# Estimation of Electrostatic Potential Fluctuations in Kelvin-Helmholtz Turbulence in Linear Plasmas using Multi-Scale CNN

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We demonstrate the estimation of electrostatic potential fluctuations in dynamically varying Kelvin-Helmholtz turbulence using multi-scale convolutional neural network. The turbulence field is obtained from simulations based on a reduced fluid model in cylindrical magnetized plasmas. The target turbulence shows limit-cycle oscillations, and coherent and spiral structures are generated and annihilated repeatedly. High accuracy of the prediction is realized for the electrostatic potential field, and the estimation of the particle flux calculated from the predicted potential agrees with the answer with 98.4% accuracy. Behavior of the prediction accuracy is also discussed by changing the hyper parameters, such as the number of filters and the size of the training data.



Keywords: deep learning, plasma turbulence, limit-cycle oscillations, velocity field, Kelvin-Helmholtz turbulence

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Particles/heat transport is determined autonomously by the turbulence generated by the plasma inhomogeneities. Understanding the characteristics of the transport based on direct measurement is an urgent issue. However, it is difficult to measure the flow field fluctuations. For instance, a huge equipment is required for the heavy ion beam probe [1], and many assumptions are needed for the Langmuir probes [2]. Additionally, there are velocimetry methods that use the image correlation technique [3], but they require assumptions such as incompressibility. Therefore, it is necessary to develop a simple and generic method.

Recently, it has become possible to observe plasma fluctuation fields as images [4]. Multi-scale convolutional neural network (CNN) have demonstrated high effectiveness in the field of image processing. In fact, multi-scale CNN based estimation of turbulent fields on the solar surface has been proposed [5, 6]. This method has been applied to magnetically confined plasmas and succeeded in estimating electrostatic potential fluctuations in drift wave turbulence [7]. In that work, the neural network, multi-scale deep learning (MSDL) [6], is designed with the density fluctuation as the input and the electrostatic potential fluctuation as the output. On the other hand, it has been pointed out that Kelvin-Helmholtz (KH) turbulence is important in basic plasma devices [8]. Since the correlation between density and potential is weak in KH turbulence, it is not obvious that the method in [7] is applicable for the KH turbulence. In this study, we apply the method presented in [7] to estimate the electrostatic potential fluctuation of the KH turbulence with dynamic variations in a linearly magnetized plasma. The flow fluctuation field is evaluated from the $E \times B$ drift with the predicted electrostatic potential fluctuations in a cold plasma approximation.

The simulations are based on a three-dimensional fluid model of a cylindrical plasma, solving an extended equations of the Hasegawa-Wakatani model [9, 10]. By introducing a vorticity source, it is possible to drive the KH instability, which is important in linear devices [11]. The obtained turbulence includes limit-cycle oscillations (LCOs) of the background field and fluctuation energy. The plasma conditions are the same as in [9]. In this study, a neural network, MSDL [6], is utilized and optimized to density fluctuations as the input data and electrostatic potential fluctuations as the output.

Multi-scale CNN consists of several spatial filters with different size in order to detect global and fine structures simultaneously [6]. The structure of a multi-scale CNN is shown in Fig. 1. In the first convolution layer shown in the left block, the convolution is performed in three dimensions along the spatial and temporal axes, resulting in a four-dimensional array containing the spatial axis, the temporal axis, and the number of filters. In the last block, shown in the right block, convolution is performed only on the spatial axis. Five kinds of special filters are used, whose size in radial and

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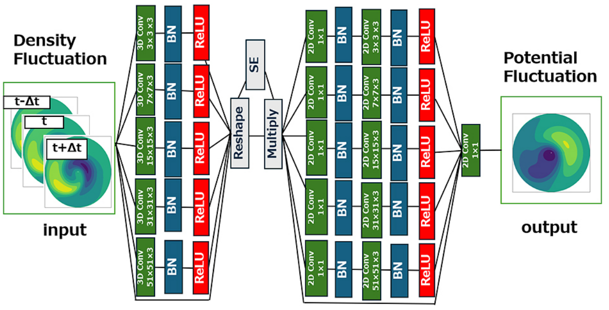


Fig. 1. Structure of multi-scale convolutional neural network, MSDL [6]. Here, green is convolution layer, blue is batch normalization layer, and SE is squeeze-and-excitation, respectively.

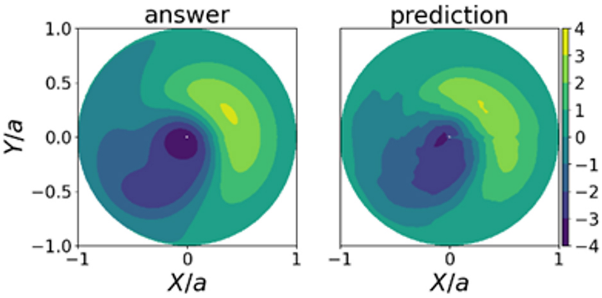


Fig. 2. Spatial distributions of electrostatic potential. Left and right panels show the simulation data and that estimated by the proposed method, respectively.

azimuthal directions are 3 × 3, 7 × 7, 15 × 15, 31 × 31, 51 × 51, where these numbers correspond to the number of pixels. The size of a pixel is $\frac{a}{86}$ and $\frac{2\pi}{64}$ in the radial and azimuthal directions, respectively, where $a$ is the plasma radius and $a$ = 10 cm in this case. The filter size of 31 pixels corresponds to the scale of the dominant mode in the simulations. The filters with sizes 15, 7 and 3 correspond to the higher harmonics of the dominant mode. The 51-pixel filter corresponds to the zonal scale. The number of frames for the training, the validation, and the test are 1170, 155, and 150, respectively, with the time interval of $\Delta t = 1$ (the time is normalized by ion cyclotron frequency). The estimation method is applied to KH turbulence to estimate the electrostatic potential fluctuations from the density fluctuations.

The snap-shots of the spatial distributions of electrostatic potentials obtained by multi-scale CNN and that obtained by simulation is shown in Fig. 2. The correlation coefficient including time evolution is 0.96, indicating that the two are in good agreement with high accuracy.

The azimuthal spectrum is evaluated to quantify the estimation accuracy. The azimuthal Fourier mode decomposition of the electrostatic potential $\phi(r, \theta, t)$ is given by

$$\phi(r, \theta, t) = \sum_m \phi_m(r, t) e^{im\theta}. \qquad (1)$$

The predicted and simulated azimuthal mode spectra for $m$ = 1, 2, 3, and 4 at $r/a$ = 0.58, where $r$ denotes the radial position and $a$ is the plasma radius, agree with each other to a high degree of accuracy. The azimuthal mode spectrum of

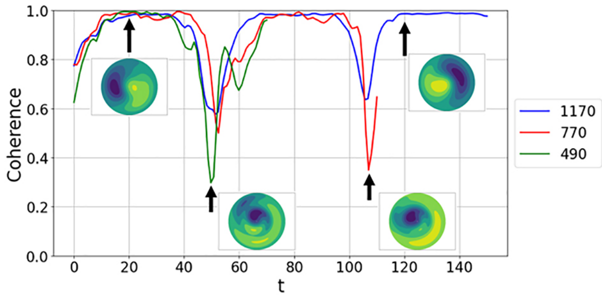


Fig. 3. Time evolution of coherence between prediction and answer. Here, the color indicates the number of frames of training data. Green, red, and blue represent the case with 490, 770, and 1170 training data, respectively.

the simulated and predicted data are introduced as ${\phi_m}^a(t)$ and ${\phi_m}^p(t)$, respectively. Their relative errors are 9.5%, 0.8%, 5.5%, and 12%, respectively. In order to improve the prediction accuracy, a new spatial filter of size 71 was added to the branched convolutional layers shown in green, as illustrated in Fig. 1. The filter is designed to capture the scale of the background field. The coherence becomes 0.99, 0.96, 0.88, and 0.74, for $m$ = 1, 2, 3, 4 respectively. Here, the coherence was 0.98, 0.89, 0.76, and 0.55 before adding the filters. The phase angle between the answers and predictions of each mode is 0.011, 0.008, and −0.007, for $m$ = 1, 2, 3 respectively, which was 0.013, −0.06, and −0.017, before adding the filters. It is noted that the relative error is calculated based on both the amplitude and phase differences between ${\phi_m}^a(t)$ and ${\phi_m}^p(t)$, whereas the coherence is determined solely from the phase information. Due to this difference, discrepancies arise in the ranking of the relative error and coherence values for each mode. Accuracy of the coherent structure is confirmed to improve by increasing the filters.

The time evolution of coherence between the simulation and the prediction is shown in Fig. 3. The coherence degrades and improves repeatedly. This oscillation is synchronized with the LCOs. By increasing the training data from 490 to 1170 ensembles. The coherence at $t$ = 49 becomes 0.65 from 0.3. In this study, we show that when the fluctuation structure evolves in a limit cycle manner, the prediction accuracy remains high for coherent structures. However, as the structure breaks down and transitions into an incoherent state, the prediction accuracy decreases. Nevertheless, we demonstrate that increasing the training data can help mitigate this decline in accuracy, even in the incoherent state. In this context, a coherent structure is defined as a state in which a single vortex stably persists, whereas an incoherent structure corresponds to a state characterized by the splitting of vortex pairs into multiple vortices or the emergence of spiral patterns.

In summary, we demonstrate the estimation of electrostatic potential fluctuations of KH turbulence by using multi-scale CNN. High accuracy of the prediction is realized for the electrostatic potential field, and the estimation of the particle flux calculated from the predicted potential is 98.4% accuracy. We also observe the improvement of the electrostatic potential fluctuations estimation for spiral structures when varying hyperparameters such as the size of the training data. This study validates the CNN model using simulation data, and the final goal is to apply the model to experimental data. Before applying the proposed method to experiments, the following extensions are required. (1) Acquire light emission intensity data and use it as input for the CNN: Currently, the CNN requires two-dimensional cross-sectional data of plasma density as input. In experiments, it is possible to obtain two-dimensional image of the light emission intensity using tomography techniques [4]. The emission intensity can be expressed as a function of density and electron temperature [12]. Therefore, it is necessary to train the CNN with considering not only the density but also the electron temperature fluctuations. (2) Eliminating noise present in actual experimental data: Noise is inevitable in experiments so that removing the noise becomes a key issue. These extensions will be reported in future.

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