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Detecting the Large-scale Wall-attached Eddies by a Machine Learning Perspective in Turbulent Boundary Layer

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SUMMARY:

With the recent advances in machine learning, strategies based on data can be used to augment wall modeling in the turbulent boundary layer. Combined with the attached eddy hypothesis, the present work applies the extreme gradient boosting model to predict the large-scale high/low-speed motions in the outer layer by the input of fixed near-wall large-scale motions. The trained extreme gradient boosting model gives well prediction of high- and low-speed regions of large-scale motions throughout the entire turbulent boundary layer given the input velocity field at $z^+ = 4$. The organized patterns of coherent structures are attached given connected features between inner and outer motions resulting in the premise of the current study. The accuracy analysis, which is defined by the percentage of the correctly predicted high-speed or low-speed regions, shows that the prediction accuracy is as high as 90% throughout the boundary layer. This study shows that there is a great opportunity in machine learning for wall-bounded turbulence modeling by connecting the flow interactions from near-wall motions to well above.

Keywords: Wall-attached eddies, Machine learning, Large-scale motions

1. INTRODUCTION AND METHODOLOGY

Townsend (1976) put out a theoretical framework for wall-bounded flow called the attached eddy hypothesis (AEH), which idealizes wall-bounded flow as a group of inertia-driven coherent structures that are self-similar and randomly dispersed in the plane of the wall. A recent summary by Marusic and Monty (2019) provides details on the main AEH assumptions and restrictions. Perry and Chong (1982) suggested that these coherent structures, or eddies, scale with the distance from the wall with the height of the eddies following a geometric development on the basis of AEH. The boundary layer community has published evidence in favor of self-similarity and wall-scaling (e.g., W. J. Baars et al., 2017; Hwang, 2015; Jiménez, 2012; Marusic, W. J. Baars, et al., 2017). Besides the foundation of AEH, Marusic, McKeon, et al. (2010) introduced a mathematical model to predict the near-wall turbulence given only large-scale information from the outer boundary layer region. Inspired by the role of near-wall motions on outer layer ones, we expect to conduct a model to predict outer layer motions based on the physical models of flow interactions from a machine learning perspective.

Extreme gradient boosting (XGBoost) is a scalable machine learning system for tree boosting

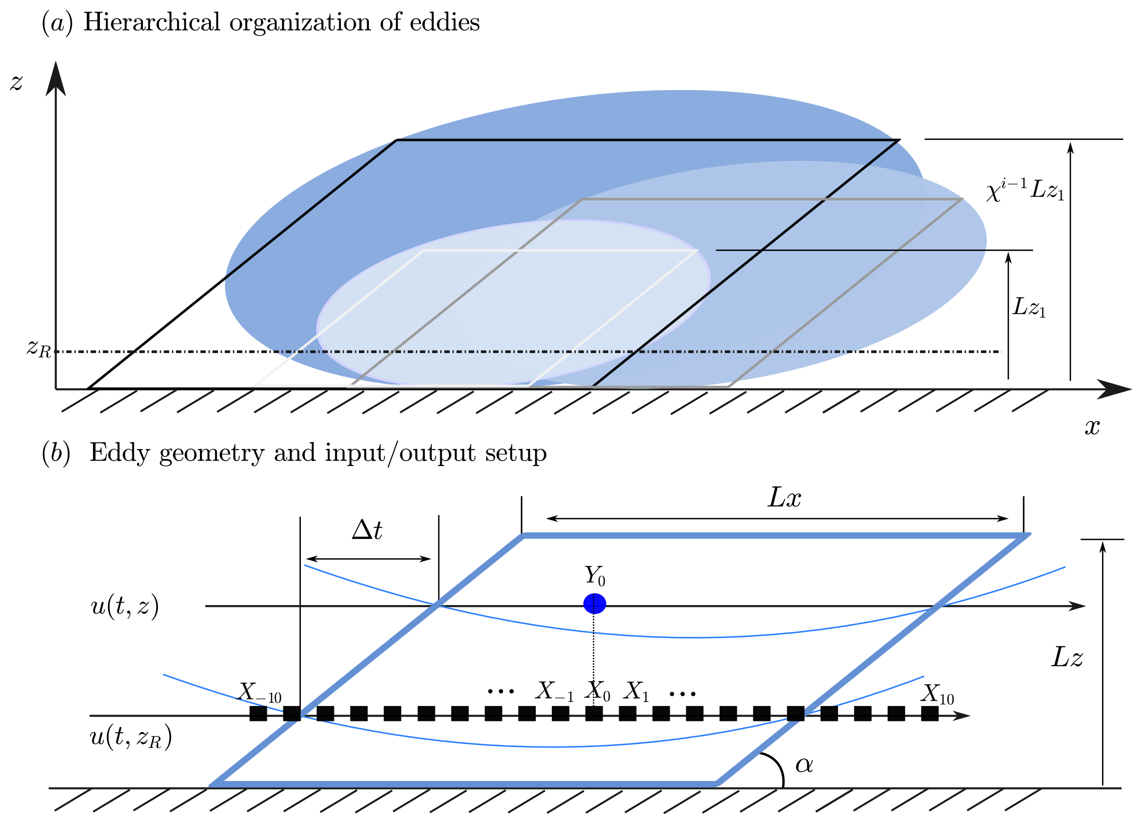

Figure 1. (a) A hierarchical range of self-similar wall-attached turbulent eddy structures, simplified by parallelograms and ellipses. An arbitrary self-similar scaling factor of $\chi = 1.2$ is chosen to proportion. (b) Illustration of the eddy geometry with streamwise wavelength Lx and wall-normal length Lz, the structure inclination angle α can equivalently be expressed as a phase shift Δt between signals at different wall-normal locations. $\{X_{-10},...,X_{-1},X_0,X_1,...,X_{10}\}$ represent the input large-scale streamwise velocity fluctuations components at the fixed near-wall height ($z_R^+ = 4$), and Y_0 indicates the signal at traveled heights in the turbulent boundary layer. The neighboring offset between $\{X_i\}(i = -10 : 1 : 10)$ is $\Delta x = 20dx$, where dx is the streamwise grid-length. The streamwise offset between X_0 and Y_0 is 0.

that was proposed by Chen and Guestrin (2016), and takes superior performance in supervised machine learning. Li et al. (2020) demonstrated the capacity of this model to recognize the physical processes involved in turbulent transport by using the XGBoost model trained using flow invariants to detect the interface between turbulent and non-turbulent flow in the wake of a circular cylinder. Given the physical models proposed in AEH, the XGBoost will be used in the current work to connect the high/low-speed regions of the large-scale motions in the outer boundary layer with the foundation of the near-wall motions.

Here, we give a short illustration of the XGBoost. XGBoost works as Newton-Raphson and a second-order Taylor approximation is used in the loss function to make the connection to the Newton-Raphson method. Each decision tree outputs an identification label $F_{x,z,t}(Y_0) \in [0,1]$ at each grid point (Y_0) to identify the flow state, where the subscripts x and z indicate the spatial locations, t represents the current tree. The final prediction, $F_{x,z}(Y_0)$, is a weighted sum of the predictions from all T-trees. We identify the region where $\hat{F}_{x,z}(Y_0)$ is bigger than a threshold $\sigma_t \in [0,1]$ as the positive prediction using the convectional criterion, i.e.

$$\hat{F}_{x,z}(Y_0) = \begin{cases} 0, & F_{x,z}(Y_0) \leq \sigma_t, \\ 1, & F_{x,z}(Y_0) > \sigma_t. \end{cases} \tag{1}$$

In addition, the accuracy of the prediction 'Ac' to the large-scale motions from the fixed near wall signal to the traveled signals in the turbulent boundary layer is defined as the percentage of the correctly predicted high-speed or low-speed regions and we note that, by definition, $0 \leq \text{Ac} \leq 1$. Notably, the parameters of the XGBoost model are set as the default in the current study.

The velocity pulsation (u) is low-pass-filtered to obtain large-scale (u_L) and small-scale (u_S) fluctuations by using the threshold wavelength of $\lambda = \delta$. u_L^+ is normalized by the friction velocity u_τ. Figure 1(a) shows an idealization of a self-similar hierarchy of wall-attached structures within the logarithmic region of a turbulent boundary layer in streamwise-wall-normal ($x-z$) plane (Baidya et al., 2019; Deshpande et al., 2019; Marusic and Monty, 2019). Here, three hierarchy levels of randomly positioned patches of coherent velocity fluctuations are taken into consideration, with each hierarchy being represented by a separate color. For simplicity, we consider the volume of influence of eddies, in each level, to be characterized by L_{zi} in z direction, with $i = 1,2,3$ denoting the i^{th} hierarchy level. Thus, self-similar eddies with their spatial length constrained by the scaling factor χ are assumed as sketched in figure 1(a). The self-similar structure feature is also identified from the coherence between the turbulence in the logarithmic region and at the near-wall reference position by W. J. Baars et al. (2017). The current work attempts to predict the high/low-speed regions of large-scale motions in the entire turbulent boundary layer from the machine-learning perspective based on the near-wall large-scale motions, as illustrated in figure 1(b). The signals used as input variables are set as large-scale streamwise velocity components labeled as $\{X_{-10}, ..., X_{-1}, X_0, X_1, ..., X_{10}\}$, with the streamwise offset $\Delta x = 20dx$ at a fixed near-wall reference position $z_R^+ = 4$. The output predicted signal obtained from the large-scale motions is located at a wall-normal range of locations higher than $z_R^+ = 4$ as well as right above the input X_0.

2. DATABASE

The dataset used in this work is taken by direct numerical simulations of turbulent channel flow (Graham et al., 2016). The DNS solves the incompressible Navier-Stokes (NS) equations in a periodic channel. The computation domain is $8\pi h \times 3\pi h \times 2h$, with Grid $N_x \times N_y \times N_z = 2048 \times 1563 \times 512$ in the streamwise (x), spanwise (y) and wall-normal (z) directions, respectively. The half-channel height is unity ($h = 1$). The offset between two horizontal neighboring grids is $dx = 8\pi/N_x$. The friction Reynolds number of the direct numerical simulations is $Re_\tau \approx 1000$, where the data can be accessed through the Johns Hopkins Turbulence Database (http://turbulence.pha.jhu.edu/).

3. RESULTS

Figure 2 gives an example of an illustration of how the model was built and used to predict the high/low-speed large-scale motions between the fixed near-wall height z_R and a wall-normal range of locations z. Figure 2(a) indicates the raw large-scale motions for the streamwise velocity collected at $z/\delta = 0.0045$ (grey) and $z/\delta = 0.1$ (blue), evidencing that highly-correlated features

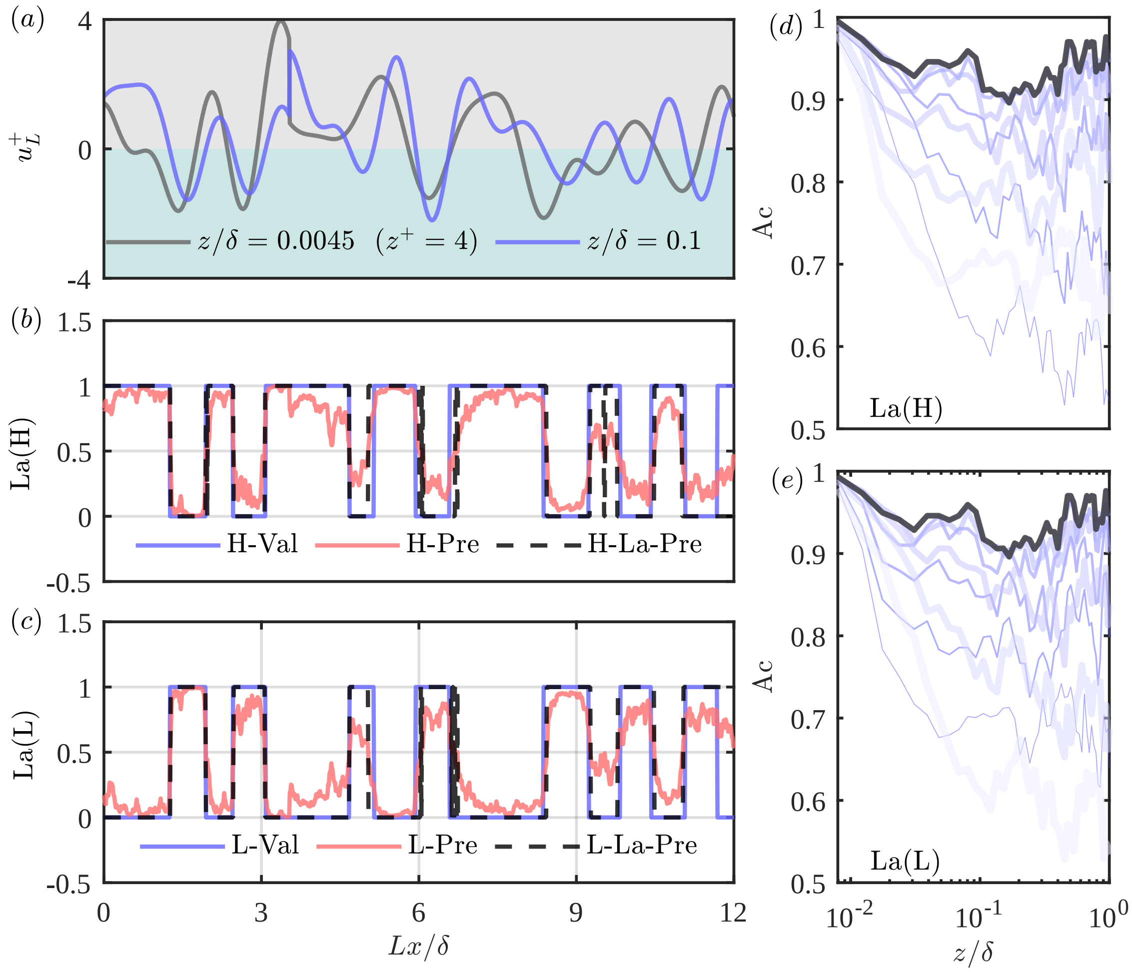

Figure 2. An example of time series large-scale streamwise velocity fluctuation at heights $z/\delta = 0.0045$ (grey) and $z/\delta = 0.1$ (blue). Black and green shadows indicate the high- and low-speed regions. (b) The labeled high-speed region at $z/\delta = 0.1$ with true or not marked by 1 or 0, respectively. The blue solid line 'H-Val' indicates the validation obtained from the large-scale signal in (a). The red line 'H-Pre' represents the prediction value $F_{x,z}(Y_0)$ by the XGBoost model, in the ranges from 0 to 1. The dashed black line 'H-La-Pre' is identified by the red line with a threshold value larger than $\sigma_t = 0.5$ as the positive prediction marked as 1, otherwise marked as 0. (c) similar to (b) but identifying the low-speed region marked as 1. (d) and (e) give the accuracy (Ac) for high-speed and low-speed prediction, respectively, as a function of wall-normal heights z/δ, with increasing threshold $\sigma_t = 0.1 : 0.1 : 0.9$ indicated by lighter and thicker shades of blue. The black lines indicate the threshold $\sigma_t = 0.5$.

between them. The prediction for high-speed regions of large-scale motions from the signal at $z/\delta = 0.1$ (blue in figure 2a) is shown in figure 2(b). 'H-Val' indicates raw large-scale motions labeled as 1 and 0 representing high-speed and non-high-speed regions, respectively. 'H-Pre' is the output of the predicted value obtained from the identification label $F_{x,z,t}$. 'H-La-Pre' is obtained from $\hat{F}_{x,z}(Y_0)$ with $\sigma_t = 0.5$ in equation (1). Similarly, figure 2(c) gives the prediction of the low-speed regions. Good matches between 'H-Val' and 'H-La-Pre' (or 'L-Val' and 'L-La-Pre') show the great performance of the current prediction model. Figure 2(c) and (d) give the accuracy (Ac) analysis for high-speed and low-speed prediction at different wall-normal heights (z/δ) and σ_t (0.1:0.1:0.9) in equation (1). Obvious to see, $\sigma_t = 0.5$ gives the best prediction, further to be used in the following sections.

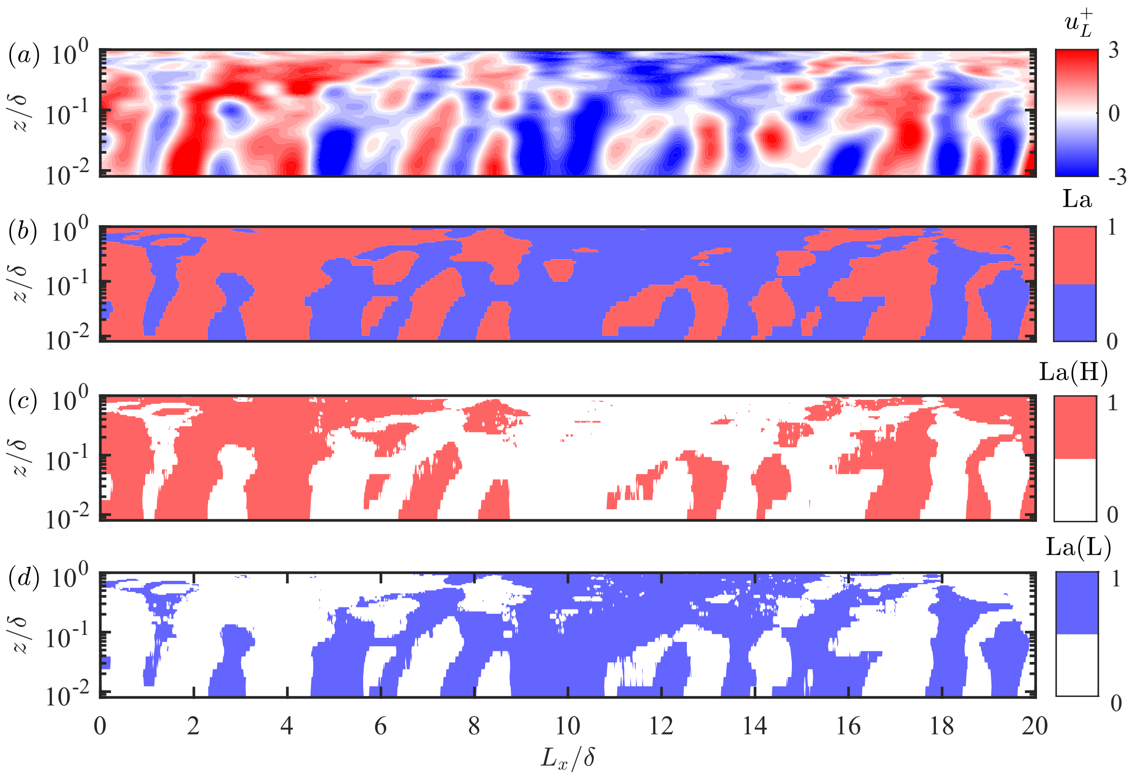

Figure 3. (a) Contours of large-scale streamwise velocity fluctuation u_L^+ in $x-z$ plane. (b) Observed high- and low-speed regions marked as 1 and 0, respectively. (c) and (d) represent the predicted high- and low-speed regions with $\sigma_t = 0.5$ by (1).

The contour of large-scale streamwise velocity fluctuation u_L^+ in $x-z$ plane is given in figure 3(a), which has been replaced by 1 (marked as red) and 0 (marked as blue), showing in figure 3(b), representing high- and low-speed regions, respectively. Figure 3(c) and (d) show the prediction of high- and low-speed regions filled with red and blue shadows representing the positive prediction obtained from 'H-La-Pre' and 'L-La-Pre' in figure 2. Obviously, the prediction is successful resulting in the physical model (AEM) based machine learning method being suitable to be a predicted way in the turbulent boundary layer.

4. CONCLUSION

A machine learning model based on XGBoost was used to detect the large-scale wall-attached eddies connecting with Townsend's AEH in the turbulent boundary layer. The model gives a prediction of the high/low-speed regions of large-scale motions that match well with the observed flow field by the input of large-scale motions in near-wall regions. It identifies that it is a successful combination of the machine learning model and physical model in the turbulent boundary layer. In the future, the structure inclination angles of the large-scale motions associated with model features (e.g., feature importance) will be studied in more detail.

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