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A deep-learning approach to analyze wavenumber-space images of gyrokinetic simulations for faster calculations

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Local flux-tube nonlinear gyrokinetic simulations have prevailed nowadays for the purpose to estimate the turbulent transport level. Even today, when high-performance supercomputers have become easy to use, it may often still take up to tens of hours to days for each case. To make matters worse, multiscale simulations covering from low to high-k turbulence have required more computing time even K-class supercomputers [1], where k is the poloidal wave number. The situation would still require long computation time even if the resources of Fugaku supercomputer were available. In nonlinear gyrokinetic simulations, the fluctuation amplitudes grow nonlinearly until saturation, where their level remains almost constant, after a linearly growing phase. If it is possible to determine the stage of the progress in the middle of the simulation, to estimate how long it needs to take to reach the saturation, or to forecast the time needed to determine the saturation level before a simulation is executed, it will be helpful to carry out simulations more effectively.

In order to make it happen, we have been developing the model to diagnose the images output from gyrokinetic simulations using a convolutional neural network (CNN). The EfficientNet [2], which emerged in 2019, has higher classification performance with fewer numbers of trainable parameters than the previous similar CNNs. It is also easily applicable to transfer learning and fine tuning. The TensorFlow/Keras-based EfficientNet has several derivatives depending upon the size of the model, and we use EfficientNet-B4, which is suitable in size for our problems. With EfficientNet-B4 as the core, transfer learning and fine tuning were applied to create the model. The images that will be fed into the model are generated from a nonlinear simulation by GKV [3]. They are the images of normalized fluctuation amplitudes in (k_x,k_y) space.

The model has been trained, resulting in the capability of classifying the simulation phases, i.e., the linear and nonlinear growing phases and the saturation phase, in nonlinear gyrokinetic simulations with GKV almost perfectly: Correct answer rate was 99.9%. It is able to predict the simulation time only from the image as a regression problem. In the training phase, a number of sets of the image and the corresponding simulation time are fed into a model. Such a trained model can predict the corresponding time given an image (Fig.1 (a)). The accuracy of the predictions is as high as R^2=0.9949, where R^2 denotes the coefficient of determination.

This powerful CNN can apply to an estimate of the time it takes to reach the saturation at an early phase of the simulation for the several cases with different initial conditions. For example, let us imagine the situation that two gyrokinetic simulations are launched with different initial fluctuation amplitudes and then are stopped in the middle of the linearly growing phase, say six hours after the start. The nonlinear simulations would last almost one and a half days by the time a saturation phase is reached if they were not stopped. At this point, the model can predict the time to saturation from the images (Fig.1.(b)). We can keep only the case judged to be the fastest and terminate else, obtaining results faster with less computational cost.

References
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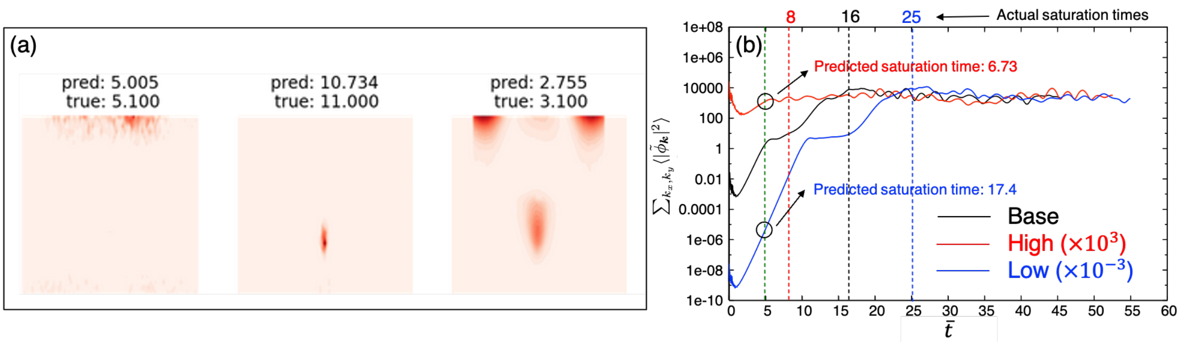

Figure 1 (a) Images of fluctuation amplitudes in (k_x,k_y) space with predictive and actual times. (b) Evolution of fluctuation amplitudes for three cases and the predictions of time to saturation at $\bar{t} = 5$.