Parallel computing accelerates sequential deep networks model in turbulent flow forecasting

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***Abstract*—This study aimed to employ deep learning capability and computing scalability to create a model and predict a velocity component of the straining turbulence flow. The turbulence flow was generated in a laboratory. The flow is seeded with tracer particles with an 8-9 μm diameter and gravity of 1.1 g/cm^3. The turbulence intensity of the flow is controlled via impeller rotation speed. The mean strain rate was $4s^{-1}$, made by two circular plates placed in the flow facility and moving toward each other in the center of the measuring area by an actuator. The dynamics of the particles are measured using high-speed Lagrangian Particle Tracking at 10,000 frames per second. The measurements were repeated 20 times to collect an appropriate dataset. Measured data from the experiment were employed to design a gated recurrent unit model. The experiment extracted data have been divided into training and test data to validate the models. Two powerful parallel computing machines, JUWELS and DEEP-EST at Juelich Supercomputing Centre, were employed to implement the model. The velocity forecasting with a gated recurrent network presents a considerable outcome and could be developed for turbulence flow cases in many applications. The scalability of the computing machine using GPUs accelerates the computing time for this model significantly for both machines, which strengthens the ability to predict turbulent flow based on the Lagrangian framework feature.**

***Index Terms*—Gated recurrent unit, turbulent flow, scalability, parallel computing, particle fluid, speedup**

I. Introduction

Turbulence flow occurs in most artificial and natural phenomena [1] [2]. There are many cases of turbulent flow in our daily life and industry. Airflow around our car, flow in the engine mixing chamber, water in the waterfall, draining water flow, and wind speed passing a wind turbine are examples [1]. Turbulence flow is random and non-repeatable, and it is possible to study this flow regime via statistics data [1]. There is no general classical physics solution for turbulence flow; thus, it is impossible to predict the flow's available data for the following period. Computational fluid dynamics is a traditional numerical approach for nonlinear problems such as turbulence flow. Direct numerical solution and large eddy simulation are the most applicable methods, but they are costly in computing. High-performance computing is an essential factor for the majority of numerical methods for turbulent flow. We are still far from the required computing cost for many actual problems and can't afford it. Recently many studies applied the artificial intelligence method to create models based on available data to predict the forward time step of the sequential dataset [3] [4] [5] [6]. Turbulence flow in Lagrangian frameworks has spatial and temporal features, and this capability could be employed in the recurrent neural networks to forecast the next period of the phenomena. In many applications of industry, research and experiment, it is possible to measure the velocity field directly or indirectly via devices such as constant temperature anemometer, flowmeter (and obtain the velocity), pitot tube, laser doppler anemometry, and light detection and ranging. This study introduces a method to use time series data consisting of velocity components and position in 2D coordinate to train the GRU model and evaluate the prediction in future time.

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II. Methodology

A. Spatiotemporal features of fluid particle

In this study, Lagrangian frameworks were employed to study the fluid particle [1] [7]. In the Lagrangian view, the particle fluid motion for each point involves the position vector and velocity vector at a particular time t. Based on this framework, the fluid particle motion is defined as [1]:

$$x_j = x_j(t, x_{j,0}), \quad j = 1, 2, 3 \tag{1}$$

$$U_j = U_j(t, x_1(t, x_{1,0}), x_2(t, x_{2,0}), x_3(t, x_{3,0})), \quad j = 1, 2, 3 \tag{2}$$

where (1) and (2) describe the fluid particle position and velocity in 3D coordinate respectively. In these presentations, x is the position, U is the velocity, and t is the time. In these equations, denote i specifies the vector components. Therefore the measured data from Lagrangian particle tracking consist of datasets present velocity and position vectors at a particular time for a fluid particle [8]. This dataset will apply in the deep learning networks to predict the next period. In this study, the measurements are 2D, and j =3 is not addressed.

B. Laboratory facility and the datasets

In this study, a dataset was used from experiments conducted for turbulence flow investigation [9] [10]. The facility is designed to generate a turbulence flow with particular turbulence intensity that is controlled via impeller speed. Eight impellers are installed in the corners and making the flow turbulent. The simulated flow had $100 < Re_{\lambda} < 500$ [9] [8]. The flow was seeded with tracer particles with a median diameter of 8–10 μm and specific gravity g/cm^3 (hollow glass). The Lagrangian particle tracking approach is employed to measure the fluid particle features. The calculated Stokes number for the particle was less than one and meet the tracing requirement. To create the strain two circular plate located in the facility moved toward each other and made the particular mean strain rate in y-direction which is $2S = 4s^{-1}$ and it is the main orientation [8]. Equation 3 describes the mean flow field $\langle \mathbf{U} \rangle$ in the facility;

$$\langle \mathbf{U} \rangle = (Sx, -2Sy, Sz), \tag{3}$$

where -2S is the primary strain rate in the y-dir, and S is the strain rate for the other two orientation. Symbol x, y and z are the particle displacement. Equation 3 defines the flow field based on the laminar flow. However it is well known in the turbulence flow the velocity is fluctuated. The measurement in area located in the center of the facility and it is equivalent to 24.5 $\times$ 24.5 mm^2 (512 $\times$ 512 pixels). High speed camera with 10000 frames per second is employed to recorded the tracer particle move. Each video included 4000 frames and to have appropriate statrtics the measurement repeated 20 times and datset consists of 80000 frames.

C. Time series data from the measurement

This study applied a suggested hybrid model to use recorded datasets, including velocity field and displacement with two components in two directions for each specific time. These data are spatial and temporal. Hence, the model predicts the velocity component in both directions and then could be developed in 3D time-series data. The primary direction of the strain in the measured data is the y-direction. Since the major fluctuation in the turbulence flow will be affected in this direction, the prediction model is performed in this direction. This model could be developed for all other directions.

D. The designed GRU model

The gated recurrent unit model was employed in this study. It is well known that recurrent neural networks can perform forecasting for sequence data via long short-term memory. GRU [11] is a derived determination of LSTM and has a bit distinction in the model architecture. GRU cell composed of hidden state, rest gate and update gate. In the proposed model, data series involving two velocity components in the x and y direction and two displacement coordinates x and y. Every traced particle fluid at a specified time has a velocity which is a function of time and position based on the Lagrangian view. Moreover, the input feature is on a different scale and then it is essential to scale them. The data are split into 80% and 20% training data and test data, respectively. To assess the model, the mean absolute error (MAE) and coefficient of determination (R^2) are measured.

E. Parallel computing

This work uses the MSAbased JUWELS system at the JSC in Germany, representing the fastest EU supercomputer with 122,768 CPU cores only in its cluster module. While JUWELS and multi-core processors offer tremendous performance, the particular challenge to exploiting this data analysis performance for ML is that those systems require specific parallel and scalable techniques. In other words, using JUWELS cluster module CPUs with Remote Sensing (RS) data effectively requires parallel algorithm implementations as opposed to using plain scikit-learn15, R16, or different serial algorithms. The computing information in this study was carried out based on these machines as below:

- JUWELS Booster Module: 1 node involves 2× AMD EPYC Rome 7402 CPU, 2× 24 cores, 2.8 GHz, 936 compute nodes, 3,744 GPUs.
- DEEP-EST, Data Analytics Module (DAM): 1 rack with 16 nodes, Nodes, 2 x Intel (R) Xeon (R) CPU, 384 GB DDR4, 2 TB non-volatile DIMM (NVM), 1 Nvidia (R) V100 (R) 32GB HBM2 GPU 1 Intel (R) Stratix 10 FPGA 32GB DDR4, Processors: 32 x Intel (R) Xeon (R) Platinum 8260M Scalable Processor @ 2.4GHz (768 cores total).

III. Result

The result of the designed model presents MAE=0.002 and R2=0.98. The assessment mentions a considerable outcome from this approach and could be developed for similar applications. The scalability of the computing machine using GPUs accelerates the computing time for this model significantly for both machines, which strengthens the ability to predict turbulent flow based on the Lagrangian framework feature.

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