GENERATING THE CLOUD MOTION WIND FIELD FROM SATELLITE CLOUD IMAGERY USING DEEP LEARNING APPROACH

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ABSTRACT

Cloud motion wind (CMW) are routinely derived by tracking features in sequential geostationary satellite infrared cloud imagery. In this paper, we explore the cloud motion wind algorithm based on the data-driven deep learning approach. And different from conventional hand-craft feature tracking and correlation matching methods, we use deep learning model to automatically learn the motion feature representations and directly output the field of cloud motion wind. In addition, we propose a novel large-scale cloud motion wind dataset (CMWD) for training deep learning models. We also try to use a single satellite cloud imagery to predict the cloud motion wind field in a fixed region, which is impossible to achieve using traditional algorithms. The experimental results demonstrate that our algorithm can predict the cloud motion wind efficiently, even with a single cloud imagery as input.

Index Terms— Cloud motion winds, dense optic flow prediction, deep convolutional neural network

1. INTRODUCTION

Cloud motion wind (CMW) is derived from geostationary satellite-observed motions of clouds features, which have been shown to provide reasonable estimates of the ambient tropospheric wind [1]. Applications of cloud motion wind are wide ranging. They provide crucial information over wide regions of the Southern Hemisphere which void of conventional ground observations and contribute to forecast diagnostics of weather conditions, as well as numerical weather prediction (NWP). In addition, cloud motion wind field can also provide basic guidance for such field as solar energy prediction [2].

Traditional cloud motion wind algorithm first generates a motion vector for each pixel using feature tracking and correlation matching methods, and then revises the vector field through a series of post-processing operations [3–5]. Among them, Lu [6] propose a new tracer selection procedure named temporal difference method to calculate the low-level atmosphere motion vectors. Bresky [7] develop a new approach that isolates the dominant local motion within a cloud scene and minimizes the smoothing of the motion estimate. Cloud motion wind algorithms have advanced in accuracy from the mid-1960s, but they usually require much computing time, especially when it comes to capturing a dense cloud motion wind field at high resolution.

The cloud motion wind algorithm is similar but not identical to the task of dense optical flow estimation in computer vision. In this paper, we will learn from this idea and use a deep learning model to predict the vector field of cloud motion wind. The reason for using deep learning approach is that it can automatically learn the representation of motion features from a large amount of data samples, and it can also greatly improve the calculation speed and efficiency of the algorithm. Many existing deep learning based optical flow estimation methods to constrain the motion between two frames by minimizing photometric and smoothing loss [8–10]. Among them, Ren [11] devise a simple yet effective unsupervised method for learning optical flow, by directly minimizing photometric consistency. Meister [12] inspired by classical energy-based optical flow methods and then design an occlusion-aware bidirectional dense flow estimation and robust census transform based unsupervised loss to evade the need for ground truth flow.

In this paper, we use a fully convolutional deep network to generate the cloud motion wind field between two geostationary satellite cloud imagery sequences. However, due to the uncertainty of atmospheric movement, brightness consistency between two adjacent satellite cloud imagery is not guaranteed, so the unsupervised optic flow estimation based on photometric consistency is not suitable for use. Therefore, in order to use deep neural network to predict the cloud motion wind field, we use a more robust PCAFlow [13] to generate rough labels for training samples in advance, and then use them as the supervision of the deep neural network for training. At the same time, in order to train our deep learning model, we propose a novel large-scale cloud motion wind dataset named CMWD, in which each sample contains two geostationary satellite cloud imagery at fixed time intervals.

We also try to use only one frame of satellite cloud imagery to estimate the cloud motion wind field. This requires the model to learn the characteristics of atmospheric movement from dataset and to have sufficient generalization ability. It should be noted that this task is not feasible for other existing cloud motion wind algorithms. However, since data-driven deep neural network can learn the hidden patterns of atmosphere motion from the dataset (for example, typhoons in the Pacific North-west can only rotate counterclockwise
but not clockwise), we can use one satellite cloud imagery to make appropriate estimates of cloud motion wind field. To our best knowledge, we are the first to use deep learning to conduct research on cloud motion wind field generation, which also provides resources for the application of deep learning in the field of weather prediction.

2. METHODOLOGY

2.1. Cloud Motion Wind Dataset (CMWD)

In order to train our data-driven based deep learning model, we propose a novel large-scale cloud motion wind dataset named CMWD, which contains 6388 training samples and 715 samples for testing from Helianthus 8 high-precision geostationary infrared meteorological satellite. Each sample consists of two geostationary satellite cloud imageries with the size of $512 \times 512$, taken one-hour intervals over a vast of the Pacific Northwest. In addition, we use the traditional unsupervised optical flow method to generate coarse labels for the training data, which can be easily implemented using many existing frameworks [13, 14]. Noted that like many existing works [15, 16], in order to visualize the output optical flow, we encode the generated two-dimensional flow, which allows us to visualize the flow field intuitively. In other words, given an RGB image pair as input, $x \in \mathbb{R}^{6 \times h \times w}$, our model needs to learn a non-linear transformation to the corresponding cloud motion wind field, $y \in \mathbb{R}^{2 \times h \times w}$, where $h$ and $w$ denote the height and width of input satellite cloud imagery respectively.

We use FlowNetS [15] as a reference network and the network structure is illustrated in Figure 1. This architecture consists of a contractive part followed by an expanding part. The contractive part takes as input two infrared cloud imageries stacked together, and processes them with a cascade of stride deconvolution layers. The expanding part implements a “skip layer” architecture that combines information from various levels of contractive part with “up convolving” layers to iteratively refine the coarse cloud motion wind field predictions.

In addition, it can be seen from Figure 1 that we use a loss which compose of a final loss and several intermediate losses placed at various stages of the expansionary part. The intermediate losses are meant to guide earlier layers more directly towards the final objective. Specifically, we use endpoint error (EPE) as the supervised training loss, and its ground truth motion field is generated by PCAFlow [13]. The EPE loss are as follows in Equation 1:

$$L_{EPE} = \sum_{i=1}^{N} \sum_{h=1}^{C} \sqrt{(x_{h1}^i - y_{h1}^i)^2 + (x_{h2}^i - y_{h2}^i)^2} \frac{1}{N \times C}.$$  

Where $N$ and $C$ represent the number of intermediate output layers and the number of flow vectors at each layer respectively, $x_{h1}^i (y_{h1}^i)$ and $x_{h2}^i (y_{h2}^i)$ represent two dimensions of the $h^{th}$ vector of the the $i^{th}$ intermediate output layer of predicted motion field (ground truth). It should be noted that

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1 The CMWD dataset, source code and pre-trained model are available at [https://github.com/chao-tan/CMWNet](https://github.com/chao-tan/CMWNet).
in order to make the generated cloud motion wind field as smooth as possible, the image size of the final output motion vector field of our model is a quarter of the input image size, and then the flow field with the same width and height as the input image is obtained via the nearest neighbor interpolation.

2.3. Implement Details

We use the Adam solver [17] with a basic learning rate of 0.001 and the first and second momentum values are 0.5 and 0.999 respectively to optimize our network. The size of input infrared cloud imagery is $512 \times 512$ and the output cloud motion wind field of our model is $128 \times 128$. It should be noted that we do not use data augmentation strategies such as random flipping, because we believe that they will affect the influence of the model to learn the motion patterns of the atmosphere. We adopt an endpoint error (EPE) loss which compose of a final loss and four intermediate losses placed at different stages of the expansionary part. Like [15], we set the weights of the five losses from bottom to top layers to 0.005, 0.01, 0.02, 0.08 and 0.32 respectively. We train our network in a total of 80 epochs with a mini-batch size of 8, and we reduce the learning rate from $10^{-3}$ to $10^{-4}$ after 50 epochs.

3. EXPERIMENTS

3.1. Experiments on Paired Cloud Imagery

We first use the paired infrared satellite cloud imagery on CMWD dataset to conduct the experiment of cloud motion field estimation. As mentioned earlier in this paper, we visualize the two-dimensional cloud motion wind field as a RGB image, so that we can intuitively compare the fitting effect of the model. At the same time, we also convert the generated vector field into two visualization products. One is the common dense vector arrow diagram. The other is the flux streamline diagram, which can continuously display the direction and intensity of the wind field. The experimental results of some testing samples are shown in Figure 2.\(^2\)

It should be noted that for the vector arrow diagram (the last row in Figure 2), we enlarge the wind arrow five times and automatically filter out the small arrows for a better visual effect. It can be seen from Figure 2 that our model can well estimate the upper-air wind motion at its location, whether it is a large air mass movement or a small-to-medium-scale anticyclonic spiral movement. As can be seen from the second and third columns of Figure 2, due to the complex fitting capabilities of our proposed model, we can use a more efficient deep neural network to fit the features movement of the input satellite cloud imagery pair. And since the rough label of the sample contains noise, we finally use the nearest neighbor interpolation to obtain a smoother result. In addition, since the neural network does not perform feature matching and other operations on a pixel-by-pixel basis, it can process high-resolution input images more efficiently. Specifically, with the input size

\[^2\text{More HD visual results are available at https://chao-tan.gitee.io/projects/cmw-net/project-page.html}\]
of $512 \times 512$, our model is more than 12 times faster than the traditional PCAFlow [13] in the inference stage.

### 3.2. Experiments on Single Cloud Imagery

We also try to use single infrared cloud imagery to estimate the cloud motion wind field, which is not feasible for conventional cloud motion wind algorithms. However, because deep neural network can learn from a large amount of data, many basic patterns of atmospheric motion (such as the high-latitude typhoon in the Northwest Pacific Ocean moving counterclockwise to the west or north in large cases) can be detected by the model, and then predict through the state of the whole cloud system. It should be noted that in this experiment, the input image is only an infrared cloud image $x \in \mathbb{R}^{3 \times h \times w}$, and other settings are same as the experiment in Section 3.1. The experimental results of some test samples are shown in Figure 3. From the experimental results, it can be seen that even with only one input image, our model is still able to make a rough estimate of cloud motion wind field under the current situation. Meanwhile, our model can separate different cloud structures in cloud imagery and make different estimates accordingly (such as continental air mass and typhoon structure). This experiment embodies the learning ability and performance of the data-driven deep learning method, and further illustrates the powerful ability of weather analysis and prediction based on artificial intelligence tools.

### 4. CONCLUSION

In this work, we propose using a deep convolutional neural network to estimate the cloud motion wind field. Meanwhile, we also present a large-scale cloud motion wind dataset for deep learning research. The experimental results illustrate the efficient performance of our model, and it can also handle the case without paired satellite cloud imagery input. In the future, we plan to use deep learning based model to process more analysis tasks of meteorological remote sensing data.

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