Unsupervised Learning of Particle Image Velocimetry

ISC 2020 Digital

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Outline

• Particle Image Velocimetry (PIV)
  From traditional method to deep learning method

• Unsupervised learning of PIV
  Our unsupervised learning method of PIV

• Results
  Comparisons with traditional PIV and supervised learning method
  Test on real experimental data

• More results
Particle Image Velocimetry
Introduction

Particle Image Velocimetry (PIV) is one of the most popular measurement techniques in experimental fluid dynamics.
Traditional Methods

• **Cross-correlation method**

Calculates a displacement by searching for the maximum cross-correlation between two interrogation windows from an image pair.

- Relatively Efficient
- Easy to implement
- Spatially sparse
- Requires post-processing
Traditional Methods

• **Optical flow method**
  Treats the PIV problem through the solution of an **optimisation problem**, seeking the minimisation of an objective function.

- Dense output
- Time consuming
Deep learning methods

• From optical flow to fluid flow

FlowNet

Deep learning methods

• Supervised learning – PIV

**Basic idea:** Train network using data with known velocity field
(Typically synthetic data e.g. simulation results)

**Several network architectures have been researched:**
PIV-DCNN, PIV-FlowNet, PIV-LiteFlowNet etc.

S. Cai, J. Liang, Q. Gao, C. Xu, R. Wei.: Particle image velocimetry based on a deep learning motion estimator. IEEE Transactions on Instrumentation and Measurement (2019b)
Challenges

• Insufficient data
There is no easily available ground truth data in real world scenarios.

• Domain mismatch

Can we go further?
Unsupervised learning of PIV
Loss function

• Unsupervised learning vs Supervised learning

How to design the loss function?
Loss function

- Photometric loss

\[ L_P(I_1, I_2, F^f, F^b) = \sum_{x \in P} \rho \left( I_1(x) - I_2(x + F^f(x)) \right) + \rho \left( I_2(x) - I_1(x + F^b(x)) \right) \]

\[ \rho: \text{Generalized Charbonnier penalty function} \]

D. Sun, et al. IJCV (2014)

Loss function

- Smoothness loss

\[ L_s(F^f, F^b) = \sum_{(s,r) \in N(x)} \sum_{x \in P} \rho \left( F^f(s) - 2F^f(x) + F^f(r) \right) + \rho \left( F^b(s) - 2F^b(x) + F^b(r) \right) \]
Loss function

• Consistency loss

\[ L_C(F^f, F^b) = \sum_{x \in P} \rho \left( F^f + F^b(x + F^f) \right) + \rho \left( F^b + F^f(x + F^b) \right) \]
Loss function

• Final integrated loss

\[
L(I_1, I_2, F^f, F^b) = \lambda_D L_D + \lambda_S L_S + \lambda_C L_C
\]
Network Architecture

• LiteFlowNet architecture

Main Features

1. Compact model size (compared to FlowNet)
2. Feature warping module (Address large displacement)

Final Pipeline

UnLiteFlowNet-PIV
Training details

• **Data:** 15,050 particle image pairs (half was used in training)
  
PIV dataset
  Shengze Cai, Shichao Zhou, Chao Xu, Qi Gao. Dense motion estimation of particle images via a convolutional neural network, Exp Fluids, 2019

• **Training iterations:** 40,000 iterations with a batch size of 8

• **Ensemble loss strategy of multi resolution outputs is applied**

\[ L_T = \sum_i w_i L_i \]
Results
Metrics

• Average Endpoint Error (AEE)

Averaged Euclidean norm of differences between estimated flow and ground truth flow matrix

\[ \text{AEE} = \| \mathbf{F}^e - \mathbf{F}^g \|_2 \]
Comparison

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<th>Methods</th>
<th>Back-Step</th>
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<th>JHTDB channel</th>
<th>DNS turbulence</th>
<th>SQG</th>
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<tr>
<td>UnLiteFlowNet-PIV</td>
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</table>

(The error unit is set to pixel per 100 pixels for easier comparison)


S. Cai, J. Liang, Q. Gao, C. Xu, R. Wei.: Particle image velocimetry based on a deep learning motion estimator. IEEE Transactions on Instrumentation and Measurement (2019b)
Results

Flow past a backward facing step

Sea Surface Flow (Driven by SQG)
Results

Flow past a circular cylinder

Error (white = zero)
Results

Sea Surface Flow (Driven by SQG)

Error (white = zero)
Real Experimental data

Time-resolved Jet Flow
(Experimental data, no ground truth)

Data source: https://www.pivchallenge.org/pub05/index.html#c
Real Experimental data

**Time-resolved Jet Flow**
(Experimental data, no ground truth)

Inputs

UnLiteFlowNet-PIV
(Our unsupervised method,
Trained by full integrated loss)

PIV-LiteFlowNet
(Supervised method)

Data source: [https://www.pivchallenge.org/pub05/index.html#c](https://www.pivchallenge.org/pub05/index.html#c)
Conclusions

• **Competitive results**
  Competitive results compared with classical PIV methods as well as existing supervised learning based methods

• **Potential generalization ability**
  Potential to generalize to complex real-world flow scenarios where ground truth is effectively unknowable

Project page with open source codes: [https://github.com/erizmr/UnLiteFlowNet-PIV](https://github.com/erizmr/UnLiteFlowNet-PIV)

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More Results
JHTDB
Isotropic turbulence
JHTDB
DNS turbulence
JHTDB Channel

Ground truth flow

UnLiteFlowNet

PIV-LiteFlowNet

Input images overlay

AEE : 8.4

AEE : 8.8
Thank you!
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