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Particle Image Velocimetry Analysis using Deep Learning for Thermal-hydraulics Experiment

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1. Introduction

Thermal hydraulic research of nuclear reactor is important in nuclear research, the flow characteristics of coolant in reactor core has a great influence on the performance and safety of nuclear power plants.

Flow visualization plays an important role in flow characteristic research, because a various flow visualization techniques help the researchers to get a deeper insight into the complex flow.

Among the flow visualization techniques, particle image velocimetry (PIV) is a widely used as flow visualization technique, which can measure velocity components of flow filed using the successive two tracer particle images.

In generally, the PIV use the cross-correlation method, which divides each image frame into grids named interrogation window. The correlation-based PIV method obtains one velocity vector for each interrogation window by searching the maximum correlation coefficient of two successive image frames and has reliability, accuracy, and robustness.

However, a proper interrogation window size in particle image pairs is required for an accurate PIV analysis. In other words, there are limitations to the correlation-based method. For instance, if the size of the interrogation window is set to be large, the resolution of the obtained velocity field will be too low. On the other hand, if it is set too small, there are not enough number of particles in each interrogation window, which means that the information of flow within the interrogation window can be lost, resulting in inaccurate analysis. Also the correlation-based method tends to average out the velocity component due to its interrogation window and underestimate small scale flow.

Despite many efforts to overcome the problem of the interrogation window size, there are still the limitations of correlation-based method related the interrogation window [1].

Therefore we adopt another practical way to obtain denser velocity field, it is optical flow techniques, which have been developed greatly for object detection in the computer vision community. These way analyzes the variations in pixel based on brightness constancy assumption. Compared with the correlation-based method, the optical flow technique can obtain one velocity vector per pixel, i.e. denser velocity field.

In this paper, we are applying the deep neural network for optical flow estimation. In the past decade, deep learning methods have been developed to solve complicated problems. Among the deep neural network, convolutional neural networks (CNNs) have recently been very successful in a variety of computer vision tasks.

The FlowNet is a deep neural network structure based on CNNs and can solve the optical flow estimation problems by receiving two images as input and estimating the optical flow as output, i.e. end to end method [2].

In this work, we use FlowNet2 evolved from the original FlowNet for PIV estimation. The FlowNet2 has the advantages of the original FlowNet and resolves issues with small displacements and noise in estimated optical flow fields [3].

The FlowNet2 uses a synthetic object images as input for optical flow estimation of rigid motion. However, we use a synthetic particle images as input for denser PIV velocity field.

There are several advantages for using the deep neural network compared to other PIV method for PIV estimation. First, the CNN model provides a dense velocity field, which means we can get detail information of the flow. Second, once the CNN model is well trained, the inference time (the time of estimation procedure) is very short (~100ms per image pair).

2. Methodology

2.1. Convolutional neural network

Convolutional neural networks (CNNs) is kind of deep neural network and recently has been widely applied in computer vision tasks. Deep neural network means there are many hidden layer in neural network (Fig. 1).

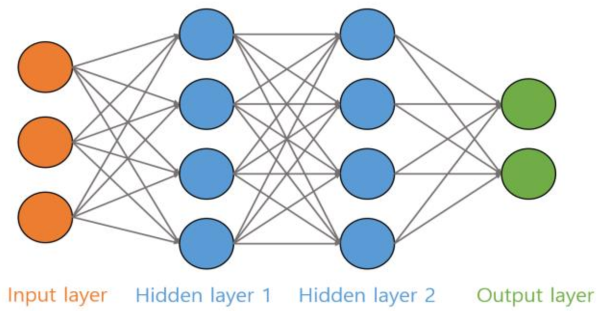


Fig. 1. A simple sketch of the deep neural network

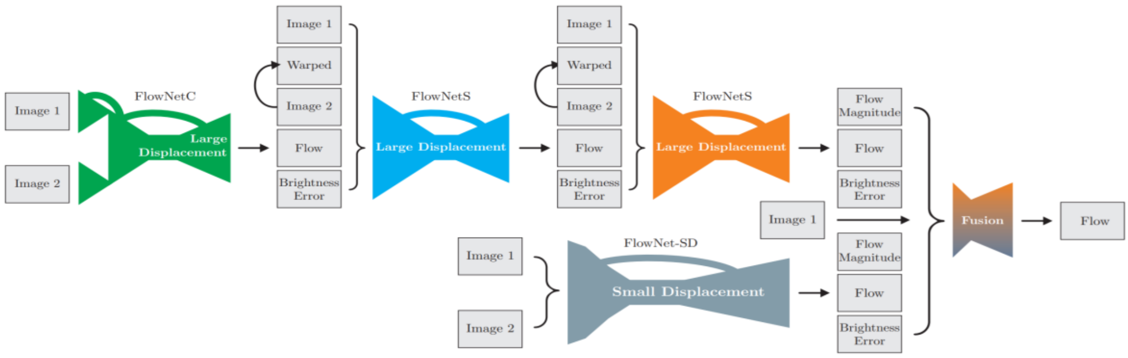


Fig. 2. The stacking architecture of complete FlowNet2 [3].

In CNNs, there are a convolution layer as a hidden layer in network and the convolution layer serves to extract feature maps of data through simple convolution operation between image and kernel (Fig. 3).

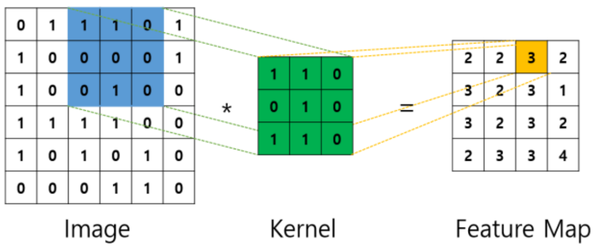


Fig. 3. The process of convolution operation.

Besides the convolution layer, there are several layer in CNNs. Typically, the pooling layer plays a role of data down sampling, which can reduce calculation amount and extract strong feature of image data.

Convolutional neural networks are consist of these layer and have strengths in end to end learning given enough labeled data. So, through FlowNet2, we can train a network to predict the velocity fields directly from the successive images.

2.2. FlowNet2

Two CNN architecture for estimating optical flow are proposed. One is FlowNetS, which is a generic architecture and another one is FlowNetC, which include correlation layer to perform matching two feature maps [2].

Through stacking these single network together with a warping of second image to form complex network, the architecture of original FlowNet evolved and its name is FlowNet2. The experiments in [3] shows that FlowNet2 has the state-of-the-art performance on rigid motion estimation.

In this paper, in order to estimate PIV problem using the advantages of CNN, we decided to use FlowNet2. The stacking architecture of FlwoNet2 is demonstrated in Fig. 2 [3].

Once the training using particle dataset is well done, we can estimate PIV problems using parameters as a result of the training. The process of PIV estimation using FlowNet2 is illustrated in Fig. 4. Two particle images that we want to know the velocity field are fed into FlowNet2 model and a dense velocity field is directly obtained.

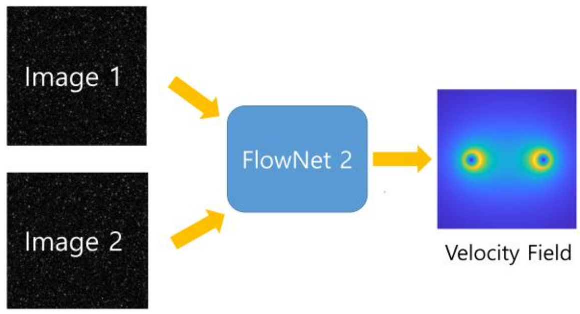


Fig. 4. The process of PIV estimation using FlwoNet2

2.3. PIV synthetic dataset

To train the FlowNet2 network, very large amount of dataset is required: the dataset consists of two input images, ground truth optical flow. Although the FlowNet2 generally uses rigid motion data of object for training, we need to training using the tracer particle data for PIV estimation.

In this work, we use a synthetic particle images because it is difficult to get a large amount of real PIV experiment data. To generate the particle images, we can use PIVlab in Matlab.

The synthetic dataset follow some rules. First, all particle can be described by a 2D Gaussian function. Second, the parameters of particle images are randomly selected within an appropriate range for the uniqueness of the image [4]. Also, the synthetic dataset is composed of various type of flows at various speeds and we have obtained more than 20K particle image pairs with ground truth velocity fields. The composition of dataset can be seen in Table I.

Table I: Synthetic particle dataset composition

A type of flow	Number of image pair
Linear flow	4000
Back-step flow	2000
Double-Rankine vortex flow	2000
Rotation flow	2000
Poiseuille flow	2000
Sink flow	2000
DNS turbulence flow	4000
Cylinder flow	2000
SQG flow (Sea surface flow driven by a Surface Quasi-geostrophic model)	3000

3. Evaluation of synthetic image pairs

To verify the performance of proposed method, we estimate the velocity fields from a synthetic particle image pairs, which are not included in the training process. The particle image pair for estimating contains double-vortex flow with the core radius of 15 pixel, which is a relatively small scale flow. To make quantitative comparisons between ground truth and estimated velocity filed, we apply root-mean square (RMS) errors:

$$\text{RMS error for } m\times n \text{ domain}$$
$$= \sqrt{\frac{1}{m\times n}\sum_{j=1}^{n}\sum_{i=1}^{m}[(u(i,j)-u_{ground-truth}(i,j))^2+((v(i,j)-v_{ground-truth}(i,j))^2]}$$

The results of estimation using proposed method are shown in Fig. 5. From this results in figure, one can conclude that the proposed method has good performance in extracting velocity fields from the successive particle image pair.

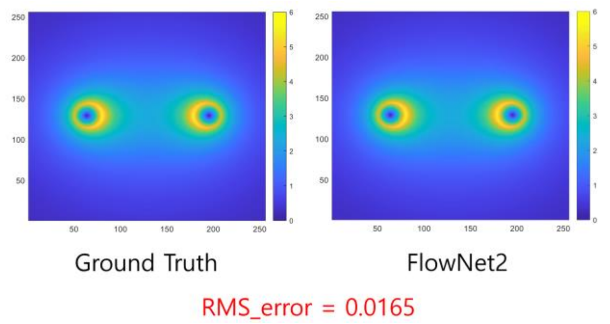
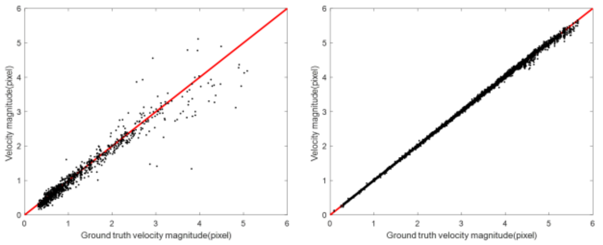


Fig. 5. The ground truth and the estimated velocity field extracted from proposed method. The color map means velocity magnitude (pixel/frame).

As shown in Fig. 6a, b, the velocity magnitudes analyzed by the proposed method are generally in good agreement with the ground truth data. However, the correlation-based PIV method underestimated high velocity, which means these method average out the velocity near the vortex core because of its interrogation window. And this results show the weakness of correlation-based PIV method in small scale flows. The proposed method proved to show good performance as a PIV estimator.



(a) (b)

Fig. 6. The velocity magnitude scatter plot for (a) the correlation method and (b) the proposed method.

4. Conclusion

In this paper, we introduce a new PIV estimator using convolutional neural network. The FlowNet2 evolved from original FlowNet is employed to estimate the velocity fields from the particle image pairs. The reason for employing the FlowNet2 is that it has the state-of-the-art performance for optical flow estimation [3].

The network of FlowNet2 is trained using a synthetic particle image dataset made by PIVlab. With the trained parameters, we can obtain a dense velocity fields from synthetic particle image pair. The proposed method was evaluated on synthetic image pairs in small scale double-vortex flow.

The proposed method successfully generates denser PIV velocity fields in good agreement with the ground truth data. However, the correlation-based method underestimated high velocity due to its interrogation window. Through this, we conclude that the proposed method is a good way to overcome the limitations of the correlation-based PIV method.

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