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Enhancing the Performance of a Rainfall Measurement System Using Artificial Neural Networks Based Object Tracking Algorithms

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***Abstract*—With the recent development of optical sensing and digital image processing techniques, high-speed cameras have been applied to measure the microphysical properties of raindrops. However, the performance of such systems are significantly affected by object tracking algorithms. In order to improve the measurement accuracy of rainfall rate and accumulated rainfall, a novel object tracking algorithm based on artificial neural networks (ANN) is proposed in this paper. The ANN model takes the features of each raindrop in the two successive images as inputs including the center coordinates, area, canting angle, the lengths of long axis and minor axis of the equivalent ellipse. The output of the ANN model is the matched probabilities of each pair of raindrops between before and after images. Experimental data were collected during a real rainfall event. Performance comparisons between the traditional and ANN based object tracking algorithms are conducted based on the experimental data. Experimental results suggest the successful matching rate is significantly increased from 87.20% to 95.60% due to the usage of the ANN based algorithm. Hence, the improved disdrometer system is capable of producing more accurate and robust measurements of rainfall status.**

***Keywords*— rainfall measurement; high-speed camera; disdrometer; object tracking algorithm; artificial neural network**

I. INTRODUCTION

In the atmospheric observations, the microphysical properties of raindrops provide valuable information for assisting the calibration of weather radar systems to improve the accuracy of weather forecast. Although the available rainfall measurement systems such as raingauges [1] and radar systems [2] are capable of providing accurate accumulated rainfall, they are not able to measure the microphysical properties of raindrops including raindrop size and raindrop motion trajectory. The challenge is that the observation of microphysical properties of raindrops is too heuristic and limited by the measuring tools.

Today, an optical disdrometer is becoming the most popular instrument for rainfall observations and analysis. Both of the particle size velocity (PARSIVEL) disdrometer [3] and a two-dimensional video disdrometer (2DVD) [4] with a more a more thorough assessment of volume effect for a raindrop are the representative disdrometers. However, the expensive cost and cumbersome volume limit its broad use in the atmospheric field. With the recent development of new optical sensing technique coupled with image processing algorithms, a range of disdrometer systems have been proposed based on high-speed cameras [5-10]. In order to measure the accurate displacement and orientation of the raindrop movement, the particle tracking velocimetry (PTV) approaches were applied to identify the motion trajectory of a raindrop. Before performing the task, some current challenges should be addressed for the estimation due to the moving raindrops with only few features [11]. Additionally, the detection and tracking of those non-rigid bodies is needed to take into account in regard to facilitating the operation [12, 13].

In previous study, a traditional object tracking method has been proposed through evaluating the similarity of two raindrops in terms of area difference, relative position and oblateness variation [9]. As the threshold is normally pre-defined, the successful matching rate is limited. In order to improve the successful matching rate and further improve the performance of the disdrometer system, a novel object tracking algorithm based on an artificial neural network (ANN) model is proposed in the paper. Comparative assessments between the traditional and ANN based object tracking algorithms are conducted. The performance of the disdrometer system with ANN based object tracking algorithm is assessed as well.

II. METHODOLOGY

A. Measurement principle

Fig. 1 shows the fundamental principle of the high-speed camera based disdrometer system. The system consists of an imaging unit, an image processing unit and a data processing unit. The raindrop images are captured by the imaging unit and then transmitted to the upper computer for image/data processing. Due to the influences of noises and non-uniform illumination, the images are pre-processed to remove the background, depress the speckle noises and enhance the region of interest. The location and shape of raindrops are detected in a gray-level image. Object tracking algorithms are used to identify the same raindrop in a sequential images and thus the motion trajectory of the raindrop can be quantified. Once the location, shape and motion trajectory are known, the rainfall rate, accumulated rainfall, rainfall intensity and size distribution will be calculated through data processing.

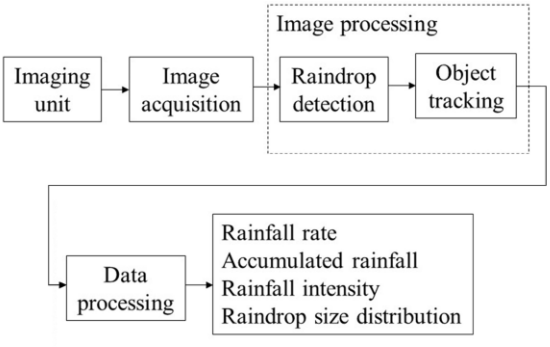


Fig. 1. Principle of the measurement system.

B. Traditional object tracking algorithm

The raindrop matching in two successive images is implemented through calculating a cost function. The cost function C_{ij} is defined as

$$C_{ij} = \alpha\Delta A_{ij} + \beta\Delta L_{ij} + \gamma\Delta O_{ij} \quad (1)$$

where, ΔA_{ij}, ΔL_{ij} and ΔO_{ij} are the area difference, relative position and oblateness variation, respectively. α, β and γ are the corresponding weights of each parameter through the iterative experiment. If C_{ij} is less the pre-defined threshold, the raindrop *i* and raindrop *j* are regarded as the same raindrop in adjacent frames. The displacement from location *i* to location *j* is the motion trajectory of the raindrop.

C. ANN based object tracking algorithm

Artificial neural network is a powerful tool for modelling a nonlinear system with multiple inputs and outputs and has been widely used in a range of prediction and classification applications [14-16]. In this study, a multi-layer back-propagation neural network is developed to identify the same raindrop in any successive images. Each raindrop *i* (i=1, 2, …, m) is equivalent to an ellipse and the center (x_i, y_i) of the ellipse is the location of the raindrop in an image. As shown in Fig. 2, the ANN model consists of an input layer, four hidden layers and an output layer. The input layer accepts the features of each raindrop in the two successive images as inputs, including the center coordinates (x_i, y_i), area s_i, canting angle θ_i, the lengths of long axis a_i and minor axis b_i of the equivalent ellipse. In our design, there are 32, 64, 64 and 32 neurons in each hidden layer, respectively. The ReLU (Rectified Linear Unit) activation function is used as the activation function between the hidden layers while the sigmoid function is applied to the output layer. The output of the model is the matched probabilities of each pair of raindrops between images. The pair of raindrops with highest matching probability is regarded as the same raindrop in the two images. The displacement from location *i* to location *j* is the motion trajectory of the raindrop during an image acquisition period.

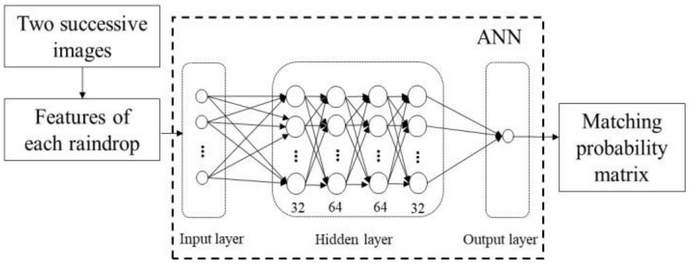


Fig. 2 Structure of the ANN model.

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Test rig

Fig. 3 shows the experimental setup of the high-speed camera based disdrometer system. The sensing unit consists of a CMOS based high-speed camera with a long depth lens, an array of blue LEDs as a backlight source and an upper computer as computation/control unit. Experimental data were collected during a rainfall event in Hsinchu, Taiwan in June 2017. A detailed description of the imaging unit is given in [9]. In this study a commercial tipping bucket type raingauge (Weiser Water Technology, model JD05) [17] with 0.5 mm resolution is used to obtain an independent reference to assess the accuracy of the measured rainfall from the proposed system. The best achievable accuracy of the reference raingauge stated in the operation manual is within ± 3%.

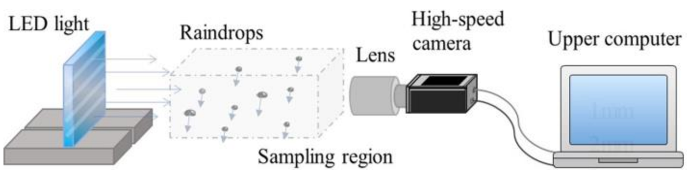


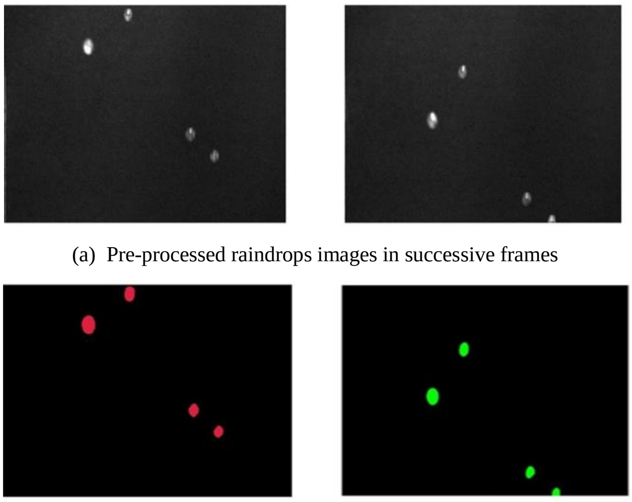
Fig. 3. Experimental setup of the high-speed camera based disdrometer system.

According to the empirical experiences in previous studies, the raindrop size is usually from 0.5 mm to 5 mm, which means that the moving velocity of a raindrop is in the range from 0 to almost 10 m/s. Thus, the spatial resolution is designed to resolve the minimum scale of 0.5 mm. The fast shutter speed of the camera is enabling the raindrop images to be captured instantaneously. A CMOS camera and a special optical lens are operated to achieve a 500 Hz frame rate, 69 µs exposure time, and 82.0 µm resolution. To prevent optical distortion of images, a lens with the depth of 120mm is employed to keep the shapes of the raindrops almost identical. The imaging system is capable of producing a field of view (FOV) of 52.5 × 39.0 mm^2. All the settings are listed in Table 1.

Table I. Settings of the experimental setup

Item	Value	Description
FOV	52.5 ×39.0 mm^2	Physical imaging area of the system
CMOS size	3.1×2.3 mm^2	Practical camera chip size
Resolution	82.0 µm	A pixel size of the physical area
Frame rate	500 Hz	Acquisition frames per second
Exposure time	69 µs	Time of the open shutter duration

In Fig. 4, the results of raindrops detected by the high-speed camera demonstrates is presented. Fig. 4 (a) illustrates typical pro-processed images of raindrops in successive frames. In order to facilitate the detection of the raindrops in each image, they are converted to binary images as shown in Fig. 4 (b). Then the motion trajectories are obtained from the calculation of the relative locations for the raindrops in successive frames.



(a) Pre-processed raindrops images in successive frames

(b) Detected binary images in successive frames

Fig. 4. Typical images of raindrops detected by a high-speed camera.

B. *Development of ANN model*

The aim of the object tracking is to find the probable trajectories of the same raindrop in any successive frames. The desired object tracking results of typical images is shown in Fig. 5. The ANN model-based object tracking algorithm is developed based on the experimental data. A total of 700 manually labeled images were used to train the ANN model. Once the maximum number of epochs is reached or the performance is minimized to the goal, the ANN is well established. Another 150 images as develop data were used to generate the ANN models, and the rest 150 images as test data were further assessed by the ANN models to determine the optimal and reliable ANN model.

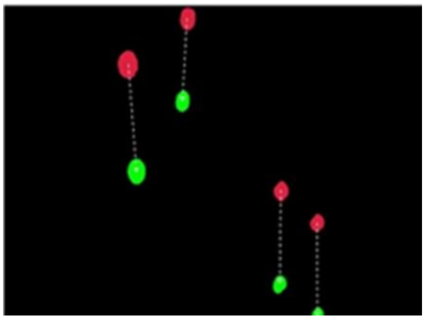


Fig. 5. Matching result of applying the object tracking algorithm.

C. *Experimental results*

Traditional and ANN based object tracking algorithms are implemented and assessed with the same test data, respectively. The performance comparison results are summarized in Table 2. It can be seen that ANN based object tracking algorithm produces higher successful matching rate than the traditional method. Moreover, the number of non-matched raindrops is reduced due to the generalization ability of the ANN model.

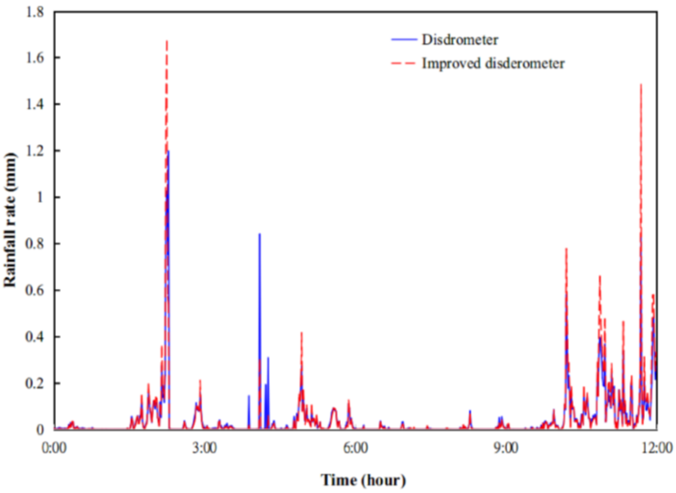
Table II. Comparison between different object tracking algorithms

	Traditional			ANN		
	Success	Failure	Non-matched	Success	Failure	Non-matched
Detected raindrops	75	11	7	87	4	2
Rate (%)	87.2	12.8	-	95.60	12.80	-

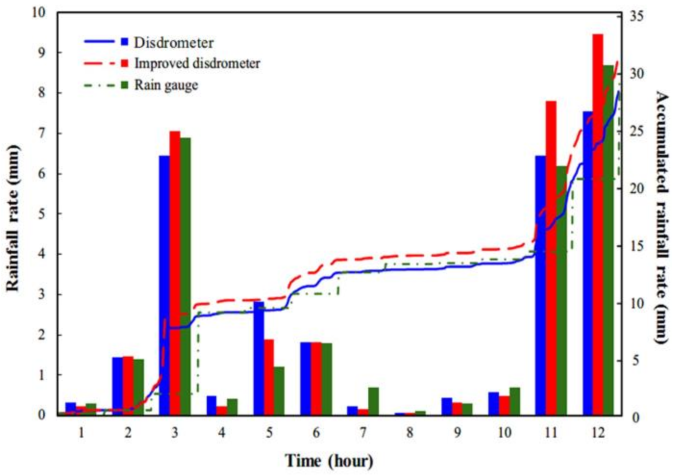
Based on the object tracking results, the rainfall rate and accumulated rainfall were calculated and shown in Fig. 6. In term of the measurements of rainfall rate in Fig.6 (a), the ANN model is more sensitive to the rainfall in comparison with the traditional measurement. As for the accumulated rainfall, the results from the improved disdrometer system with ANN object tracking algorithm are closer to the measurements from the reference rain gauge. The relative error of the accumulated rainfall from the improved disdrometer system is less than 3 %.

IV. CONCLUSIONS

An ANN based object tracking algorithm has been developed to match the raindrops in successive images. The effectiveness of this method has been verified through a range of experimental tests. Based on the experimental data, the ANN based object tracking algorithm outperformances the tradition object tracking algorithm. The successful matching rate has been increased from 87.2% to 95.6%. Meanwhile, the performance of the disdrometer system has been significantly enhanced. In comparison with the reference data from the raingauge, the relative error of the accumulated rainfall from the improved disdrometer system is less than 3%. It has been found that improved disdrometer system with ANN based object tracking algorithm is capable of producing more accurate and robust measurements of rainfall. This outcome can be extended to other applications of object tracking algorithms in other different fields.



(a) Measurements of rainfall rate



(b) Measurements of accumulated rainfall

Fig. 6. Comparison results between the disdrometer system and rain gauge.

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