

Application of EEMD combined with cross-correlation algorithm in Doppler flow signal

SHI Fengdong^{1,2*}, GONG Ruishi¹, LIANG Tongtong¹, LÜ Dong³

1. School of Control Science and Engineering, Tiangong University, Tianjin 300387, China;

2. National Demonstration Center for Experimental Engineering Training Education, Tiangong University, Tianjin 300387, China;

3. Tianjin Tenlink Electronic Technology Co., Ltd., Tianjin 300393, China

*Corresponding author: SHI Fengdong (shifengdong@tiangong.edu.cn)

Received: October 14, 2023

Revised: December 28, 2023

Accepted: January 25, 2024

Abstract: To address the issue of low measurement accuracy caused by noise interference in the acquisition of low fluid flow rate signals with ultrasonic Doppler flow meters, a novel signal processing algorithm that combines ensemble empirical mode decomposition (EEMD) and cross-correlation algorithm was proposed. Firstly, a fast Fourier transform (FFT) spectrum analysis was utilized to ascertain the frequency range of the signal. Secondly, data acquisition was conducted at an appropriate sampling frequency, and the acquired Doppler flow rate signal was then decomposed into a series of intrinsic mode functions (IMFs) by EEMD. Subsequently, these decomposed IMFs were recombined based on their energy entropy, and then the noise of the recombined Doppler flow rate signal was removed by cross-correlation filtering. Finally, an ideal ultrasonic Doppler flow rate signal was extracted. Simulation and experimental verification show that the proposed Doppler flow signal processing method can effectively enhance the signal-to-noise ratio (SNR) and extend the lower limit of measurement of the ultrasonic Doppler flow meter.

Key words: ultrasonic Doppler flow meter; ensemble empirical mode decomposition (EEMD); cross-correlation; fast Fourier transform (FFT) spectrum analysis; energy entropy

0 Introduction

Non-contact installation, high precision, broad measurement range, and high cost effectiveness render the ultrasonic flow meter a pervasive tool in diverse spheres of production and daily life^[1,2]. By utilizing ultrasonic waves to transmit flow rate information, a diverse array of ultrasonic flow meter models can be developed^[3]. In addition to original frequency difference and time difference methods, supplementary techniques such as beam displacement, correlation, Doppler, and displacement have been introduced. Notably, the Doppler method holds paramount importance within the realm of ultrasonic flow meter technology, particularly in accurately measuring the flow of mixed media fluids^[4]. Primarily utilized for extensive flow measurements in industrial operations and daily activities, ultrasonic flow meters encounter challenges in maintaining high measurement accuracy during low flow rate assessments due to their susceptibility to high-frequency interference from the transducer and propagation noise within the

fluid^[5].

To address this issue, numerous researchers have proposed various signal processing solutions for ultrasonic flow meters. For example, Suñol et al.^[6] proposed an algorithm based on cross-correlation technique to determine crossing time and designed an ultrasonic flow meter to improve the accuracy of flow rate measurements by utilizing an analytically derived reference wave obtained from an acoustically forced underdamped oscillator model. Tian et al.^[7] studied the characteristics of ultrasonic echo energy and developed a digital signal processing method for ultrasonic gas flow meters by fitting peak echo energy, which is suitable for measuring high flow rate fluids while ensuring computational efficiency and real-time performance. Hamouda et al.^[8] indirectly measured crossing time by calculating the phase difference between the received signals in upstream and downstream directions, and then combined it with a least-squared sinusoidal fitting technique to mitigate the effects of jitter noise and offset. Gryshanova et al.^[9] combined analytical and computational techniques in investigation of correction factor for ultrasonic flow meters

to improve their accuracy, and obtained the actual average flow rate in the cross section of the meter from a specific mathematical dependency describing rate distribution by integration technique. Murakawa *et al.*^[10] proposed a method based on standard deviation to accurately measure the steam flow in low signal-to-noise ratio (SNR) environments. Sun *et al.*^[11] proposed EEMD-WT-SSA algorithm by combining ensemble empirical mode decomposition (EEMD), wavelet threshold (WT) denoising and singular spectrum analysis (SSA) for MEMS vector hydrophone denoising.

In this study, we proposed a method by combining EEMD with cross-correlation for signal filtering and denoising. The primary objective is to enhance the measurement accuracy of the ultrasonic Doppler flow meter, particularly at a lower flow rate. The experimental validation of the Doppler flow meter has confirmed the effectiveness of the proposed algorithm in mitigating signal distortion and significantly improving measurement accuracy at a lower flow rate.

1 Ultrasonic Doppler flow signal processing algorithm

1.1 An overview of proposed algorithm

Ultrasonic Doppler flow meters have numerous advantages compared to other types of flow meters, and therefore can be well-suited for diverse fluid flow measurements in industrial applications. However, most of the existing research on flow meter technology has predominantly concentrated on time difference flow measurement, with comparatively less attention given to Doppler flow meters. Consequently, improving the accuracy in low flow rate measurements has been a challenge.

In this work, we proposed an algorithm that takes advantages of EEMD and cross-correction algorithm. First of all, EEMD was used to decompose the Doppler flow signal into n intrinsic mode functions (IMFs) arranged in order of descending frequency, and subsequently the energy and energy entropy values of all IMF components, along with residual component, were calculated. Furthermore, the IMF components of the Doppler signal were filtered and reorganized, and then divided into two equal halves. Finally, cross-correlation algorithm was used to reduce the noise of the signal in the low and medium frequency ranges, thereby enhancing the accuracy of the Doppler frequency shift measurement. The specific process of the algorithm is illustrated in Fig.1.

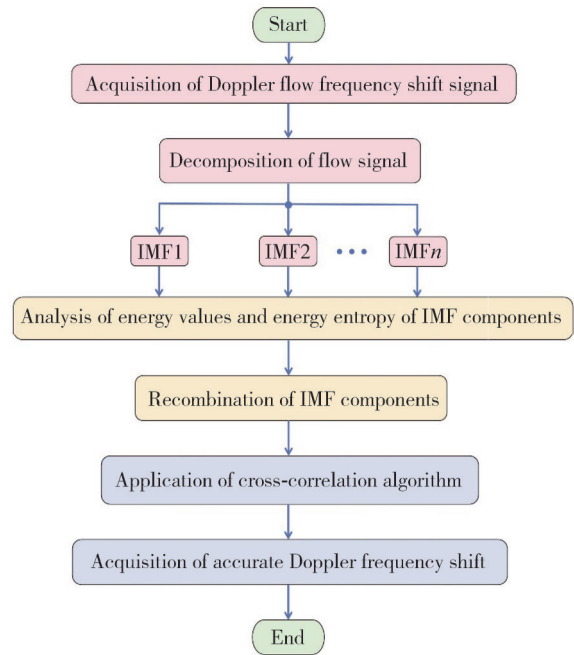


Fig. 1 Flow chart of EEMD with cross-correlation algorithm

1.2 EEMD

EEMD is an adaptive signal time-frequency decomposition technique that autonomously decomposes a signal into high-frequency and low-frequency IMPs based on the signal's characteristics^[12]. However, EEMD is susceptible to issues such as mode conflation and endpoint effect, which may compromise its accuracy and reliability^[13]. To address these concerns, EEMD was introduced as an improved version of EMD^[14]. It is a noise-assisted analysis algorithm that enhances the decomposition process by utilizing multiple groups of Gaussian white noises. These noises are added to the original signal to produce noisy signals denoted as $x_i(t)$, and then decomposed by EMD to produce IMF components for all decomposition groups. Subsequently, these IMF components are averaged to obtain the IMF components in each order^[15-17]. In this way, the interference caused by noisy signals is effectively reduced, and the inherent problem of mode mixing in the EMD process is mitigated, resulting in an improved SNR.

To elucidate the fundamental principle of EEMD, we first introduce M sets of Gaussian white noises, denoted as $n_i(t)$, to the original signal $x(t)$, and obtain the noisy signals as

$$x_i(t) = x(t) + n_i(t), \quad i = 1, 2, \dots, M. \quad (1)$$

Subsequently, the noisy signals are decomposed into individual orders of components and residual components by EMD. Each IMF component

corresponds to a distinctive oscillatory pattern within the signal and can effectively capture local characteristics across various scales. Furthermore, the obtained residual term represents the average trend or the remaining low-frequency component after the extraction of the IMF components. Thus, we get the decomposition formula for EMD signals as

$$x_i(t) = \sum_{j=1}^J c_{i,j}(t) + r_{i,j}(t), \quad j = 1, 2, \dots, J, \quad (2)$$

where $c_{i,j}(t)$ stands for the j th IMF for the i th iteration; $r_{i,j}(t)$ is the residual function of the signal $x_i(t)$, which captures the average trend of the signal; and J denotes the total number of IMF components. The aforementioned two steps are iteratively repeated for each $x_i(t)$ signal with the addition of Gaussian white noise, and the EMD is independently performed to acquire the set of IMF components as

$$\{c_{1,j}(t), c_{2,j}(t), \dots, c_{M,j}(t)\}. \quad (3)$$

Based on the principle that the statistical value of uncorrelated sequences is zero, we get the final IMF components by EEMD as

$$c_j(t) = \frac{1}{M} \sum_{i=1}^M c_{i,j}(t), \quad (4)$$

where $c_j(t)$ is the j th IMF component by EEMD.

1.3 Energy entropy

Information entropy serves as an effective quantitative measure of information content^[18,19]. The underlying principle is that events with lower occurrence probabilities carry a higher amount of information. A higher information entropy indicates increased uncertainty and reduced information content within the signal. Consequently, as the signal becomes more disordered and approaches white noise, the information entropy grows larger. In the case of decomposing ultrasonic Doppler flow signals using EEMD and producing $c_j(t)$, assuming that the number of IMF components is J , the energy of each IMF order and its residual component can be calculated by

$$E_j = \int |c_j(t)|^2 dt, \quad j = 1, 2, \dots, J, \quad (5)$$

and total energy is

$$E = \sum_{j=1}^J E_j. \quad (6)$$

Then, we get the energy entropy based on EEMD as

$$H_j = - \sum_{j=1}^J p_j \log_2 p_j, \quad (7)$$

where p_j is the proportion of the j th energy component,

and it is denoted as

$$p_j = E_j/E. \quad (8)$$

1.4 Cross-correlation algorithm

The cross-correlation algorithm is employed to quantify the correlation between two functions at distinct time points and enhance the SNR of the noisy signal by exploiting the uncorrelated nature of the useful signal and the noise signal^[20]. Moreover, the cross-correlation algorithm effectively preserves the frequency characteristics of the useful signal. Therefore, it is suitable for calculating the Doppler frequency shift.

The signals $g(t)$ and $f(t)$ are composed of the useful signals $G(t)$ and $F(t)$, along with the respective noise signals $n_g(t)$ and $n_f(t)$. By leveraging the characteristic of the cross-correlation algorithm to extract the useful signals containing noise, we can get the cross-correlation function $R_{gf}(\tau)$ for $g(t)$ and $f(t)$ as

$$R_{gf}(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T g(t) f(t + \tau) dt, \quad (9)$$

where τ is the delay time, and T is the sampling time. Since there is no correlation between the useful signals and the noise signals or between the noise signals themselves, there is no correlation between $\{G(t), F(t)\}$ and $\{n_g(t), n_f(t)\}$, or between $n_g(t)$ and $n_f(t)$. Consequently, after removing the noise, Eq. (9) is rewritten as

$$R_{gf}(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T G(t) F(t + \tau) dt. \quad (10)$$

2 Ultrasonic Doppler signal analysis and processing

2.1 Acquisition of Doppler shift signal

According to the Doppler effect, for accurate measurement of fluid flow rate using a Doppler flow meter, it is crucial to have air bubbles or suspended particles in the fluid within the pipeline^[21]. When the transmitting transducer emits a fixed-frequency ultrasonic wave, the bubbles or suspended particles in the liquid serve as the “first observer” to experience relative motion with the propagating sound wave. Upon these bubbles or suspended particles are reflected, they act as the “sound source”, while the receiving transducer serves as the “second observer” to detect the relative motion. Thus, the frequency difference between the transmitting and receiving transducers corresponds to the Doppler shift. Since the magnitude of Doppler frequency shift is directly proportional to the the fluid flow rate within the pipeline, the fluid flow rate can be accurately

determined at that instant^[22]. Fig.2 illustrates a schematic diagram of the ultrasonic Doppler flow meter, where θ represents the angle between the ultrasonic transducer and the fluid flow rate u .

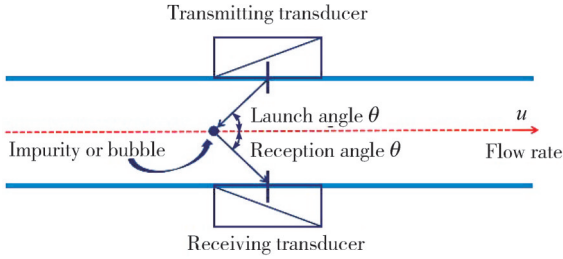


Fig. 2 Schematic diagram of Doppler flow rate measurement

Initially, the ultrasonic transmitting transducer and the ultrasonic receiving transducer are securely positioned on the exterior of the pipe. The ultrasonic transmitting transducer emits a 1 MHz ultrasonic signal into the pipe by means of a sound wedge. The noisy signal received by the ultrasonic receiving transducer is processed to obtain the ultrasonic Doppler frequency shift signal. Fig.3 shows the flow chart of acquiring the Doppler shift signal. The 1 MHz reference signal transmitted by the ultrasonic transducer and the received signal are combined in the mixer circuit, where the frequency shift signal contains high-frequency noise. Subsequently, the low-pass filtering process preserves the difference frequency signal. Eventually, the difference frequency signal is amplified to obtain the frequency shift signal corresponding to the Doppler flow, and then it is digitally filtered to obtain the precise flow rate signal.

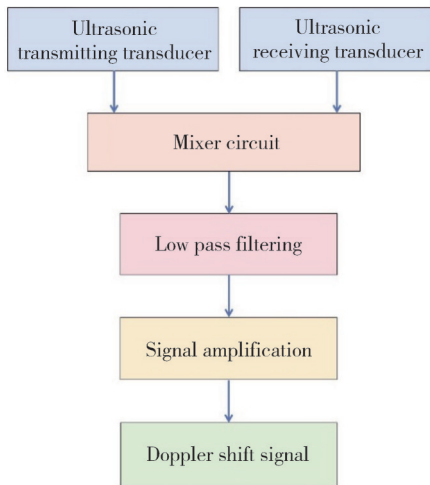


Fig. 3 Flow chart of Doppler shift signal acquisition

In the given scenario, ultrasonic signals propagate through the fluid medium at a speed of c . When f_1 is the frequency of the ultrasonic transmitting transducer, and f_2 is the frequency of the ultrasonic receiving transducer, we can get the Doppler frequency shift and the relationship between Doppler shift and fluid flow rate,

which is expressed as

$$\Delta f = f_2 - f_1 = \frac{2u \cos \theta}{c} f_1. \quad (11)$$

Thus, the fluid flow rate in the pipeline to be measured is

$$u = \Delta f \frac{c}{2f_1 \cos \theta}. \quad (12)$$

2.2 Analysis of Doppler shift signal

In this section, we analyze the Doppler shift signal in time domain and frequency domain, as shown in Fig.4 and Fig.5, respectively.

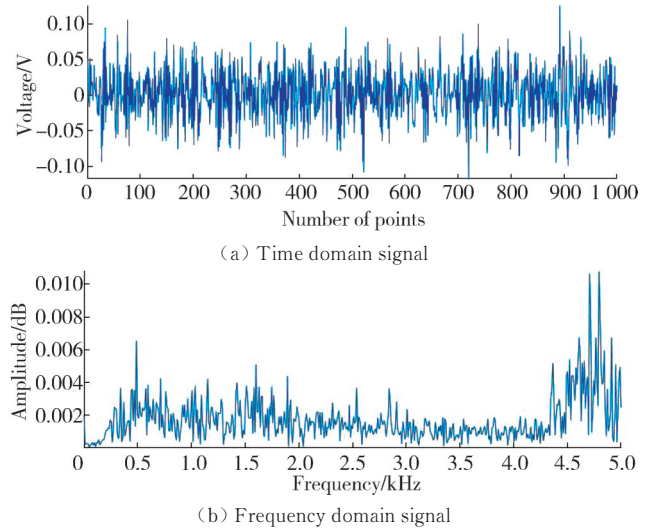


Fig. 4 Doppler frequency shift signal at flow rate of $0.5 \text{ m} \cdot \text{s}^{-1}$

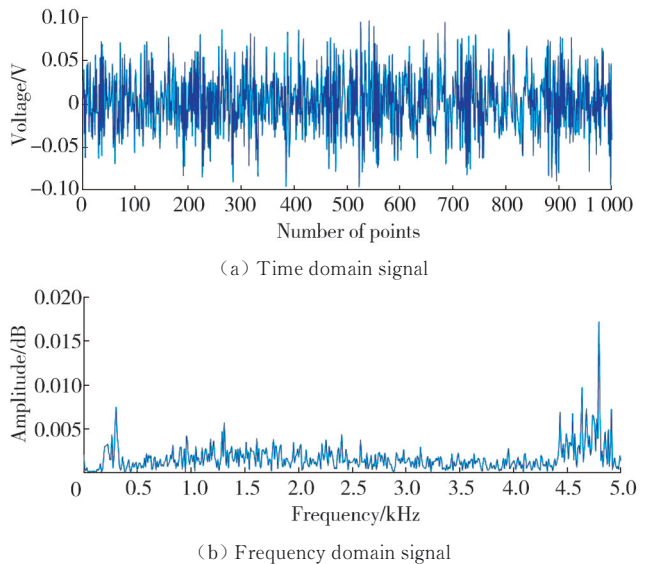


Fig. 5 Doppler frequency shift signal at flow rate of $0.3 \text{ m} \cdot \text{s}^{-1}$

Fig.4 (a) and Fig.5 (a) present the Doppler shift signal with noise interference at fluid flow rates of $0.5 \text{ m} \cdot \text{s}^{-1}$ and $0.3 \text{ m} \cdot \text{s}^{-1}$, respectively. Time domain analysis shows that the Doppler shift signal has significant burr

noise, which may affect the stability of the Doppler shift signal and call out a challenge in obtaining accurate Doppler frequency. Subsequently, frequency domain analysis using fast Fourier transform (FFT) shows that there are bubbles or suspended particles in the fluid, which may introduce reflection noise to the Doppler frequency shift signal. Additionally, installation of the ultrasonic transducer probe causes interference with the Doppler signal and produces various frequency peaks on the spectrogram of the Doppler signal. These factors result in substantial errors during flow rate calculation. To accurately determine the frequency shift of the Doppler signal, digital signal processing is necessary. Similarly, Fig.4 (b) and Fig.5 (b) illustrate the Doppler frequency shift signal characteristics in frequency domain at fluid flow rates of $0.5 \text{ m}\cdot\text{s}^{-1}$ and $0.3 \text{ m}\cdot\text{s}^{-1}$, respectively.

2.3 Processing of Doppler shift signal

The ultrasonic Doppler flow signal at a low flow rate is characterized by its weak and distorted characteristics, which makes it challenging to obtain accurate measurements. To address this issue, digital signal processing is performed to remove noise. In this study, EEMD and cross-correlation algorithm are combined to extract valuable signals and enhance the SNR. Since the high-frequency IMF components obtained by EEMD consist of noisy signals whereas the low-frequency IMF components mainly contain useful signals along with some residual noise, the denoising method based on EEMD focuses on extracting the low-frequency IMF components and eliminating the noise in the high-frequency IMF components. Hence, it is crucial to accurately measure the difference between the low-frequency IMF components and the high-frequency IMF components during the denoising process by EEMD.

Initially, the ultrasonic Doppler frequency shift signal is decomposed by EEMD to produce multiple IMF components and one residual component, as shown in Fig. 6. It can be seen that the high-frequency IMF1 component predominantly represents the high-frequency noise signal. Subsequently, we use the method combining energy values with energy entropy to extract and reconstruct the decomposed signals, thereby eliminating high-frequency noise and removing low-frequency interference.

The energy value and energy entropy of the IMF components obtained by EEMD are calculated by Eqs. (5) – (8), as depicted in Fig.7. It can be seen that when the flow rate is $0.5 \text{ m}\cdot\text{s}^{-1}$, IMF1 component has

the highest energy, and the low-frequency component behind IMF5 component has almost no energy. To effectively extract and reconstruct the IMF component signal, energy value and energy entropy are combined for evaluation. Higher energy entropy signifies greater uncertainty and a reduced amount of information within the signal, which means its proximity to white noise. Since the IMF1 component has the largest energy entropy, the energy value and energy entropy can be neglected from IMF5 component onwards on the assumption that this component contains no useful information. Consequently, signal recombination is performed exclusively for the IMF2–IMF5 components. Likewise, the energy and energy entropy at a flow rate of $0.3 \text{ m}\cdot\text{s}^{-1}$ are analyzed, and the Doppler flow signal is reconstructed, as shown in Fig.8.

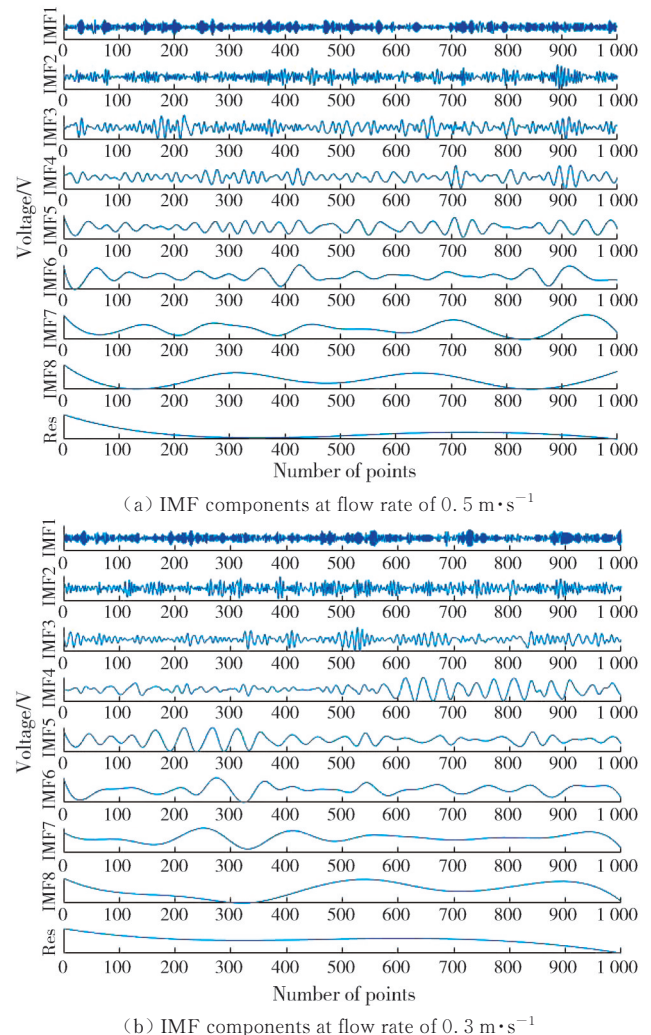
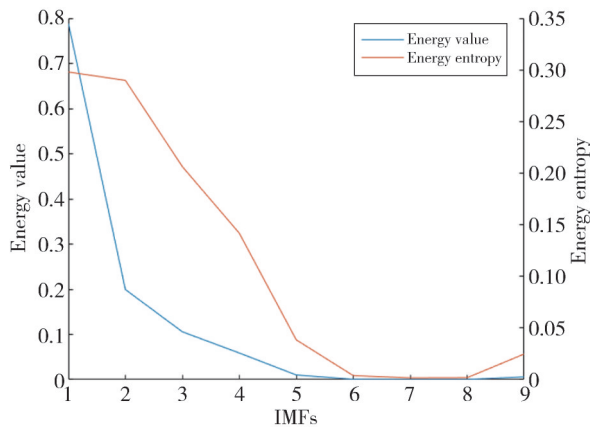


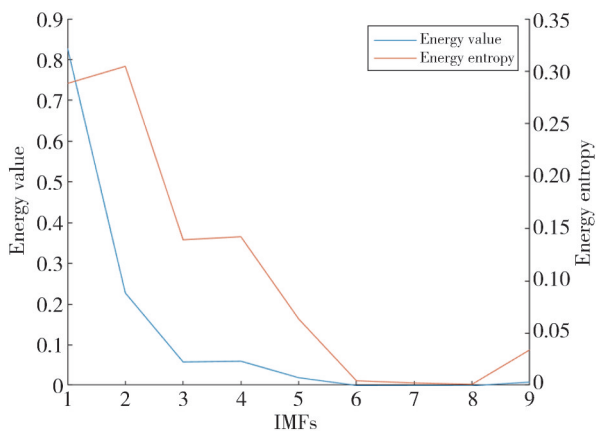
Fig. 6 EEMD results of flow rate signal

Fig. 8 demonstrates that the frequency shift of the reconstructed Doppler flow signal can be calculated. However, since the obtained measurement accuracy is not ideal, it is necessary to further reduce the noise. In this study, cross-correlation algorithm is adopted to

reduce the noise and enhance the SNR while preserving the signal's frequency.

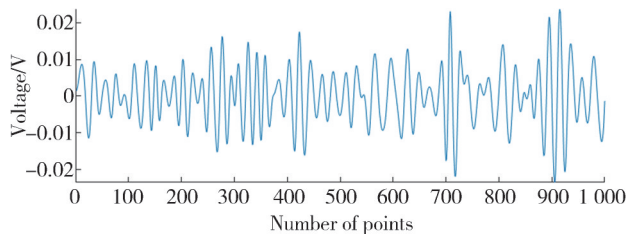


(a) At $0.5 \text{ m}\cdot\text{s}^{-1}$

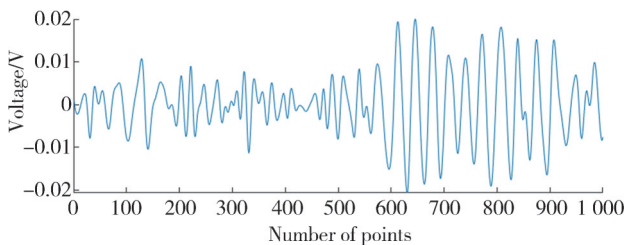


(b) At $0.3 \text{ m}\cdot\text{s}^{-1}$

Fig. 7 Diagram of energy entropy and energy value of IMF components



(a) Doppler flow rate signal at $0.5 \text{ m}\cdot\text{s}^{-1}$

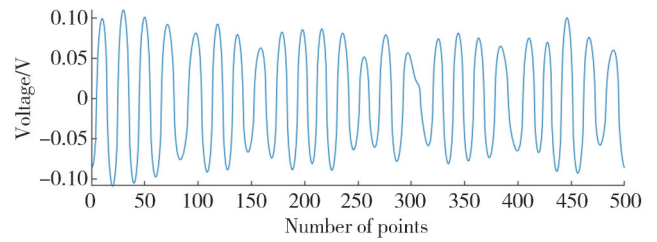


(b) Doppler flow rate signal at $0.3 \text{ m}\cdot\text{s}^{-1}$

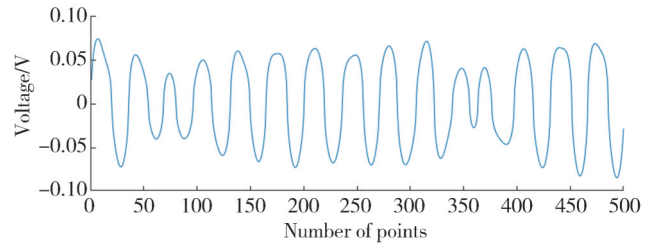
Fig. 8 Recombined Doppler flow rate signal

Initially, the reconstructed Doppler flow frequency shift signal is divided into two halves, denoted as $x_1(t)$ and $x_2(t)$. Subsequently, a cross-correlation calculation is performed on the divided signals according to Eq. (10). The cross-correlation effect of the intercepted

signal is shown in Fig.9.



(a) Cross-correlation signal at $0.5 \text{ m}\cdot\text{s}^{-1}$



(b) Cross-correlation signal at $0.3 \text{ m}\cdot\text{s}^{-1}$

Fig. 9 Cross-correlation waveform of frequency shift signal

It can be observed from Fig.9 that the Doppler flow signal by denoising and cross-correlation filtering, exhibits regular periodic variations. The Doppler frequency shifts are 478 Hz and 304 Hz, respectively. By substituting these frequency shifts into Eq. (12) for Doppler flow calculation, the measured fluid velocity in the pipe is $0.512 \text{ m}\cdot\text{s}^{-1}$ and $0.324 \text{ m}\cdot\text{s}^{-1}$, respectively.

Furthermore, it is evident that the high-frequency noise has been eliminated by EEMD, and low- and medium-frequency noises have been removed by cross-correlation algorithm. The simulation results show that the waveforms are relatively smooth and well-defined without any burr noise, which proves that the proposed method has a notable denoising effect.

3 Experimental verification

To validate the functionality and various indicators of the ultrasonic Doppler flow meter proposed in this study, an indoor fluid flow test platform was constructed. The measurement accuracy of fluid flow was assessed by comparing the flow meter designed with the proposed algorithm with a standard flow meter. The test setup utilized a DN150 pipe to measure the fluid flow containing bubbles or suspended particles, and the fluid flow velocity in the pipe was controlled within the range of $0.2 \text{ m}\cdot\text{s}^{-1}$ to $2.0 \text{ m}\cdot\text{s}^{-1}$ by adjusting the frequency of the inverter on the fluid flow test platform. In this experiment, the microcontroller STM32F407 was chosen as the central control and signal processing unit. The received signal from the ultrasonic transducer was amplified and subjected to hardware filtering. Then, the combination of EEMD with cross-correlation algorithm

was applied to the Doppler frequency shift flow signal to obtain a frequency shift signal with a higher SNR. Finally, Eq. (12) was employed to calculate the instantaneous fluid flow rate within the pipe. The test results are presented in Table 1.

Table 1 Experiment results on an indoor fluid flow test platform

Actual flow rate/(m·s ⁻¹)	Measured flow rate/(m·s ⁻¹)	Relative error/%
0.200	0.192	4.0
0.300	0.289	3.7
0.500	0.486	2.8
0.800	0.782	2.3
1.000	0.983	1.7
1.500	1.480	1.3
2.000	1.978	1.1

It can be seen from Table 1 that at a lower fluid flow rate, the relative movement between the liquid and the bubbles or suspended particles may lead to the difference between the actual flow rate and the measured value, resulting in a deviation in the Doppler frequency shift. Additionally, the EEMD combined with cross-correlation filtering method can significantly reduce the relative error between the test result and the actual values on low fluid flow rate conditions. These results indicate that the proposed fluid flow rate measurement method exhibits high-accuracy and reliable measurements. Consequently, the algorithm can be effectively employed in practical fluid flow rate measurement scenarios.

4 Conclusions

This study aimed to improve the accuracy of ultrasonic Doppler flow meter by denoising algorithm of EEMD combined with cross-correlation algorithm under low fluid flow rate conditions. By extracting IMF signals using EEMD with energy entropy, high-frequency noise was eliminated from the Doppler frequency shift signal, and a smoother reconstituted signal was obtained. Concurrently, the cross-correlation algorithm was used to further refine the reconstituted Doppler frequency shift signal to obtain more accurate measurements of fluid flow rate. The experimental results show that the proposed algorithm effectively extracts the Doppler frequency shift signal submerged in noise interference, thereby enhancing the SNR at low fluid flow rates and expanding the measurement range of lower limit of ultrasonic Doppler flow meter.

Acknowledgement

This work was supported by National Natural Science Foundation of China (No.61973234), and Tianjin Science

and Technology Plan Project (No.22YDTPJC00090).

Declaration of conflicting interests

The authors have no conflict of interests related to this publication.

References

- [1] FANG L D, MA X Y, ZHAO J X, et al. Development of a high-precision and wide-range ultrasonic water meter. *Flow Measurement and Instrumentation*, 2022, 84: 102118.
- [2] LYNNWORTH L C, LIU Y. Ultrasonic flowmeters: Half-century progress report, 1955 – 2005. *Ultrasonics*, 2006, 44: e1371-e1378.
- [3] YI B, ZHANG F X. Ultrasonic flow measuring and its development. *Journal of Test and Measurement Technique*, 1995, 9(1): 14-18.
- [4] XU X L, YANG D Y, CHEN J. Design of ultrasonic Doppler flowmeter. *Instrumentation Technology and Sensors*, 2016(3): 41-43.
- [5] ROSHANAIE S H, ASKARI MOGHADAM R, TARVIRDIZADEH B, et al. Theoretical and experimental evaluation of small flow rate ultrasonic flowmeter. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 2022, 44(8): 323.
- [6] SUNOL F, OCHOA D A, GARCIA J E. High-precision time-of-flight determination algorithm for ultrasonic flow measurement. *IEEE Transactions on Instrumentation and Measurement*, 2019, 68(8): 2724-2732.
- [7] TIAN L, XU K J, MU L B, et al. Energy peak fitting of echo based signal processing method for ultrasonic gas flow meter. *Measurement*, 2018, 117: 41-48.
- [8] HAMOUDA A, MANCK O, HAFIANE M L, et al. An enhanced technique for ultrasonic flow metering featuring very low jitter and offset. *Sensors*, 2016, 16(7): 1008.
- [9] GRYSANOVA I, RAK A, KOROBKO I. The investigation of the correction factor for ultrasonic flow meters. *Measurement*, 2023, 219: 1-11.
- [10] MURAKAWA H, ICHIMURA S, SUGIMOTO K, et al. Evaluation method of transit time difference for clamp-on ultrasonic flowmeters in two-phase flows. *Experimental Thermal and Fluid Science*, 2020, 112: 109957.
- [11] SUN S G, PANG Y, WANG J Q, et al. EEMD harmonic detection method based on the new wavelet threshold denoising pretreatment. *Power System Protection and Control*, 2016, 44(2): 42-48.
- [12] CHENG J S, YU D J, YANG Y. A fault diagnosis approach for roller bearings based on EMD method and AR model. *Mechanical Systems and Signal Processing*, 2006, 20(2): 350-362.
- [13] SHRIVASTAVA Y, SINGH B. A comparative study of EMD and EEMD approaches for identifying chatter frequency in CNC turning. *European Journal of Mechanics-A/Solids*, 2019, 73: 381-393.

- [14] WU Z H, HUANG N E. Ensemble empirical mode decomposition: a noise-assisted data analysis method. *Advances in Adaptive Data Analysis*, 2009, 1(1): 1-41.
- [15] ZHAO H M, SUN M, DENG W, et al. A new feature extraction method based on EEMD and multi-scale fuzzy entropy for motor bearing. *Entropy*, 2016, 19(1): 14.
- [16] WANG Z Y, QIU J, LI F F. Hybrid models combining EMD/EEMD and ARIMA for long-term streamflow forecasting. *Water*, 2018, 10(7): 853.
- [17] LIU D, LIAO X, OUYANG S, et al. Combined EEMD with a novel flexible wavelet threshold function for weighing signal denoising approach. *Journal of Sensors*, 2022, 2022: 5314532.
- [18] XIAO Y C, KANG N, HONG Y, et al. Misalignment fault diagnosis of DFWT based on IEMD energy entropy and PSO-SVM. *Entropy*, 2017, 19(1): 6.
- [19] HUAI Q, LIU K, QIN L, et al. Backup-protection scheme for multi-terminal HVDC system based on wavelet-packet-energy entropy. *IEEE Access*, 2019, 7: 49790-49803.
- [20] KLAUSEN A, ROBBERSMYR K G. Cross-correlation of whitened vibration signals for low-speed bearing diagnostics. *Mechanical Systems and Signal Processing*, 2019, 118: 226-244.
- [21] GODFREY NNABUIFE S, KUANG B Y, WHIDBORNE J F, et al. Non-intrusive classification of gas-liquid flow regimes in an S-shaped pipeline riser using a Doppler ultrasonic sensor and deep neural networks. *Chemical Engineering Journal*, 2021, 403: 126401.
- [22] NGUYEN T H L, PARK S. Multi-angle liquid flow measurement using ultrasonic linear array transducer. *Sensors*, 2020, 20(2): 388.

基于 EEMD 互相关算法在多普勒流量信号中的应用

史风栋^{1,2*}, 巩瑞士¹, 梁通通¹, 吕东³

1. 天津工业大学 控制科学与工程学院, 天津 300387;

2. 天津工业大学 工程训练国家级实验教学示范中心, 天津 300387;

3. 天津腾领电子科技有限公司, 天津 300393

摘要: 针对超声多普勒流量计在低流速信号采集中易受噪声干扰而导致测量精度不高的问题, 提出了一种集合经验模态分解 (Ensemble empirical mode decomposition, EEMD) 结合互相关的信号处理算法。首先, 利用快速傅里叶变换 (Fast Fourier transform, FFT) 频谱分析确定信号的频率范围。其次, 以一定频率进行数据采集, 将采集到的多普勒流速信号应用 EEMD 算法进行分解, 得到一系列本征模态函数 (Intrinsic mode functions, IMFs)。最后, 结合能量熵对 IMFs 进行重组, 并对重组后的流速信号进行互相关降噪处理, 以提取理想的超声多普勒流速信号。仿真和实验结果表明, 采用 EEMD 结合互相关算法可有效提高多普勒流量信号的信噪比, 并扩展超声多普勒流量计的测量下限。

关键词: 超声多普勒流量计; 集合经验模态分解; 互相关; 快速傅里叶频谱分析; 能量熵

引用格式: SHI Fengdong, GONG Ruishi, LIANG Tongtong, et al. Application of EEMD combined with cross-correlation algorithm in Doppler flow signal. *Journal of Measurement Science and Instrumentation*, 2025, 16(1): 58-65.