

# TH-LDV: Transformer-based Hybrid method for Signal Detection in Laser Doppler Velocimetry

Yue Wang, Ruifeng Li, Changsong Liu, Liangrui Peng, Ning Ding, Gang Yao

Department of Electronic Engineering, Tsinghua University, Beijing, China

1277698780@qq.com, lrf23@mails.tsinghua.edu.cn, {lcs, plr}@tsinghua.edu.cn, {dn22, yg19}@tsinghua.org.cn

**Abstract**—Laser Doppler velocimetry is important for flow particle velocity measurement with various applications, including biomedical engineering and environmental monitoring. However, laser Doppler signals in real applications often encounter substantial noise from multiple sources. Accurately detecting laser Doppler signals is essential for ensuring measurement precision. This paper proposes a Transformer-based hybrid method for signal detection in laser Doppler velocimetry (TH-LDV), which is a combination of deep learning approach and traditional approach. For the deep learning approach, a Transformer-based model is designed for laser Doppler signal detection; For traditional approach, dynamic threshold with constant false alarm rate is explored. The proposed Transformer-based hybrid method uses Transformer for learning non-linear representation of laser Doppler signal, and false alarm rate-aware thresholding method for detection decision. The detected signals are used to estimate Doppler frequency for velocity calculation. Experimental results on both simulation and real data demonstrate the effectiveness of the proposed method.

## I. Introduction

Laser Doppler velocimetry (LDV) is non-contact measurement technique for accurately measuring flow particle velocity [1]. The principle is to detect the Doppler frequency shift in monochromatic laser light which is scattered from flow particles [2]. Its applications span diverse fields such as aerospace, metallurgy, biomedical engineering and environmental monitoring. A significant challenge is that the laser Doppler signals are interfered with considerable noise from multiple sources including ambient light, system noise, etc. Factors such as uncertainty in signal frequency and location, the variable lengths of Doppler signals at different frequency levels, and fluctuations in particle density further increase detection difficulty. Consequently, the ability to effectively distinguish laser Doppler signals from noise is critical for ensuring measurement precision.

Traditional Doppler signal detection methods primarily focus on identifying peak values and signal-to-noise ratios to set thresholds for screening Doppler signals [3]. Some methods are implemented in electronic circuits, such as DSP and FPGA [3], [4]. These energy-based detection methods generally exhibit a limited capacity to adapt to the diverse noise interferences and fluctuations found in practical applications, particularly in low signal-to-noise ratio scenarios.

This paper introduces a novel Transformer-based hybrid

method for laser Doppler signal detection, named as TH-LDV. This method integrates deep learning approaches with traditional techniques. The deep learning approach is adopted to leverage the nonlinear representation capabilities of deep neural networks to enhance signal detection in noisy environments. After comparing three deep learning architectures including Multi-Layer Perceptron (MLP) [5], Long Short-Term Memory (LSTM) [6] and Transformer, we propose a Transformer [7] based method for laser Doppler signal detection. In order to adapt to low signal-to-noise ratio conditions, we explore a dynamic threshold detection algorithm with a constant false alarm rate, and further incorporate a false alarm rate-aware thresholding technique into the Transformer-based method. The detected laser signals will be processed in frequency domain to estimate Doppler frequency.

For laser Doppler signal processing in frequency domain, various methods have been proposed, such as spectral analysis [8]–[10], frequency tracking demodulation [11], [12], counting-type signal processing, digital correlation algorithm [13], and digital FFT algorithm [14], [15]. In this paper, we adopt FFT for frequency domain analysis.

To validate the performance of the proposed method, simulation data and real data of laser Doppler signals under different signal-to-noise ratio conditions are used.

The main contributions of this paper can be summarized as follows:

1. We propose a novel Transformer based method for effective detection of laser Doppler signals.
2. We investigate a dynamic threshold detection method with a constant false alarm rate, and incorporate a thresholding method into the Transformer-based model.
3. Experimental results on both simulation data and real data validate the performance of the proposed method in detecting laser Doppler signals in noisy situations.

## II. Preliminary

In this section, we provide a brief overview of the mechanism behind dual-beam double-scattering laser Doppler velocimetry, along with a description of the laser Doppler signal.

### A. The mechanism of dual-beam double-scattering laser Doppler velocimetry

The optical principle of laser Doppler velocimetry is based on the Doppler effect. Double-beam double-

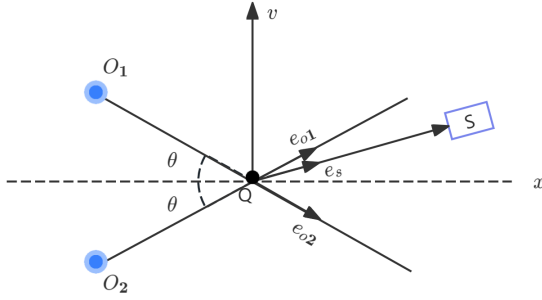


Fig. 1: The light path structure of double-beam double-scattering mode laser Doppler velocimetry

scattering mode is widely used in laser Doppler velocimetry. The laser Doppler velocimetry is equipped with an incident light unit and a light receiving unit. The incident light unit employs two intersecting laser beams to illuminate flow particles. The intersecting beams create an interference pattern at their convergence point. As flow particles randomly pass through this measurement volume, their motion relative to the laser beams causes a frequency shift in the scattered light due to the Doppler effect, which is proportional to the particle's velocity. The term "dual scattering" refers to the scattering of light from the particles back to the light receiving unit with non-fixed position. enhancing signal strength and improving the signal-to-noise ratio, particularly for low density flow particles. The light path structure of a laser Doppler velocimetry utilizing double-beam double-scattering mode is illustrated in Fig. 1. In Fig. 1,  $e_{o1}$  and  $e_{o2}$  denote the unit vectors of the directions of the two light beams, respectively.

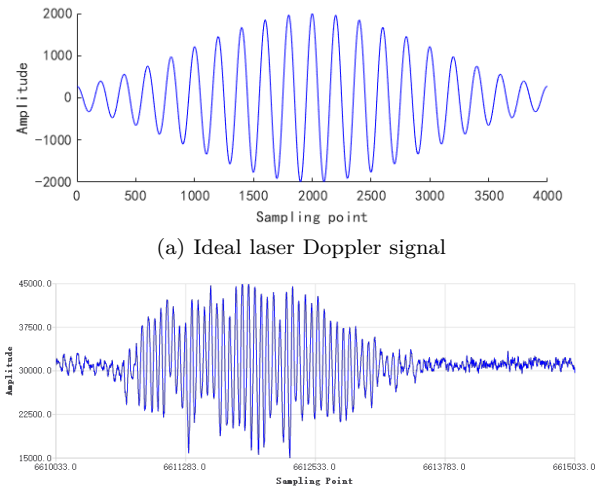
The scattered light signals are processed to calculate particle velocities based on the detected Doppler frequency shifts. This method offers non-contact measurement, high precision, and the capability to assess a wide range of fluid velocities while minimizing disturbance to the flow field [16].

The relationship of Doppler frequency shift  $f_d$  and flow particle velocity  $\vec{v}$  is formulated in Eq. (1), where the wavelength of laser is denoted as  $\lambda$ , and the angle of the incident light is denoted as  $\theta$ , as shown in Fig. 1. Without loss of generality, the analysis in this paper will use one-dimensional Doppler signal analysis as an example.

$$|\vec{v}| = \frac{\lambda \cdot f_d}{2 \sin \theta} \quad (1)$$

### B. Brief description of laser Doppler signal

The mathematical description of an ideal laser Doppler signal is given in the Eq. (2)[16], and its signal envelope presents the shape of a Gaussian curve, as shown in the Fig. 2a. However, noise typically stems from factors such as the random motion of microscopic particles, electronic



(b) Example of a real noisy laser Doppler signal

Fig. 2: Laser Doppler signal

devices, and the external environment, and it causes distortion in the waveform of Doppler signals. A real noisy laser Doppler signal is shown in Fig. 2b.

$$x(t) = i_a \exp \left\{ - \left[ \frac{2\sqrt{2}(t - t_0)}{\tau} \right]^2 \right\} \cos [2\pi f_d(t - t_0)] + n(t) \quad (2)$$

where  $x(t)$  is the received signal at time  $t$ ,  $i_a$  is the light intensity,  $t_0$  is the time of arrival,  $\tau$  is the pulse width,  $f_d$  is the Doppler frequency shift, and  $n(t)$  represents additive noise.

### III. Method

In this section, We first explore dynamic threshold method with constant false alarm rate for laser Doppler signal detection, and then investigate three deep learning-based methods. We further combine the deep learning-based method with a false alarm rate-aware thresholding technique.

#### A. Dynamic Threshold Based Doppler Signal Detection Method

The principle of Doppler signal detection algorithm based on dynamic threshold is Neyman-Pearson criterion The Neyman-Pearson criterion maximizes the detection probability while ensuring a controlled false alarm rate through likelihood ratio tests. It is applicable in scenarios requiring binary hypothesis testing, such as laser Doppler signal detection. In laser Doppler signal detection, false alarm errors are more crucial than false negative detection errors, as noises will affect the Doppler frequency estimation. Therefore, applying the Neyman-Pearson criterion is a viable approach to establish a reasonable detection threshold that effectively controls the false alarm rate.

The relationship between the decision threshold  $T$  and the false alarm rate  $P_{fa}$  is presented in Eq. (3) [17], where  $U$  is the noise energy level, which is obtained by selecting one or more reference units (or signal windows) containing noises, and  $n$  is the number of reference units, such as 32.

$$T = U \cdot \left[ P_{fa}^{-\frac{1}{2n}} - 1 \right] \quad (3)$$

The relationship between the detection probability of the signal  $P_d$ , the signal-to-noise ratio SNR and the false alarm rate  $P_{fa}$  is presented in the Eq. (4), where  $n$  is the number of reference units.

$$P_d = \left( 1 + \frac{P_{fa}^{-1/2n} - 1}{1 + 10^{SNR/10}} \right)^{2n} \quad (4)$$

One minor problem is how to choose the length of the reference unit, because signals with different frequencies have different signal lengths. In this paper, bandpass filter banks with different frequency ranges are used to filter the signal, as the flow particles may have a distribution of different velocities. For different frequency ranges, we will use corresponding length of the reference unit in order to estimate the noise energy level used in the calculation of thresholds in the dynamic threshold method (abbreviated as DT).

## B. Laser Doppler Signal Detection Based on Deep Learning Architectures

We compare three main deep learning architectures on a simplified laser Doppler classification task. The three main deep learning architectures include Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Transformer. MLP is a feedforward network that captures non-linear relationships between outputs and inputs. To better model temporal dependencies, LSTM which incorporates gating mechanisms is introduced. Moreover, Transformer with self-attention mechanism has shown abilities to model global temporal dependencies on various machine learning tasks.

After comparison of the three deep learning models, a Transformer-based sequence modeling method is designed to predict the start and end positions of laser Doppler signals.

1) Signal Pre-processing: To explore the deep learning architectures, we use two kinds of tasks. The first task is a simplified laser Doppler classification task, and the second task is a sequence modeling task for laser Doppler signal detection.

For the simplified laser Doppler classification task, signals are divided into segments with fixed length, each containing 512 data points. The binary label for each segment indicates whether it contains a laser Doppler signal. These segmented signals and their corresponding labels are fed into the deep learning model for training.

For the sequence modeling task, point-wise binary annotations are adopted instead of segment-wise binary annotations.

2) Three Deep Learning Models : We investigate three deep learning models on the simplified laser Doppler classification task, including MLP, LSTM, and Transformer. All of these three methods use *sigmoid* function as the activation function in the output layer.

For the MLP model, a straightforward three-layer architecture is employed. the MLP model has relatively few parameters (4.74M, 1M=10<sup>6</sup> parameters).

For the LSTM model, an architecture of four stacked LSTM layers is adopted. The LSTM model contains 19.20M parameters.

For the Transformer model, we adopt an encoder-only architecture with multi-head self-attention mechanism; additionally, a learnable class token was incorporated into the model to enhance the capture of global information. The designed Transformer model for signal classification task has only 3.37M parameters.

3) Transformer-based hybrid Signal Detection Method: We further propose a Doppler signal detection method using transformer-based sequence modeling method.

The structure of the Transformer model is shown in Fig. 3, An encoder-decoder architecture is employed, and a 1D-CNN layer is appended to the input layer, functioning to extract local temporal features and reduce dimensionality of the raw input data. The encoder comprises four Transformer encoder layers, and the number of multi-head is 4. The decoder comprises two linear layers. *sigmoid* function is adopted as the activation function in the output layer of the light-weight decoder. The designed Transformer model for sequence modeling has 19.48M parameters.

In order to adapt to low signal-to-noise ratio conditions, We incorporate a false alarm rate-aware thresholding technique within the Transformer-based sequence modeling architecture, in light of the dynamic threshold detection algorithm with a constant false alarm rate described in Section III-A. By dynamically adjusting thresholds based on real-time noise levels and false alarm rates, the proposed Transformer-based hybrid method (abbreviated as TH) aims to reduce false positives of the detected laser Doppler signals.

## C. System Implementation

We design and implement a laser Doppler velocimeter for measuring flow particles. The laser Doppler velocimeter consists of a hardware system and a software system.

The hardware system includes an incident light unit, a receiving light unit, a digital acquisition card, a USB transmission line, and a computer. The incident light unit and the receiving light unit constitute an optical system. The laser Doppler signals are converted into analog electrical signals by photodetectors in the receiving light unit. Then the digital acquisition card converts analog electrical signals into digital signals with a sampling rate of 10MHz. The digital signals are transferred to a computer via a USB interface.

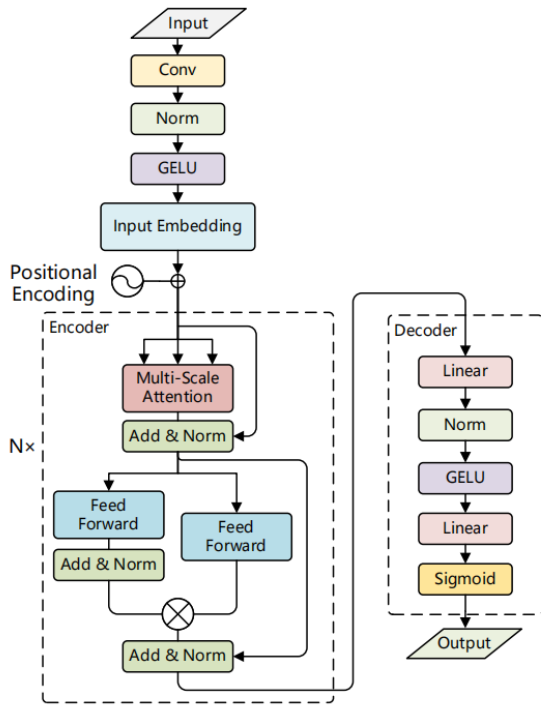


Fig. 3: The Transformer-based architecture

The software system in the computer has the workflow of four steps: a) Data acquisition: It supports dual-channel interface and can continuously receive the data collected by the digital acquisition card; b) Signal detection: The Doppler signal is detected from the collected data by a dynamic threshold method or a deep learning-based method; c) Signal processing in frequency domain: The frequency spectrum of the detected signal is analyzed by an FFT algorithm, and the Doppler frequency is obtained; d) Data analysis: The flow particle velocity is calculated according to the Doppler frequency.

#### IV. Experimental Results

##### A. Experimental setup

Our experiments are carried out on both simulation data and real data.

For simulation data, the Doppler signals are generated according to the Eq. (2) using a Matlab program. In addition, the sampled data contains Gaussian background noise, and the signal-to-noise ratio with Doppler signal is between 5dB-10dB. 40 signal segments are generated, each with a duration of 1 second and a sampling rate of 10 MHz. The number of Doppler signals within each segment are random. The 40 signal segments are partitioned into training, validation, and test sets in a ratio of 0.7:0.15:0.15. containing 220086, 33518, and 28961 laser Doppler signals, respectively. An example of simulation data is shown in Fig. 4,

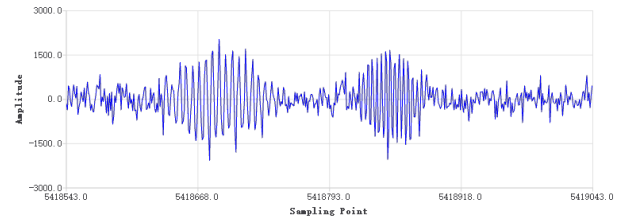


Fig. 4: An example of simulation data containing Doppler signals

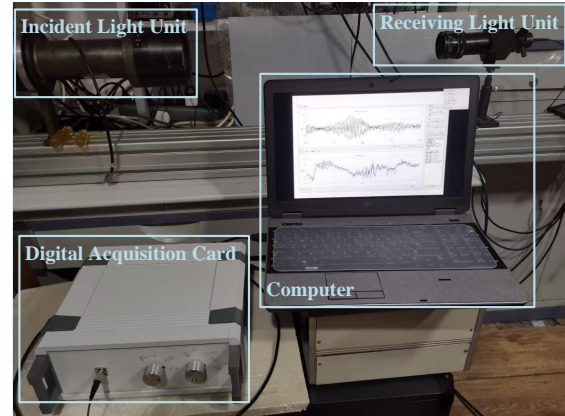


Fig. 5: The self-developed laser Doppler velocimetry

For real data, the samples are acquired by a self-developed laser Doppler particle velocimeter, as shown in Fig. 5. A daily humidifier is employed to produce water mist particles. Samples are manually labeled to indicate the beginning and end of each laser Doppler signal. A subset containing 100 laser Doppler signals is selected. The real data are partitioned into training and test sets in a ratio of 0.5:0.5. The training set is used to fine-tune the deep learning model which is pretrained on simulation data.

Training deep learning models for laser Doppler signal detection is conducted on a GPU server using Nvidia RTX 5060Ti. During the training process, the batch size is set to 32 for the MLP and LSTM models, and 4 for the Transformer model, respectively. The Adam optimizer is adopted with an initial learning rate of 0.001 and dynamic learning rate adjustment. All models are trained for 100 epochs.

For the evaluation metrics of laser Doppler signal detection, recall, precision, and F1 score are utilized. When assessing performance with noisy signals, the false alarm rate and signal-to-noise ratio (SNR) are also considered.

##### B. Experimental results on simulation data

1) comparisons of different deep learning models: The experimental results of different deep learning models are shown in Fig. 6. The Transformer-based method

**Performance Comparison of Different Models Across Thresholds**

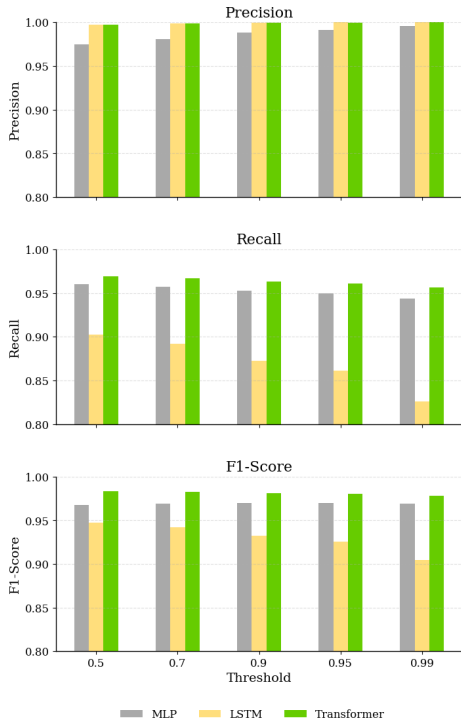


Fig. 6: Performance Comparison of Three Deep Learning Models with Different Thresholds

demonstrates the best performance, While the LSTM outperforms the MLP in terms of precision.

### C. Main results on simulation data

Performance comparisons for the dynamic threshold method (“DT”) and TH-LDV method (“TH”) are conducted on simulation data with varying false alarm rates. The dynamic threshold method is presented in Section III-A, which is a traditional time domain signal detection method with constant false alarm rate. TH-LDV method is the proposed Transformer-based hybrid method for laser Doppler signal detection, which combines the Transformer model with dynamic thresholding method to handle the noisy signals. The results is shown in Table II. The dynamic threshold method and TH-LDV method demonstrate similar performance in terms of Precision. However, the TH-LDV method exhibits significantly better performance in both Recall and F1 score.

### D. Experimental results on real data

We further evaluated the Transformer-based model on a real-world dataset.

Performance comparison of the dynamic threshold method (“DT”) and TH-LDV method (“TH”) on real data is shown in Table II. The proposed TH-LDV method has achieved better overall performance (indicated by F1 score) than the dynamic threshold method.

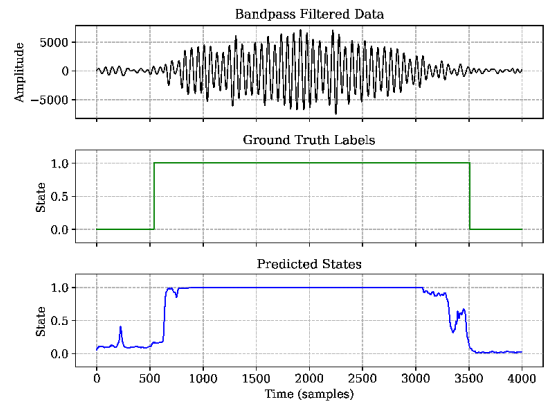


Fig. 7: Example of predicted results of the proposed Transformer-based model

TABLE I: Performance Comparison of the Dynamic Threshold method (“DT”) and the TH-LDV method (“TH”) on simulation data using different controlled false alarm rates

FAR	Recall		Precision		F1 Score	
	DT	TH	DT	TH	DT	TH
$10^{-2}$	0.556	0.988	0.933	0.992	0.697	0.996
$10^{-3}$	0.386	0.993	0.990	0.999	0.555	0.996
$10^{-4}$	0.189	0.982	0.998	1.0	0.318	0.991

An example of the results is shown in Fig. 7. The first row presents the bandpass filtered data of the original signal in Fig. 2b, the second row is the ground truth annotations used for testing, and the third row displays point-wise prediction results.

For the example of real laser Doppler signal shown in Fig. 2b, the frequency spectrum diagram obtained by FFT after using TH-LDV for signal is shown in Fig. 8. The Doppler frequency corresponding to the maximum amplitude in the frequency domain in Fig. 8 is  $165163Hz$ . The velocity of flow particles corresponding to Fig. 2b is finally calculated as  $1.246m/s$  according to Eq. (1).

### V. Conclusion

In this paper, a Transformer-based hybrid method is proposed for detecting laser Doppler signals, which integrates the advantages of deep learning and traditional methods. The proposed method adopts a Transformer

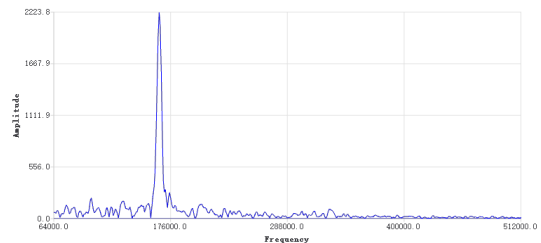


Fig. 8: Frequency domain diagram of real Doppler signal

TABLE II: Performance Comparison of the Dynamic Threshold method(“DT”) and the TH-LDV method(“TH”) on Real Data

	DT	TH
Recall	0.620	0.924
Precision	1.000	0.980
F1 score	0.765	0.951

architecture, incorporating a false alarm rate-aware thresholding strategy to make inference of the Sigmoid activation in the output layer. Experimental results on both the simulation data and real data validate the effectiveness of the proposed approach, demonstrating its superior detection performance and generalization ability. Future work will explore lightweight deep learning architectures for real-time deployment.

#### References

- [1] Y. Yeh, H. Cummins, et al., “Localized fluid flow measurements with an He-Ne laser spectrometer,” *Appl. Phys. Lett.*, vol. 4, no. 10, pp. 176–178, 1964.
- [2] J. Foremen, R. Lewis, J. Thornton, and H. Watson, “Laser Doppler velocimeter for measurement of localized flow velocities in liquids,” *Proceedings of the IEEE*, vol. 54, no. 3, pp. 424–425, 1966.
- [3] H.-H. Qui, M. Sommerfeld, and F. Durst, “Two novel Doppler signal detection methods for laser Doppler and phase Doppler anemometry,” *Measurement Science and Technology*, vol. 5, no. 7, pp. 769–778, 1994.
- [4] B. Yang, P. Ou, and Z. Lin, “Design and implementation of signal acquisition system for Laser Doppler Velocimeter,” in *International Conference on Instrumentation, Measurement, Computer, Communication and Control*, 2013, pp. 1237–1241.
- [5] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, “Learning representations by back-propagating errors,” *Nature*, vol. 323, no. 6088, pp. 533–536, 1986.
- [6] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
- [7] A. Vaswani, N. Shazeer, N. Parmar, et al., “Attention is all you need,” in *Advances in neural information processing systems*, 2017, pp. 5998–6008.
- [8] N. S. Berman and J. W. Dunning, “Pipe flow measurements of turbulence and ambiguity using laser-Doppler velocimetry,” *Journal of Fluid Mechanics*, vol. 61, no. 2, pp. 289–299, 1973.
- [9] D. K. McLaughlin and W. G. Tiederman, “Biasing correction for individual realization of laser anemometer measurements in turbulent flows,” *Physics of Fluids*, vol. 16, no. 12, pp. 2082–2082, 1973.
- [10] L. Lading, “Analysis of signal-to-noise ratio of the laser doppler velocimeter,” *Opto-electronics*, vol. 5, no. 2, pp. 175–187, 1973.
- [11] M. Deighton and E. Sayle, “An electronic tracker for the continuous measurement of doppler frequency from a laser anemometer,” *DISA information*, vol. 12, no. 2, 1971.
- [12] C. Zhang, Y. Zhang, and X. Wang, “Extended spectrum modulation method for MTEM harmonic noise filtering,” *Journal of Applied Geophysics*, vol. 208, p. 104872, 2023.
- [13] T. Nakajima, Y. Ikeda, N. Kurihara, and R. Matsumoto, “Burst digital correlator for LDV signal processing,” *Transactions of the Japan Society of Mechanical Engineers, Part B*, vol. 56, no. 527, pp. 273–279, 1989.
- [14] L. Lading and K. Andersen, “Estimating frequency and phase for velocity and size measurements,” in *International Congress on Instrumentation in Aerospace Simulation Facilities*, 1989, pp. 274–290.
- [15] J. Zhang Hongbo Yang, “A high precision signal processing method for laser Doppler velocimeter,” *Journal for Light-and Electronoptic*, vol. 186, 2019.
- [16] X. Shen, *Laser Doppler Velocimetry Technology and Applications (in Chinese)*. Tsinghua University Press, 2004.
- [17] F. HM, “Adaptive detection mode with threshold control as a function of spatially sampled clutter-level estimates,” *Rca Rev.*, vol. 29, pp. 414–465, 1968.