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Localizing and tracking of in-pipe inspection robots based on distributed optical fiber sensing[☆]

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ABSTRACT

Ensuring the safe transportation of energy relies heavily on the timely safety inspection and pigging of energy pipelines using in-pipe inspection robots known as Smart/Intelligent PIGs. Addressing the potential risks of PIG block incidents and the limitations of excessive speed in the maintenance, real-time localization and tracking of these inspection robots has become imperative. However, traditional localization and tracking methods present a challenge due to their resource-intensive nature, requiring significant manpower and resources. To overcome this limitation and enhance the intelligence of the robot operation monitoring, this paper proposes an innovative artificial intelligence (AI) integration algorithm framework based on distributed optical fiber sensing (DOFS) for real-time localization and tracking of robots. It adopts noise reduction and reconstruction techniques in signal processing, effectively enhancing the quality of optic fiber vibration signals. Notably, the integration of two distinct features that complement each other enables dual verification of tracking detection, ultimately bolstering the system's effectiveness and trustworthiness. Besides, a logical reasoning-based localization decision strategy further enhances the system's capabilities, allowing for controlled tracking intervals and step sizes that can be tailored to meet the task requirements under diverse working conditions. The collaboration of three modules makes it feasible to monitor dynamic changes of the detection robot in the pipeline along the direction of operation. The experimental results convincingly demonstrate that the integrated framework possesses several key advantages of remarkable robustness, real-time performance, and minimal error. It underscores the system's potential to ensure energy pipeline safety efficiently and effectively.

1. Introduction

Pipelines are the most reliable, convenient, and cost-effective transportation mode of fluid energy, such as oil and gas [1]. However, long-distance pipelines in open environments present significant safety risks [2–4]. Especially as pipelines age, the likelihood of accidents sharply increases, making the current period particularly challenging for energy pipelines worldwide [5]. For instance, statistics indicate that the United States experiences an average of 420 energy pipeline accidents annually, while Europe witnesses around 225 incidents per year. Meanwhile, China has suffered more than 1500 pipeline accidents in the past decade alone. Consequently, both governments and industries have recognized the paramount importance of pipeline safety [6].

To ensure safe operation and improve the intrinsic safety level of pipelines, the oil and gas industry has proposed the implementation of intelligent pigging technology (including pigging and in-pipe inspection) [7]. This technology stands as a critical means of detecting and maintaining pipeline safety. By using an in-pipe inspection robot (Smart PIG), not only can it prompt detect pipeline defects, but corrosion products can also be removed from inside the pipeline [8]. Therefore, the function of in-pipe inspection robots can provide the basis for decision-making on pipeline maintenance and improve transportation efficiency. However, it may occasionally encounter stuck incidents or travel at excessive speeds [9]. It poses significant safety risks to the pipeline and hinders effective maintenance. Therefore, real-time

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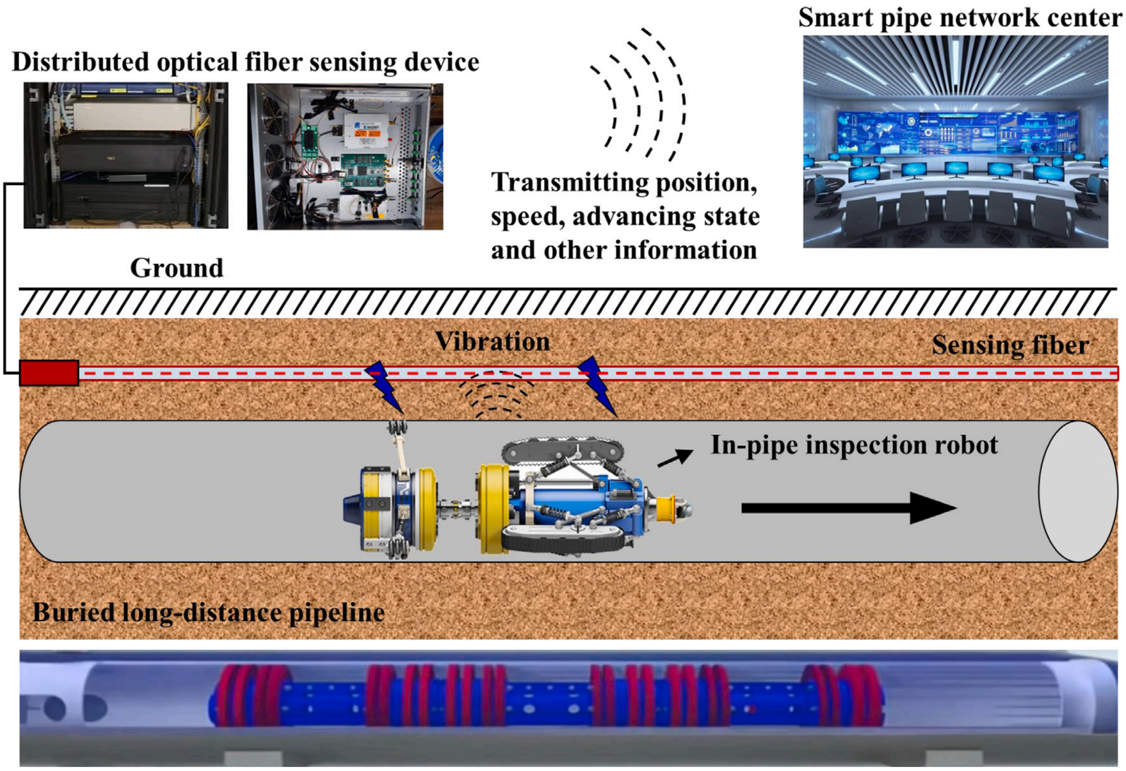

Fig. 1. The schematic diagram of the monitoring system based on DOFS technology for the localizing and tracking of the in-pipe inspection robot.

localization and tracking of in-pipe inspection robots become of utmost importance.

At present, various Smart PIG localization methods are available, such as the acoustic wave method, electromagnetic induction method, and pressure pulse method [10–12]. However, these approaches have certain limitations. For example, the acoustic method is only suitable for shallow-buried pipelines, the electromagnetic induction method is constrained by the magnetic field range, and the detection range is small. The pressure pulse method can only provide approximate and coarse position data. To address these constraints and fulfill the need for a long-distance, anti-interference, accurate, and real-time tracking solution, distributed optical fiber sensing (DOFS) technology emerges as the most fitting choice. It can achieve the remote, on-line, real-time, label-free, and multi-parameter detection [13]. DOFS offers the ideal features required for the effective localization of in-pipe inspection robots, ensuring improved pipeline safety and enhanced operational efficiency.

Distributed optical fiber vibration/acoustic sensing (DVS/DAS) system is one of the most important pipeline safety warning technologies due to its high sensitivity and precision, long-distance detection capability, and anti-electromagnetic interference [14]. Liu et al. proposed an improved positioning algorithm to improve the positioning accuracy for the long-range asymmetric fence perimeter application. It can achieve detection of 96.60% of positioning errors distributed within the range of 0–20 m at the sensing length of 75 km [15]. Sun et al. used an improved vibration imaging and CNN-based approach for intelligent sensing detection [16]. However, its remarkable sensitivity also renders it susceptible to external complex noise in practical application scenarios. Therefore, the primary challenge in utilizing DVS/DAS technology for localizing and tracking in-pipe inspection robots lies in the effective extraction and efficient processing of the signals [17].

To tackle these issues, we propose an integrated algorithm framework based on artificial intelligence (AI) that incorporates signal denoising, feature extraction, and tracking monitoring. Based on the signal quality and noise sources, the adaptive denoising reconstruction method is selected to facilitate signal feature extraction [18,19]. Furthermore, we develop two distinct feature extraction methods and established a localization judgment strategy based on logical reasoning. This novel approach uses optical fiber signals for real-time tracking of the position, velocity, and travel status of the in-pipe inspection robots, thereby liberating manpower, achieving precise localization, and elevating the intelligence level of pipeline sense.

Our main contributions are summarized as follows:

(1) This paper proposes an integrated framework for localizing and tracking in-pipeline inspection robots using DVS/DAS. The method accurately determines the robot's status information during operation and effectively monitors for issues like getting stuck or moving too fast, enabling timely responses to ensure safety.

(2) Compared with prior work, our algorithm framework is faster and more lightweight. By combining signal preprocessing, feature extraction, and logic reasoning technology, it meets the real-time requirements in the pipeline scenario and has significant practical value. Moreover, it allows for flexible control of tracking intervals and step sizes to adapt to various working conditions.

(3) We extensively explore the effective information of optical fiber signals and extract the stacked peak-to-peak and average energy spectrum of the slices to pinpoint the in-pipe inspection robot's location within the defense zone. The effectiveness of the proposed method is validated through experiments using real-world pigging operation data.

The remainder of this paper is as follows. Section 2 reviews the research problem statement and related works on DVS/DAS in pipeline monitoring scenarios. Section 3 illustrates the integrated framework for intelligent localization and tracking, along with the signal processing methods. Section 4 shows the experimental design and results to demonstrate the superior performance of our proposed algorithm. Finally, Section 5 summarizes the paper and outlines the future work.

2. Problem statement

There has been significant and continuous growth in the literature dedicated to exploring the application of DOFS technology in pipeline monitoring [20,21]. However, most of these studies have focused on the identification and location of external threats to pipelines, neglecting the need for monitoring internal inspection efforts [22–24]. A substantial amount of research on external event recognition has also demonstrated that the DOFS technology has strong perceptual capabilities, enabling it to capture vibration signals transmitted along the pipeline's interior [25,26].

2.1. Related works on pipeline monitoring based on DVS/DAS system

DVS/DAS technology plays a crucial role in monitoring the safety of long-distance pipelines [27]. Currently, this technology has gained industry recognition. In another work, we reviewed the research of signal processing and pattern recognition in DOFS technology through bibliometrics [28]. For pipeline monitoring scenarios, Tejedor presented a real-time early warning system to monitor activities along the pipeline and analyze possible threats [29]. Yang et al. constructed a multi-feature fusion convolution neural network (CNN) and LightGBM model based on two new complementary spatial–temporal features and achieved an effective recognition rate of more than 95% in the real environment [30]. Wu et al. proposed a source localization method that utilizes collaborative energy to estimate the vertical offset distance of specific vibration sources and their threat level to buried optical fibers [31]. Jin et al. integrated time and frequency information to generate 2-D time–frequency images and established a deep learning network for pattern recognition. The average recognition accuracy of the nine common sensing events is 96.67%, and the detection time is 0.2391 s [32]. Due to the long distance of oil and gas pipelines, the cost of verifying and intervening in external damaging events increased significantly [33]. DAS is used for real-time pipeline leakage detection, which can accurately locate the leakage with a small aperture [34].

However, due to the complex environment of long-distance pipelines, it is still a challenging problem in practical applications to classify and identify various vibrations with a high recognition rate [35]. More fine-grained recognition tasks need to be implemented in pipeline monitoring scenarios. This includes the localizing and tracking of detectors inside the pipeline.

2.2. Localization and tracking problems of in-pipe inspection robot

As shown in Fig. 1, buried long-distance pipelines are typically accompanied by communication optical cables. Therefore, unused dark fibers can be used as sensing fibers. By installing our self-developed DOFS device at the station or valve chamber, it is possible to achieve safe monitoring of pipelines within a range of 80 km. The localization and tracking of the in-pipe inspection robot are transmitted to the sensing fiber through the vibration generated by the robot in contact with the pipeline wall during the pipeline inspection process. The DOFS system collects and demodulates vibration signals through the upper computer. Then, based on our proposed integrated localization and tracking algorithm, real-time information such as the position, speed, and advancing state of the Smart PIG can be obtained. Finally, the monitoring and identification information is transmitted through the internal network to the smart pipeline network center and announcements are made. The sensing setting parameters of our developed DOFS device are shown in Table 1.

Due to the accumulation of impurities within pipelines and complex working conditions (such as changes in transmission pressure, external terrain, etc.), the in-pipe inspection robots are prone to getting stuck or traveling at excessive speeds. The former can cause the robot to stall, potentially blocking the conveying medium (oil, natural gas, etc.) and excessive local pressures. In severe cases, safety accidents such as pipeline damage, breakage, and even explosions may occur. On the other hand, the latter can render cleaning pipeline operations ineffective, failing to maintain and inspect pipelines while wasting considerable manpower and resources. Therefore, the location and tracking of in-pipe inspection robots are particularly crucial.

Table 1
The physical parameters of sensing setup for the DOFS device.

Sensing setup	Parameter	Sensing setup	Parameter
Channel	2	Frequency response	2 kHz @ 40 km
Monitoring distance	80 km	Data transfer interface	250 MB/s @ PCIE
Spatial resolution	50 m	Communication protocol	MQTT

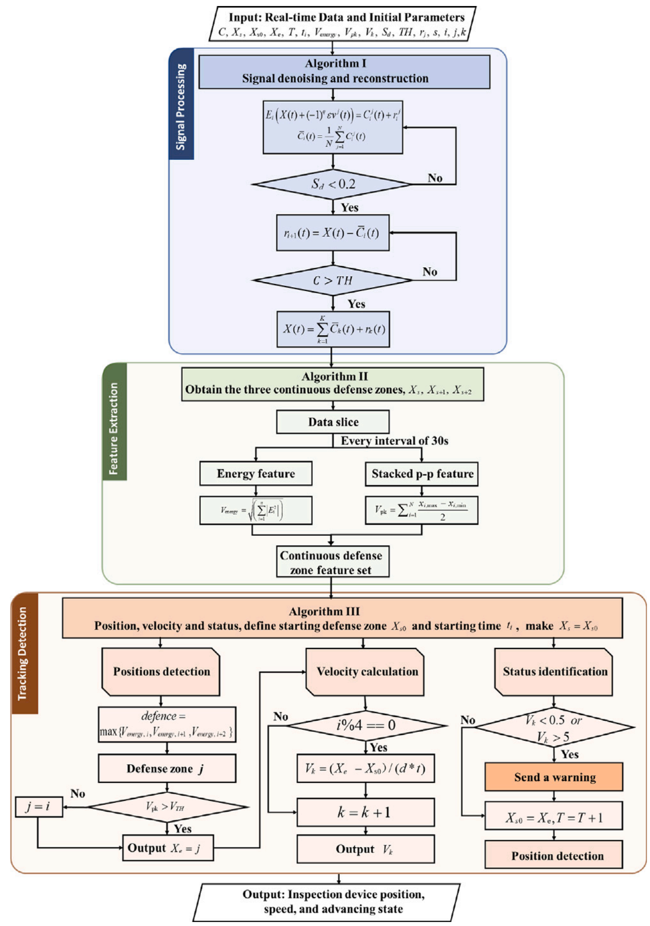

Fig. 2. The framework diagram of localization and tracking integrated algorithm.

3. The proposed integrated system framework

3.1. Overall framework

As shown in Fig. 2, our proposed algorithm framework is divided into three parts, including signal processing, feature extraction, and tracking detection. Among them, the signal processing part mainly consists of signal denoising and reconstruction. The main methods and operation steps are shown in Fig. 2. The input is the slice of the original signal based on our set step size (default 30 s). Then, the preprocessed signal slice is input to the second feature module, where the complementarity and effectiveness of the two features proposed are demonstrated in the multi-scale signal analysis. Finally, the set of continuous defense zones features is input into the tracking detection module, where the real-time position, running speed and travel status of the in-pipe inspection robot are obtained through a logic reasoning algorithm. The starting defense zone number, start time, and judgment conditions of the robot are also required inputs in the step.

3.2. Multi-scale signal analysis

We analyze the optical fiber signal of pipeline inspection and pigging operations in the natural gas pipeline network of Zhejiang

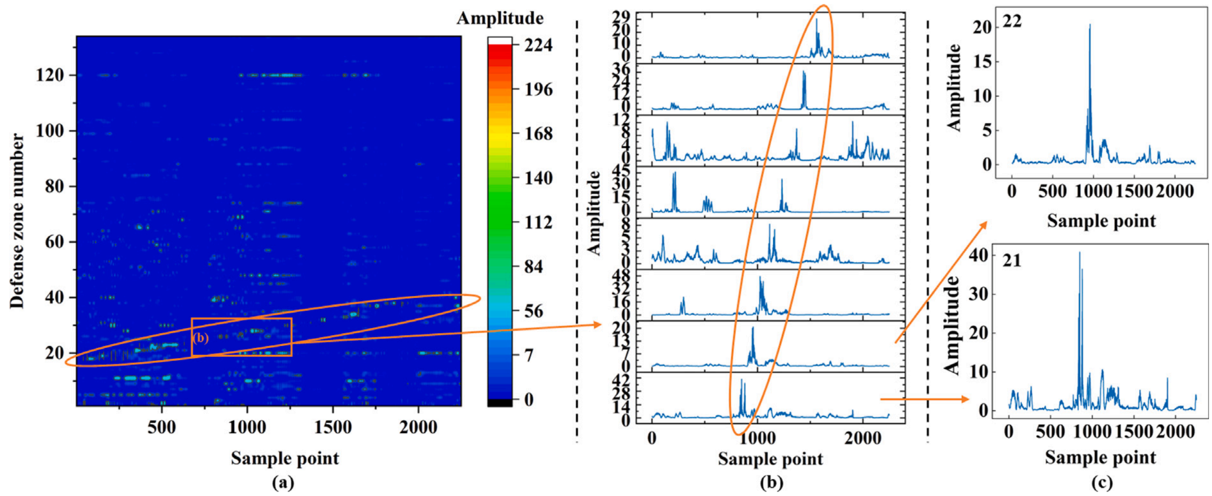

Fig. 3. Multi-scale signal analysis. (a) The waterfall map of multiple defense zones. (b) The signal change of continuous defense zone 21 to 28. (c) The signals of defense zones 21 and 22. Among them, one sample point is 0.25 s.

Province, China over the past two years. The records covered different factors such as operation purposes, lengths, and specifications of the in-pipe inspection robots. It is found that the signal movement trajectory can be observed, but the signal processing method is needed to improve signal quality and a fast-tracking strategy is sought. As for Fig. 3, we selected one of the pigging operations for illustration. The signal is a continuous time signal from continuous defense zone 21 to 28. The purpose of this operation is to pig the pipe, and the vibration emitted by the robot and the pipeline wall would be more significant.

As shown in Fig. 3(a), a waterfall plot recording of 1 km distance is captured. The horizontal axis represents the sample point, which we plot at a sampling frequency of 4 Hz, with a sample point of 0.25 s. The vertical axis represents the number of defense zones. It can be seen that there is a track moving forward (yellow oval block diagram). The signal in the middle section can be amplified as shown in Fig. 3(b). The signal of continuous defense zones 21 to 28 can see a signal with a large energy moving along the direction of the increase of the defense area number with the passage of sample point. This direction is also the direction and position of the robot. Further magnifying the signal of defense zones 21 and 22, it can be found that the signal quality is high. As shown in Fig. 3(c), the signal of the defense zone where the internal detection robot is located is significantly higher than the signal amplitude of the adjacent defense zone. Therefore, it is easy to determine the defense zone of the robot. However, the defense zone 24 in Fig. 3(b) is subject to strong interference and features need to be extracted after noise reduction for judgment.

3.3. Three modules with implementation methods

In this section, we introduce the specific operation details of the three modules for the localization and tracking integrated algorithm.

3.3.1. Signal processing

The DOFS system is affected by the noise of the system itself and the external environment due to its high sensitivity. Therefore, it is necessary to denoise the original signal. Due to the mode mixing and randomness of the noise signal, and the non-stationary features of the original vibration signal, complementary ensemble empirical mode decomposition with adaptive noise (CEEMDAN) is used to reduce the noise of the collected signal [36]. The process of signal denoising and reconstruction is shown in Fig. 2. First, white Gaussian noise (WGN) is added to the signal to be decomposed, and the new signal obtains the first intrinsic mode function (IMF) by empirical mode decomposition (EMD) [37]. Then, the IMF of CEEMDAN is obtained by the overall average of the generated N modal components. The decomposition process is defined as follows:

$$E_i\left(X(t)+(-1)^q\varepsilon\upsilon^j(t)\right)=C_i^j(t)+r_i^j \tag{1}$$

$$\bar{C}_i(t)=\frac{1}{N}\sum_{j=1}^{N}C_i^j(t) \tag{2}$$

$$r_{i+1}(t)=X(t)-\bar{C}_i(t) \tag{3}$$

where $X(t)$ denotes an original signal, and $E_i(\cdot)$ represents the ith IMF obtained by EMD. $\upsilon^j(t)$ represents the WGN, ε and j denote the standard level of white noise and the number of times white noise is added, respectively. q represents a constant, with values of 1 or 2. $C_i^j(t)$ shows the ith IMF obtained by the j^{th} EMD, r_i means the residual error, and $\bar{C}_i(t)$ is the ith IMF of CEEMDAN. Repeat the above process until the residual error is a monotonic function, and the decomposition cannot continue. The number of IMF obtained is K, and $X(t)$ is decomposed into:

$$X(t)=\sum_{k=1}^{K}\bar{C}_k(t)+r_k(t) \tag{4}$$

Finally, the most relevant IMF components are removed to obtain the denoised reconstructed signal. The test results show that the signal-to-noise ratio (SNR) of 6000 continuous real-time data can reach 8.57 dB after CEEMDAN denoising.

3.3.2. Different complementary feature construction

We construct two different features for dual verification of tracking detection as shown in Fig. 2. To ensure optimal real-time performance of the algorithm framework, both features are derived from time-domain signals. This approach utilizes the original signal without the need for feature extraction by transforming other domain space. First, the average energy spectrum feature is constructed by calculating the vibration energy during slice time. According to the energy feature, we can detect energy spikes that occur due to collisions between the in-pipe inspection robot and the pipe wall within three consecutive defense zones. In Eq. (5), the energy value is obtained by summing up the squares of the E_i accumulation, followed by taking the square root:

$$V_{\text{energy}}=\sqrt{\left(\sum_{i=1}^{n}\left|E_i^2\right|\right)} \tag{5}$$

Then, a stacked peak-to-peak feature is further applied to set a threshold to determine whether the tracking algorithm has lost track. The calculation method is as follows:

$$V_{\text{pk}} = \sum_{i=1}^{N} \frac{x_{i,\max} - x_{i,\min}}{2} \tag{6}$$

where $x_{i,\max}$ and $x_{i,\min}$ represent the ith maximum and minimum peak-to-peak values. N defaults to 3. The feature can reflect the overall characteristics of signals, avoiding threshold misjudgment caused by weak signals.

3.3.3. Logical judgment for localization and tracking

The tracking detection module extracts feature values from three consecutive defense zones based on the previous two modules. These feature values are then sorted, and the defense zone with the highest energy value is selected. Subsequently, we determine whether the V_{pk} of the chosen defense zone exceeds the threshold value V_{TH}, so as to determine the defense zone where the robot is located. The V_{TH} is set to judge the effectiveness of the vibration signal. The forward speed of the robot is calculated according to the moving distance of the defense zone in the continuous time. As shown in Fig. 2, the initial position and time of the robot are re-determined cyclically, enabling position calculations for the next moment. The average speed is obtained through the accumulation of continuous position superposition. According to the average speed, whether the PIG traveling state is normal or not is judged.

$$V_k = \left(X_e - X_{s0}\right) / (d \times t) \tag{7}$$

where X_e and X_{s0} represent the current number and the start zone number. d and t represent the defense zone range and time step, respectively. The monitoring range of a defense zone used in this paper is 50 m, and the time step setting is 30 s. The velocity is calculated every four-time steps, that is, we obtain V_k every 120 s. In the status identification, the system sends a warning when V_k is below 0.5 m/s or above 5 m/s.

4. Experimental verification

4.1. Experimental design and data acquisition

This section provides a detailed demonstration of the experimental operation steps, collected on-site data, verification methods and so on.

4.1.1. Experimental scenario setup

As shown in Fig. 4, we conducted experiments on internal inspection tasks for natural gas pipelines in Zhejiang Province, China. Fig. 4(a) illustrates the structure of the in-pipe inspection robot, primarily consisting of a magnetic core and leather cap, designed to match the diameter of the pipeline undergoing inspection or cleaning. The initial step of pipeline internal inspection and pigging operation involves placing the robot into the launcher at the natural gas station, as shown in Fig. 4(b). After opening the valve, the robot advances through the pipeline by using pressure differences inside the pipeline. As shown in Fig. 4(c), natural gas pipelines are buried underground. Traditional tracking methods rely on pipeline inspectors to follow the direction of the PIG and verify its passage along marked points using magnetic detectors. Meanwhile, we collected and obtained optical fiber sensing data based on DVS systems installed alongside the pipeline. We also observed real-time waveform changes in the signal during the progress of the PIG. Additionally, Fig. 4(d) presents a simulation displaying the motion state of the PIG inside the pipeline. The robot cleans up corrosion products and accumulated residues left on the pipeline wall along the direction of pipeline transportation and detects pipeline defects.

Table 2
The basic operation information of three pipelines.

No.	Run length (m)	Number of checkpoints	Operation time (s)	Average speed (m/s)
1	17,350	9	10,320	1.68
2	11,550	6	7080	1.63
3	8550	4	4230	2.02

4.1.2. Dataset acquisition

We obtained multiple pigging and inspection records for three pipelines during the period of 2022–2023, which included the magnetic testing records of the inspectors along the pipeline and the pressure wave records of the station. In addition, we extracted DVS system vibration data along with the corresponding operating time to verify the localization and tracking algorithm. Table 2 shows the basic operational information of the three pipeline pigging operations. The table displays the run length of the operation, the number of checkpoints, the operation time, and the average speed. The data is collected in the actual operation and serves as a reference standard for tracking detection results.

4.1.3. Implementation details

The dual-Siamese network is implemented using the signal processing toolkit PyEMD version 1.2.3. All the input of time series has been segmented to 120 points (i.e. 30 s) since the default judgment step size of the proposed algorithm with localization and tracking is 30 s. Considering the deployment of the remote workstation in the intelligent pipe network platform, all experiments were performed on Windows 10 using a single NVIDIA GeForce RTX 3060 GPU with 12 GB memory.

4.1.4. Evaluation indicators

To evaluate the tracking detection performance of different methods, we designed and calculated two indicators. The standard average position error (SAPE) is used as the main indicator, as shown in Eq. (8). It represents the standard value of the average deviation of each defense zone during a pigging operation. Therefore, SAPE is used as the main evaluation indicator.

$$SAPE = \frac{\sum_{i=1}^{N} \left|L_{i,A} - L_{i,C}\right|}{N \times M} \tag{8}$$

where $L_{i,A}$ and $L_{i,C}$ are the actual and calculated positions of the ith checkpoint, respectively. N and M represent the number of checkpoints and the number of defense zones. Besides, the standard average speed error (SASE) is also used as an additional evaluation indicator as shown in Eq. (9).

$$SASE = \frac{\sum_{i=1}^{T} \left|S_{\text{i,A}} - S_{i,C}\right|}{M} \tag{9}$$

where $S_{i,A}$ and $S_{i,C}$ show the actual average speed and calculated average speed of the ith checkpoint respectively. T represents the time step. These two indicators are specifically established to evaluate the accuracy of tracking and detection algorithms, and can also compare the effectiveness of different pre-processing methods.

4.2. Experimental statistical results and quantitative analysis

To verify the advantages of the localization and tracking integrated system proposed in this paper, we considered different signal processing methods to verify the contribution of the CEEMDAN of signal denoising and reconstruction.

Fig. 5 shows the statistical results of our comparison of EMD, ensemble empirical mode decomposition (EEMD), and CEEMDAN. Fig. 5(a)–5(c) record the localization results of three methods. Among them, the horizontal and vertical axes represent the time step and defense zone, respectively. The red dots mean the confirmed true position of the PIG. This is a record tracked by the inspector along the pigging route

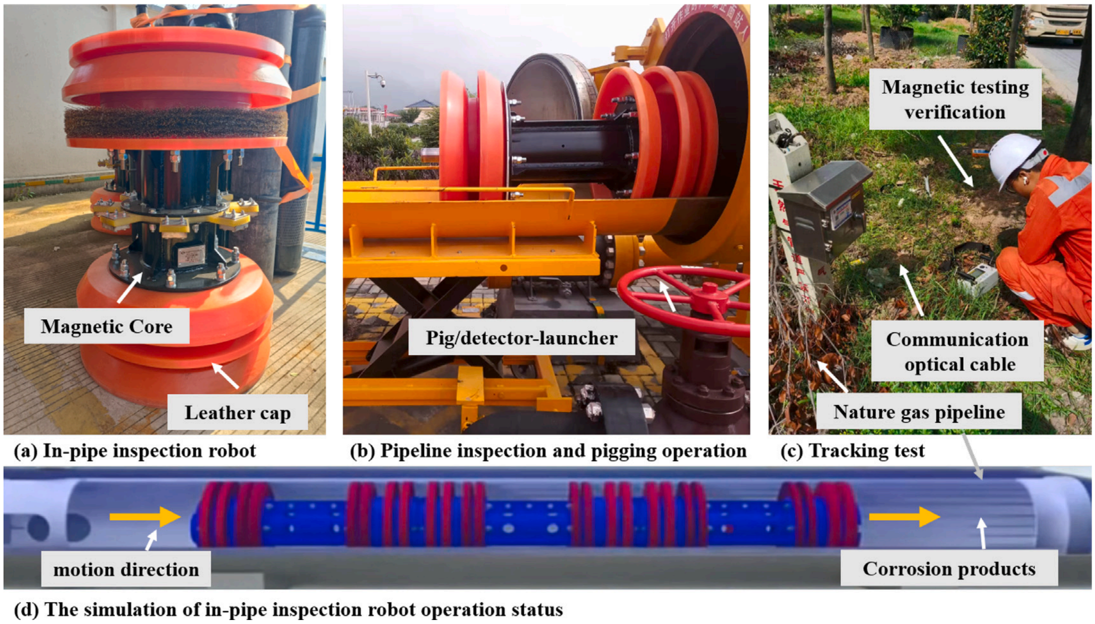

Fig. 4. The on-site and simulation process of pipeline internal inspection and pigging operation.

Table 3
Evaluation indicators for three localization and tracking algorithms.

No.	Time_step	Number of defense zones	EMD		EEMD		CEEMDAN	
			SAPE (10^{-3})	SASE (m/s)	SAPE (10^{-3})	SASE (m/s)	SAPE (10^{-3})	SASE (m/s)
1	344	346	36.82	0.4556	19.38	0.4557	**1.62**	**0.3026**
2	236	230	7.77	0.5163	10.59	0.6175	**1.41**	**0.4159**
3	141	170	19.50	0.5028	7.09	0.4963	**1.77**	**0.4515**
Mean	240.33	248.67	21.36	0.4916	12.35	0.5232	**1.60**	**0.3900**

or a record of pressure changes in the valve chamber where the PIG passes. Therefore, it can be confirmed that the specific defense zone number passed by the PIG at the corresponding time. The solid blue line represents the defense zone of the PIG determined in real time by the CEEMDAN method. The orange dashed line represents the real-time acquisition of the PIG movement defense zone using the EEMD method. The green dotted line denotes the use of the EMD method to determine the defense zone where the PIG is located in real-time. From the Fig. 5(a)–5(c), the CEEMDAN method is used to extract features and judge the location of defense areas more accurately. The results of evaluation indicators SAPE and SASE calculated are shown in Table 3.

According to the comparison of statistical results, it can be seen that CEEMDAN has the lowest SAPE on three pipelines with different operation distances, and the difference is not significant with the average 1.6×10^{-3}. On the other hand, the SAPE differences between EMD and EEMD are large for different pipelines. Compared to the second pipeline with a shorter distance, the average error of EMD on the first pipeline with a longer distance is 5 times higher. However, the third shortest pipeline has a slight increase in error compared to the second pipeline. This indicates that the robustness of these two methods is insufficient. The EEMD results show that the longer the distance, the larger the SAPE. Overall, EMD and EEMD effects are prone to randomness and instability.

Fig. 5(d)–5(f) record the tracking speeds of three methods. Among them, the horizontal and vertical axes represent the time step and velocity calculation, respectively. The color representation for velocity statistics and position statistics is the same. The solid red line represents the average speed between determined points. The color blue, orange, and green respectively denote the calculation results of the three methods. The distribution of velocity statistics is not significant. However, it can be seen that the longer the pigging distance, the larger the deviation range above and below the red line. After calculating the indicator of SASE, it can be found that the results of the three methods are close. As shown in Table 3, the CEEMDAN method is still better overall than the other two methods. The lowest SASE of 0.3026 m/s is reached on the first pipeline, and the average SASE of the three pipelines is 0.39 m/s. The performance of the EMD method takes second place. EEMD performs the worst, with an average SASE of 0.5232 m/s for the three pipelines.

The three signal-processing methods showed significantly different results. This is due to EMD and its deformations have significant advantages in nonlinear and non-stationary signal analysis. Compared with the traditional time–frequency analysis technology, its decomposition is based on the signal itself and overcomes the problems such as adaptive. However, the problem of modal aliasing and endpoint effects is its inherent shortcoming. Besides the vibration from PIG and pipe walls, there are also external vibration events in different zones. Therefore, modal aliasing problems often occur, which leads to drift in localization and tracking. Although EEMD utilizes the statistical characteristics of Gaussian white noise with uniform frequency distribution, it changes the extreme point characteristics of the signal by adding different white noise of the same amplitude each time, thereby effectively suppressing the generation of modal aliasing. However, the EEMD method has randomness, and the initial random factors may affect the judgment results, and as the distance of the pigging operation increases, the cumulative error will also increase. Compared to the first two methods, CEEMDAN has better stability.

4.3. Other comparative analysis and discussion

The operation condition information and advancing state results of the three pigging/inspection operations are listed in Table 4. From the

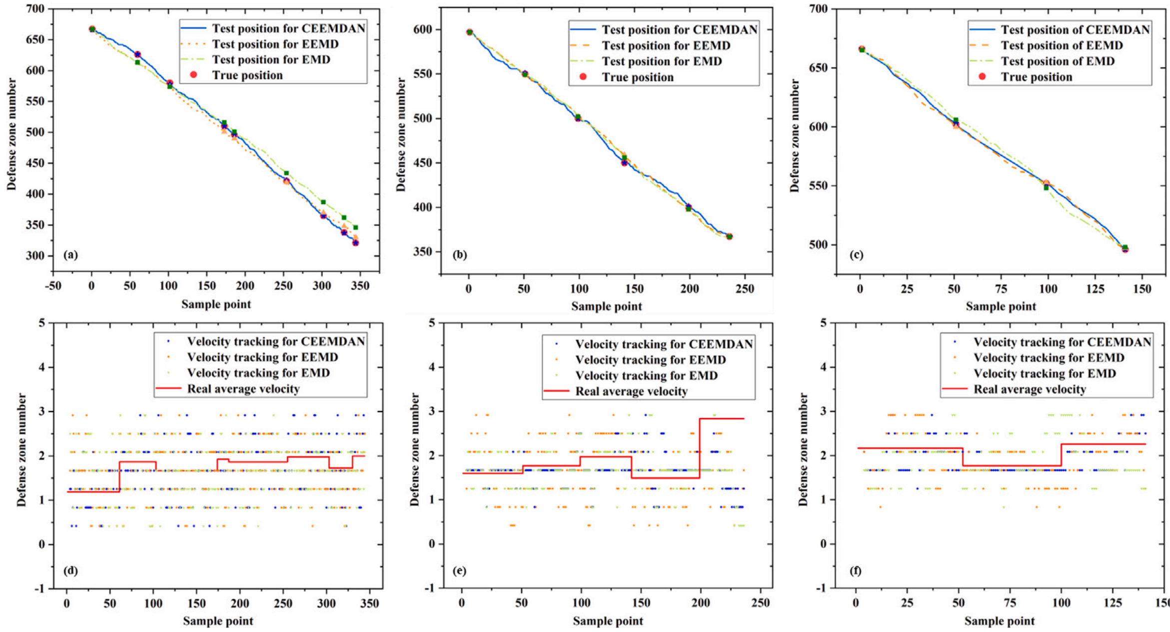

Fig. 5. The statistical results of comparative experiments.

Table 4
The condition information and advancing states of pigging and inspection operations.

No.	Operation purpose	Operation pressure (Mpa)	Flow rate (10^4 m^3/h)	Advancing state
1	Inspection	3.59	1.9	Stop the PIG once without getting stuck
2	Inspection	3.80	1.9	Stop the PIG four times without getting stuck
3	Pigging	3.80	2.5	No stopping

table, it can be seen that the operation of the in-pipe inspection robot in the pipeline with high pressure and high throughput is relatively stable, and the risk of blockage and PIG stoppage is low. The main reason is that the operating pressure of the pipeline is the power source for the operation of the robot. The higher the pressure, the more powerful the robot is. Meanwhile, when encountering blockage, the higher the pressure, the faster the driving pressure difference is established, thereby improving the stability of the robot's operation. The in-pipe inspection robot did not experience any stuck issues in the three pipelines, but there are records of slow stopping in the first two pipelines. There is no stagnation phenomenon in the third pipeline due to the high operating pressure and flow rate.

Compared with other pipeline PIG tracking methods, our proposed method has significant advantages in continuous monitoring, without relying on signal receivers and transmitters, and without the need for human tracking. Simultaneously competitive in response time and tracking accuracy. Compared to the method based on image object detection tasks [17], our proposed integrated framework is more practical. Low-performance requirements for computers that need to be deployed and able to meet real-time requirements. Compared to the method that requires waterfall recognition, the proposed method can be directly processed after signal acquisition, saving more time required for signal processing.

While real-time localization of the in-pipe inspection robot can be achieved through optic fiber sensing monitoring, challenges arise when tracking pipelines with strong interference or over long distances. In such cases, the accumulation and deviation of errors become unacceptable. To tackle this issue, we will further consider supplementing the optic fiber tracking results with data obtained from pressure wave detection in the station or valve chamber. By appropriately integrating these detection results, we can significantly enhance the robustness of DOFS technology for PIG localization and tracking system.

5. Conclusion

To ensure the safe operation of energy pipelines, this paper proposes an advanced monitoring framework for in-pipe inspection robots, utilizing cutting-edge distributed optical fiber sensing technology. The framework tracks real-time information about the position, speed, and advancing states of the robot through optical fiber signals. The proposed three-module collaboration includes signal processing, feature extraction, and tracking detection, enabling dynamic monitoring of the detection robot's movement along the pipeline during operation. Compared to other methods for PIG tracking, our framework boasts significant advantages in long-distance continuous monitoring. Furthermore, it offers the flexibility to control tracking intervals and step sizes to cater to various task requirements under different working conditions. The experiments demonstrate the framework's capability to achieve acceptable tracking errors, showcasing robustness even when confronted with changes in operation conditions, such as different operation objectives or varying pipeline lengths. The average SAPE and SASE of the proposed framework on the three tested pipelines are 1.6×10^{-3} and 0.39 m/s, respectively. Looking ahead, our endeavours involve extending this framework to multi-source perception technology by integrating pressure sensors better to safeguard the daily operation and maintenance of energy pipelines.

CRediT authorship contribution statement

Chengyuan Zhu: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yanyun Pu:** Validation, Supervision, Software. **Yiyuan Yang:** Writing – review & editing, Writing – original draft, Supervision. **Zhuoling Lyu:** Visualization, Validation, Data curation. **Chao Li:** Validation, Supervision, Funding acquisition. **Qinmin Yang:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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