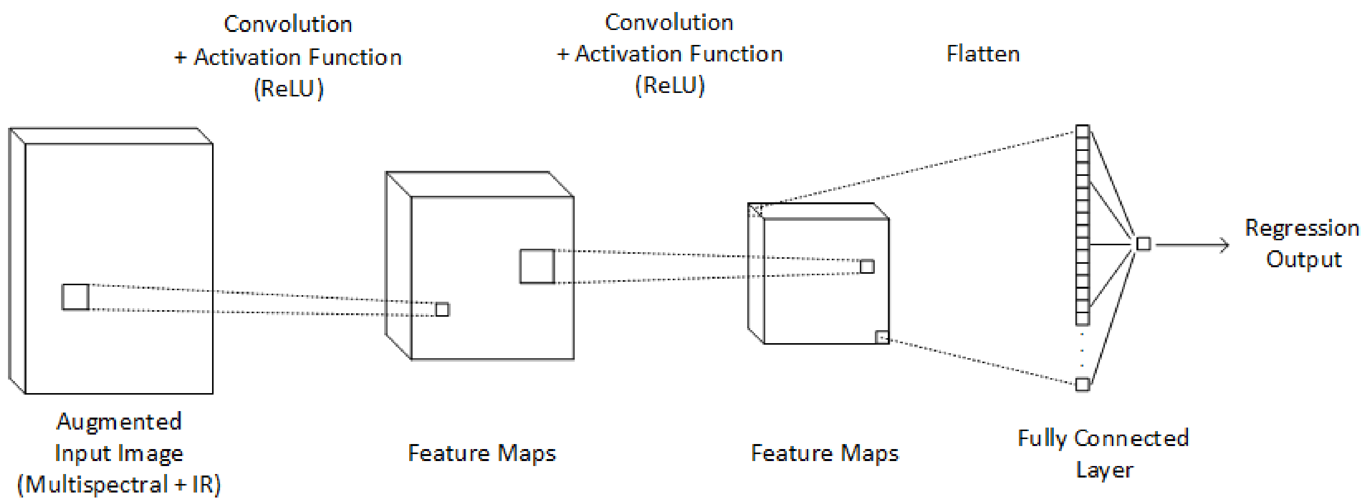

Fig. 5. Structure of Convolutional Neural Network for Soil Moisture Retrieval

duct self-training with backpropagation techniques. The feature maps obtained from the second convolution layer is converted into a 1-dimensional vector. This procedure is called as flattening. The fully connected layer is a conventional neural network structure with multiple layers of perceptrons for regression. The weights and biases of perceptrons are optimized during training to enhance the regression performance. This layer gets the 1-dimensional vector from the flattening as input and returns a single number, which is the prediction on the soil moisture level at the point where the input image is obtained. As a result, the proposed CNN-based soil moisture retrieval model in Fig. 5 takes stacked IR and multispectral image as an input and returns the soil moisture level prediction. The training and test of the proposed model with the data from the trial explained in Section 2 are described in the following section.

4. TRAINING AND TESTING OF CNN-BASED SOIL MOISTURE RETRIEVAL MODEL

The training and testing results for the designed CNN-based soil moisture retrieval model with the airborne remotely sensed data are proposed in this section to show the applicability of the CNN to the soil moisture retrieval. In the trial described in Section 2, the soil moisture measurements are conducted for 130 points. 110 points are randomly selected among those points and the data of these selected points are utilized for training the soil moisture retrieval model. Another randomly chosen 10 points are defined to be the data set for validations during training the model. The remaining 10 points are utilized as test data set for the trained model. The input image size for each point is defined to be $p = 1$. The distribution of the actual soil moisture level are addressed in Fig. 6 for each data group.

As discussed in Section 3, the CNN-based model proposed in this paper has 2 convolution layers. The size of the filter is defined to be 1 for both layers. The number of filters for the first and second convolution layers are selected to be 15 and 5, respectively. The activation function is ReLU.

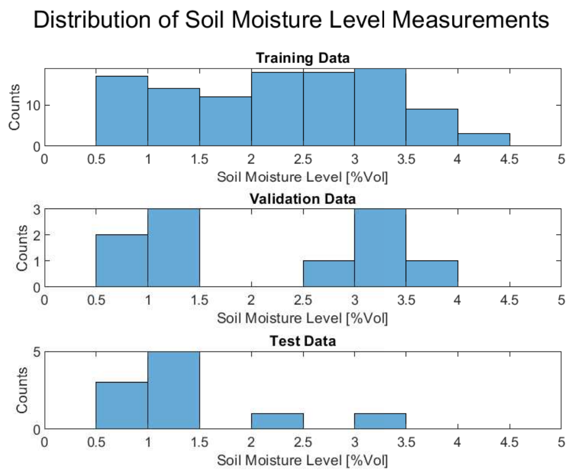

Fig. 6. Soil Moisture Level Measurement Distribution

For the model training, the Adam optimizer, which is an extension of stochastic first-order gradient descent algorithm, is used. The maximum number of epochs is chosen to be 1000. Validations are designed to be conducted for every 50 epochs. The initial learning rate is defined to be 0.1, and it is reduced by 10% every 100 epochs. The training results and the prediction results with test data set are addressed in Fig. 7 and 8, respectively.

The elapsed time for training is 17 seconds. It is shown in Fig. 7 that loss function and root mean square error (RMSE) of the training data set diminishes fast. The loss function drops from 3.0542 to 2.785×10^{-4}, and the RMSE decreases from 2.4715%Vol to 2.3601×10^{-2}%Vol. The validation results show similar trends. The loss function of the validation set starts from 1.6669 and diminishes to 9.8833×10^{-5}. The RMSE goes down from 1.8259%Vol to 1.4059×10^{-2}%Vol.

The prediction errors and corresponding prediction error levels in percentages with the test data set are proposed in Fig. 8. The prediction error is defined by substracting the predicted soil moisture level from the acutual measurement, and its corresponding prediction error level

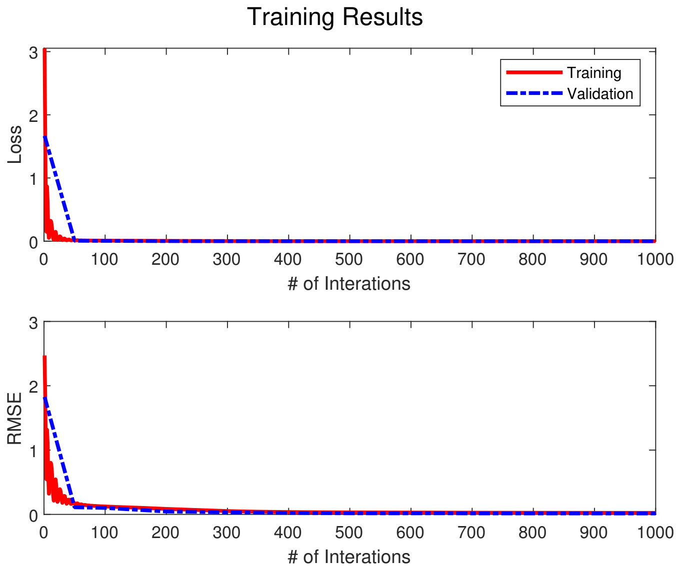

Fig. 7. Training Results for CNN-based Model

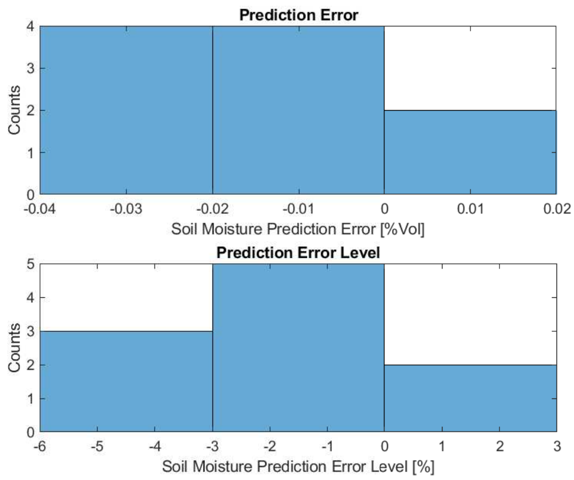

Fig. 8. Prediction Results with Test Data Set

is designed to be the ratio between the prediction error and the actual measurement. The magnitude of prediction error is shown to be less than 0.04%Vol, and the RMSE is calculated to be 2.0163×10^{-2}%Vol. This results in the less than 6% of prediction error level, and the root mean square of the prediction error level in percentage is 2.4509%, showing that the prediction error is small with the test data set.

5. CONCLUSION

Soil moisture retrieval for agricultural field covered by canopy using the remotely sensed airborne data is discussed in this paper. The remote sensing platform is selected to be a small quadrotor UAV equipped with IR and multispectral image sensors. In order to minimize the information loss of the input images and intake possibility of finding uncovered relationships between the images and soil moisture level, CNN is applied for soil moisture retrieval model design. The cropping and stacking images to define an input image of a certain soil moisture measurement point is addressed. The overall architecture and principles of the proposed CNN-based model are described. The training and testing results indicate that the soil moisture retrieval model proposed in this paper shows small estimation error with the test data set.

In further studies, training and testing of proposed CNN-based soli moisture retrieval model with a larger size of dataset could be conducted to verify the applicability of the model more clearly. The effects of the input image size, spatial resolution change due to platform altitude change, and hyperparameter tuning on the CNN-based soil moisture retrieval model are required to be studied for the enhancements on training speed and estimation performance.

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