DESIGN AND DEVELOPMENT OF A COMPACT INTELLIGENT CABLE PULLING SYSTEM FOR POWER CABLES

Yan FENG[1], Yufang LIN[1], Zongsheng XU[1], Sikai XIONG[1], Xinyu PEI[2], Xiongfeng HUANG[2,*]

With the continuous expansion of urban power networks and increasing complexity of underground pipeline systems, traditional cable traction methods are limited in construction safety, l intelligence, and operational efficiency. To address these challenges, a compact intelligent traction system is designed for power cables. The system consists of an intelligent traction head, an underground communication network, and a ground-based data processing center, with functions of multi-sensor data acquisition, real-time status monitoring, path reconstruction, and risk prediction. In the system design, an improved YOLOv9 (You Only Look Once version 9) model is introduced to recognize the pipeline environment, enhancing the detection of small-scale targets and environmental anomalies. In addition, inertial navigation technology is used to achieve autonomous positioning and three-dimensional reconstruction of the cable traction path, ensuring high accuracy and continuity of trajectory recording. A hybrid "wired + wireless" communication network combined LoRa (Long Range wireless communication) protocol with composite flexible cables is further established to guarantee reliable data transmission in complex underground environments. The experimental results demonstrate that this system can achieve strong performance in trajectory monitoring, environment perception, and hardware reliability, meeting the practical requirements of cable installation. These findings can improve power construction safety and automation, providing a technical support for subsequent cable operation and emergency maintenance.

Keywords: Power cable, intelligent traction system, YOLOv9, inertial navigation, LoRa communication

1. Introduction

With the development of urban power grids and the increasing complexity of underground pipeline systems, the installation of underground power cables is facing increasingly strict construction standards and technical requirements. In this process, the cable traction system plays an important role as a key piece of equipment, undertaking essential tasks such as pulling, positioning, and transmitting cables. Its performance will directly determine the construction quality and operational safety of the cable network [1-2].

[1] Wuhan Huayuan Electric Power Design Institute Co., Ltd, Wuhan, 430050, China
[2]* School of Electrical Engineering and Automation, Hefei University of Technology, Hefei, 230009, China, corresponding author: E-mail: hfut_huangxf@hfut.edu.cn

Conventional cable traction systems often combine steel mesh sleeves and standard traction heads. Since these methods are widely applied, they have significant limitations in complex and variable conditions of underground passages. Traditional systems lack real-time monitoring and feedback on the traction states and environmental conditions during cable pulling. As a result, potential risks (such as over-tension, excessive bending, or mechanical compression) cannot be detected in time, leading to cable stretching, twisting, or insulation degradation, and posing serious safety hazards [3]. Existing systems often lack precise control and limitation mechanisms for traction force. When navigating complex passage structures or multiple bends, operators often rely on manual experience to determine traction strategies, making it difficult to scientifically evaluate risks and increasing the likelihood of cable damage. In addition, conventional traction heads are prone to structural wear or failure under long-distance, multi-bend, and high-friction conditions, reducing traction efficiency and cable quality [4-5].

A more critical challenge is the lack of trajectory recording and positioning capabilities in traditional systems. Once a cable is installed, its exact route in the conduit is difficult to reconstruct, creating substantial obstacles for subsequent inspection, maintenance, and emergency repair [6]. During urgent fault restoration, the inability to locate cables precisely can severely hinder repair efficiency and even threaten the stability of the power supply system.

To overcome these challenges, it is important to develop a compact, integrated, and intelligent cable traction system equipped with a monitoring platform. Such a system should combine real-time sensing and regulation of parameters (such as traction force, speed and tension) with visual feedback and warning functions for the surrounding environment, thereby ensuring intelligent and safe management throughout the entire installation process. Furthermore, the system should support digital recording and management of cable trajectories, providing accurate data for future maintenance and emergency operations. Combined with advanced technologies (including multi-sensor fusion, inertial navigation [7], image recognition [8-9], and remote communication), this system can achieve autonomous perception, intelligent decision-making, and coordinated platform operation. This approach can improve construction safety and automation, and reduce maintenance costs, paving the way for a new stage of intelligent construction and refined operation in underground cable engineering.

2. System architecture of the compact intelligent traction system for power cables

To address key challenges in underground cable installation such as narrow conduit structures, uncertain environmental conditions, cable vulnerability, and limited operation visibility, a compact intelligent traction system has been developed. This system integrates traction state monitoring, environmental perception, and trajectory recording into a unified framework. Its overall design follows an engineering logic of "state perception → data acquisition → data transmission → data processing → risk warning", incorporating key modules such as mechanical sensing, visual perception, inertial navigation computation, and platform interaction. These modules ensure that the construction process is safe, efficient, and traceable. As shown in Fig. 1, the system architecture comprises three main components: the intelligent traction head, the underground communication network, and the ground-based data processing center.

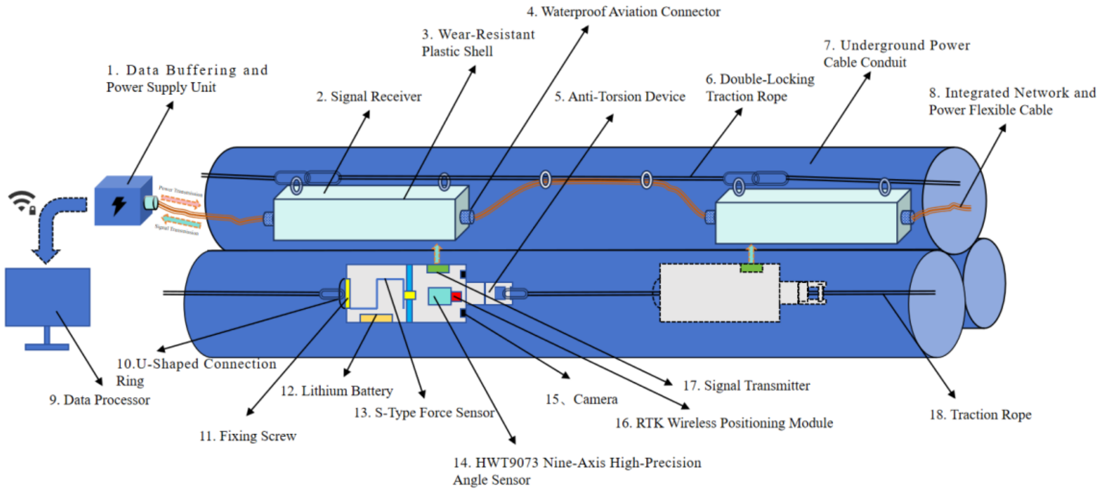


Fig. 1. Architecture of the compact intelligent power cable traction system

2.1 Intelligent Traction Head

As the core sensing unit of the system, the functions of the intelligent traction head integrate the components: an anti-torsion device, U-shaped coupling ring, lithium battery, S-type force sensor, dual cameras, a nine-axis high-precision attitude sensor (HWT9073), an RTK (Real-Time Kinematic) wireless locator, and a signal transmitter. The rear U-shaped coupling ring is fixed to the cable through a locking mechanism, and the S-type force sensor continuously monitors the traction force in real time to prevent overload. At the front end, the anti-torsion device ensures cable stability by preventing twisting during the pulling process. In the traction process, the attitude sensor, cameras, and locator simultaneously collect acceleration, angular velocity, environmental images, and positioning data. They are transmitted to the underground communication network by the signal transmitter.

2.2 Underground Communication Network

The underground communication network adopts a hybrid “wired + wireless” architecture. Signal receivers are deployed at 30 m intervals in adjacent conduits along the traction path. These receivers collect data from the traction head via LoRa wireless communication, and then relay the data and power through waterproof aviation connectors integrated with composite flexible cables. The information is ultimately delivered to the ground-based data buffering and power supply unit. In addition, the network supports node selection, enabling the traction head to automatically switch to the optimal receiver based on signal strength, thereby ensuring continuous data transmission even under complex underground conditions (such as severe signal attenuation caused by surrounding soil, multipath fading within concrete conduits, moisture or water accumulation, and frequent bends or branching structures).

2.3 Ground Data Processing Center

As the command hub of the system, the ground data processing center conducts multi-dimensional analysis on the data transmitted from the underground network. A two-level early warning mechanism is established based on traction force thresholds, with over 90% triggering a deceleration command and over 95% initiating a shutdown. In addition, an improved YOLOv9 model is used to identify foreign objects and anomalies within the conduit. Combining the data from the nine-axis sensor and RTK module, the system applies a strapdown inertial navigation algorithm to reconstruct the three-dimensional traction path and generate a topological map. Through this closed-loop control process, the system combines real-time traction force monitoring, environmental perception, trajectory reconstruction, and threshold-based control. Real time detection of abnormal conditions such as excessive traction force, environmental obstructions, or abnormal motion states can trigger automatic deceleration or shutdown commands. At the same time, the recorded traction states and three-dimensional cable trajectories are stored as digital assets, which can be used for post-installation inspection, fault localization, and maintenance planning, providing data-driven and intelligent support for operation and maintenance.

3. Data Collection and Processing in a Miniature Intelligent Traction System for Underground Power Cables

The underground cable pipeline presents a complex environment, where foreign objects and anomalous conditions may hinder the operation of the intelligent traction head, and the enclosed setting renders conventional GPS positioning ineffective. To address these challenges, the system uses dual front-end cameras to capture images, leveraging an enhanced YOLOv9 model [10-11] for environmental recognition and improve operational efficiency and safety. In parallel, an Inertial Navigation System (INS) is adopted for autonomous localization. Through multi-source data fusion, including motion state, traction force, visual perception, and positioning information, cumulative errors in trajectory estimation are effectively corrected. The high-precision and stable cable trajectory provides a reliable digital representation of the installed cable pathway. Furthermore, abnormal events such as excessive traction force, unexpected trajectory deviation, or environmental obstruction can be automatically identified and recorded during the pulling process. These digital records and event logs enable condition-based assessment, historical traceability, and data-driven maintenance of cable pathways, rather than only relying on periodic inspection or manual experience.

3.1 Underground Cable Pipeline Environment Monitoring based on an Enhanced YOLOv9 Model

To address the issue of missed detections for small targets in the YOLOv9 model, an MSAN (Multi-Scale Attention Neck) neck structure is designed to replace the original Neck component. Compared with the traditional design, the MSAN neck combines the SPDconv (Spatial Pyramid Depthwise Convolution) module with the CSP-OK (Cross Stage Partial with Omni-Kernel) module. The structure of the CSP-OK module is shown in Fig. 2. This module consists of an OK (Omni-Kernel) branch and a large residual branch. In the OK branch, features are first split through a 1×1 convolution, and then processed in parallel through a large branch (63×63 depthwise convolution + 1×63 / 63×1 convolution) to capture local context. The Global branch uses a dual-domain attention mechanism that combines DCAM (Dual-Domain Channel Attention Module) with FSAM (Frequency-Spatial Attention Module). DCAM extracts frequency-domain features through FFT/IFFT and applies channel attention, and FSAM performs spatial attention weighting in the frequency domain to enhance the feature importance of small targets. The SPDconv module utilizes multi-scale convolution kernels (1×1, 3×3, 5×5) to fuse features with different receptive fields, improving adaptability to variations in object sizes and enhancing the detection of foreign objects.

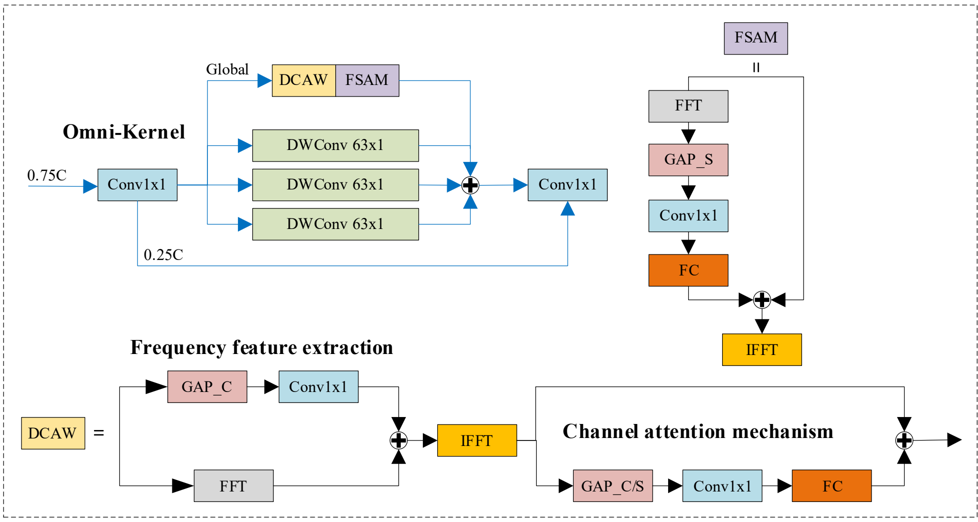


Fig. 2. Network architecture of the CSP-OK module

To address the issue of insufficient accuracy in bounding box regression, a dynamic non-monotonic focusing mechanism is proposed to replace the CIoU (Complete Intersection over Union loss) in the original loss function of the YOLOv9 model with Wise-IoU (WIoU) [12]. This dynamic non-monotonic focusing mechanism no longer uses traditional IoU to evaluate the quality of anchor boxes, but evaluates through outliers based on the intelligent gradient gain allocation strategy. This enables WIoU to reduce the importance of high-quality anchor boxes, reduce the harmful gradients generated by low-quality samples, and focus on low-quality anchor boxes, ultimately improving the accuracy of the detector.

The outlier β is defined as follows:

$$\beta=\frac{L_{IoU}^{*}}{L_{IoU}}\in[0,+\infty] \tag{1}$$

where L_{IoU}^{*} represents the monotonic focusing mechanism. The hyperparameter α used to construct the non-monotonic focusing coefficient of WIoU is as follows:

$$\mathcal{L}_{WIoU}=r\left(\exp\left(\frac{(x-x_{gt})^2+(y-y_{gt})^2}{W_g^2+H_g^2}\right)\right)$$

$$r=\frac{\beta}{\delta\alpha^{\beta-\delta}} \tag{2}$$

where W_g and H_g represent the minimum bounding box dimensions; x and y are the center coordinates of the anchor boxes; x_{gt} and y_{gt} are the center coordinates of the target boxes; r is the dynamic non-monotonic focusing coefficient; β is the outlier; α and δ are hyperparameters. This coefficient achieves dynamic allocation of gradient gains for different quality anchor boxes by combining outliers and hyperparameters, reducing the importance of high-quality anchor boxes and minimizing the harmful gradients of low-quality samples. This enables the model to focus more on low-quality anchor boxes, thereby improving the detection accuracy. The overall loss function after improvement is defined as follows:

$$L=\lambda_{box}\cdot\frac{1}{N}\sum_{i=1}^{N}\left(1-L_{WIoU}\left(B_i,\widehat{B}_i\right)\right)+\lambda_{cls}\cdot\frac{1}{N}\sum_{i=1}^{N}L_{BCE}\left(p^i_{cls},t^i_{cls}\right)+\lambda_{dfl}\cdot\frac{1}{N}\sum_{i=1}^{N}L_{DFL}\left(p^i_{dfl},t^i_{dfl}\right) \tag{3}$$

The total loss L is composed of three parts: WIoU, BCE, and DFL. They are adjusted by the weight hyperparameters λ_{box}, λ_{cls}, and λ_{dfl} respectively, and the average loss of all samples is calculated. The first part is the bounding box loss and calculated based on WIoU.$L_{WIoU}\left(B_i,\widehat{B}_i\right)$represents the WIoU loss between the i-th predicted bounding box B_i and the real bounding box $\widehat{B}_i$. The second part is the classification loss, using BCE loss. $L_{BCE}\left(p^i_{cls},t^i_{cls}\right)$ measures the difference between the i-th predicted class score p^i_{cls} and the real class label t^i_{cls}, aiming to solve class imbalance. The third part of the loss is the distribution focal loss.$L_{DFL}\left(p^i_{dfl},t^i_{dfl}\right)$ calculates the loss between the i-th predicted bounding box position distribution p^i_{dfl} and the real distribution t^i_{dfl} by modeling the bounding box position as a distribution, thereby enhancing the adaptability of the model to target position changes.

3.2 Trajectory Monitoring of the Intelligent Traction Head Based on Inertial Navigation

The inertial navigation system integrated into the intelligent traction head is centered on an Inertial Measurement Unit (IMU), combining accelerometers, gyroscopes, and a data processing module. Its working principle follows a closed-loop process of motion parameter sensing, attitude updating, and trajectory estimation:

First, sensor data acquisition is conducted: the accelerometer continuously measures the linear acceleration of the traction head along the x, y, and z axes in real time (with a sampling frequency of 50-100 Hz), and the gyroscope synchronously records the angular velocity along the three axes. These measurements generate a time-stamped acceleration vector $\vec{a}(t)=[a_x(t),a_y(t),a_z(t)]$ and angular velocity vector $\vec{w}(t)=[w_x(t),w_y(t),w_z(t)]$.

Then coordinate system and attitude initialization are conducted, using the East-North-Up (ENU) coordinate system as the navigation reference. The initial attitude calibration establishes a transformation matrix $C_b^n(0)$ from the body coordinate system to the navigation coordinate system. At the same time, auxiliary sensors (such as magnetometers) in the static state are used to initialize the attitude quaternion q (0), thereby avoiding the gimbal lock problem in Euler angles.

Finally, attitude updating is conducted. Based on the gyroscope angular velocity data, the attitude variation of the traction head is calculated in real time using the quaternion update formula:

$$q(t+\Delta t)=q(t)+\frac{1}{2}q(t)\otimes\Delta q(t) \tag{4}$$

where$\Delta q(t)=[0,w_x(t)\Delta t,w_y(t)\Delta t,w_z(t)\Delta t]$and $\otimes$ denotes the quaternion multiplication. The acceleration $\vec{a}(t)$ in the body coordinate system is transformed into the navigation coordinate system $\vec{a}_n(t)$ through the transformation matrix C_b^n. According to two successive integrations, the velocity $\vec{v}_n(t)=\int_0^t\vec{a}_n(\tau)d\tau+\vec{v}_n(0)$ and displacement $\vec{r}_n(t)=\int_0^t\vec{v}_n(\tau)d\tau+\vec{r}_n(0)$ are obtained sequentially. The preliminary trajectory is formed and the updated attitude is used to dynamically adjust the transformation matrix.

At the same time, inertial will accumulate errors over time, leading to drift. To address this issue, the system will detect the moment when the traction head is stationary or experiences a sudden state transition (with acceleration approaching zero) and enforces a velocity reset ($\vec{v}_n(t)=0$). Each reset effectively suppresses the accumulation of integration errors, ultimately resulting in three-dimensional trajectory coordinates within the underground cable conduit.

4. Communication Network Design for Underground Cable Conduit Environments

4.1 Data Transmission Protocol and Adaptive Retransmission Mechanism

Considering the requirements of underground environments for communication range, power consumption, and anti-interference capability, the system adopts the LoRa wireless communication protocol as its core transmission protocol [13]. LoRa use spread spectrum modulation to achieve an effective communication distance of 50-100 m in underground conduits, with a receiver sensitivity as low as -148 dBm, making it well-suited for scenarios with severe signal attenuation. In addition, its low-power characteristics are matched with the lithium battery power supply of the intelligent traction head, extending continuous operating time. To balance transmission rate and anti-interference capability, LoRa supports dynamic adjustment of the spreading factor (SF7-SF12): under strong electromagnetic interference, the protocol automatically switches to a higher spreading factor to reduce the bit error rate. In stable environments, a lower spreading factor is selected to improve transmission speed (up to 50 kbps), thereby meeting the real-time transmission requirements of high-volume data (such as images and trajectories).

The protocol stack follows a three-layer architecture consisting of a physical layer, MAC (Medium Access Control) layer, and application layer. The physical layer handles signal modulation and demodulation to ensure reliable wireless transmission of raw data. The MAC layer incorporates a slotted ALOHA (Additive Links On-line Hawaii Area) mechanism [14], which allocates transmission slots through time-division to prevent data collisions between multiple nodes. The application layer defines a standardized data frame format that includes device ID, data type (such as environmental images, trajectory coordinates, and traction force values), timestamp, and CRC32 checksum, ensuring that the ground data processing center can accurately parse heterogeneous multi-source data for categorized processing and associative analysis.

To further improve the stability and reliability of the underground communication link, the system has implemented an adaptive retransmission mechanism. The receiver verifies data frame integrity through CRC32; if the check fails, it will immediately issue a retransmission request. If retransmission fails three consecutive times, the node switching function will be triggered. The intelligent traction head can automatically select an alternative receiver with strong signal strength to prevent single-point link failures caused by data loss.

4.2 Communication Module Selection and Deployment Scheme

The wireless communication between the intelligent traction head and the signal receiver adopts the SX1278 LoRa module. It supports a maximum transmit power of 20 dBm and a receiving sensitivity of -148 dBm. It can output the RSSI (received signal strength indicator) in real time and support data for the node selection function. The signal receiver is equipped with the same type of LoRa module.

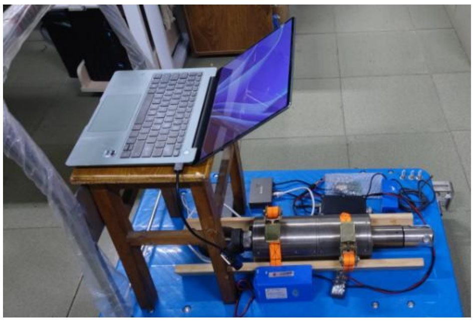
For data transmission and power supply between underground nodes and the ground terminal, a shielded four-core composite flexible cable is employed. Two cores are used for power transmission, supplying DC 48V to the underground signal receiver; the other two cores adopt the RS485 bus [15] standard for data transmission, supporting a maximum baud rate of 115200 bps. This design provides a strong resistance to electromagnetic interference, effectively reducing the impact of motors, metallic structures, and other interference sources in the pipeline. The connection interface between the signal receiver and the composite cable adopts an M12 waterproof aviation plug with an IP68 protection rating, ensuring no leakage in humid or waterlogged pipeline environments. The ground terminal is equipped with a data buffer and power supply device. It integrates a 16GB storage chip capable of caching raw data within 24 hours and providing continuous and stable power supply for underground nodes.

The deployment of signal receivers follows the principle of “longitudinal coverage + key reinforcement”. In the adjacent parallel pipeline where the intelligent traction head operates, signal receivers are deployed every 30 m along the axis direction. This interval is determined based on field tests: when the spacing is ≤30 m, the LoRa signal transmission loss within a DN200 mm metal pipeline can be controlled within 80 dB and allows the SX1278 module to stably receive data. If the spacing exceeds 50 m, the signal loss increases by over 100 dB and may lead to transmission interruptions. All receivers are connected in series through the composite cable. In a single node failure, the overall link communication remains unaffected, thereby enhancing the fault tolerance of the network.

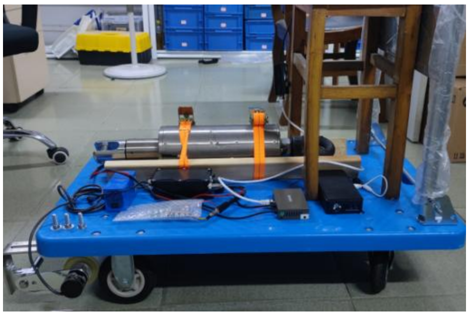
The node selection function is implemented through the intelligent traction head, which collects the RSSI values of each receiver in real time. The microprocessor dynamically selects the node with the highest RSSI [16] as the current communication target and updates the selection result every 5 s. When the RSSI of current node is detected to fall below -120 dB, the system immediately switches to the next optimal node to ensure transmission continuity. Through the above module selection and deployment design, the underground communication network can achieve a two-way data transmission delay of ≤1 second, with a packet loss rate controlled within 0.5%. This provides reliable communication support for real-time monitoring and remote control of the intelligent traction system.

5. Experiment and analysis

To verify the accuracy of the positioning trajectory of the traction head, an experimental setup equivalent to actual cable laying is constructed. For simulating the traction process, a custom flat cart equipped with a rotary encoder and a measuring wheel is built to mimic cable pulling, as shown in Figs. 3(a), 3(b), and 3(c):



(a) Scenario1



(b) Scenario 2

(c) Scenario 3 (d) Scenario 4

Fig. 3. Experimental simulation scenarios

The experiments were conducted in office corridors and a lobby, as shown in Fig. 3(d). The traction head moves in different orientations and attitudes. After starting from an initial point, it travels different distances in different directions, and then returns to the starting point to form a closed path with overlapping start and end positions. The coordinate deviations between the start and end points under different distances and experimental conditions were observed to obtain the measured positioning accuracy.

In this experiment, the traction head moved 3 m, 23.345 m, and 55.919 m, respectively. The experimental results are shown in the Table 1.

Table 1

Positioning test results

Measurement serial number	Moving distance of traction head (m)	Coordinate values of starting point and ending point XYZ (m)	Errors (m)
1	3	(0, 0, 0)→(0.00153, -0.00286, -0.00001227)	0.0032
2	23.345	(0, 0, 0)→(-0.087, -0.121, 0)	0.149
3	55.919	(0, 0, 0)→(0.1, 0.25, 0)	0.269

Under the experimental conditions with relatively simple equipment and without precise initial calibration, the positioning errors were satisfactory. In the actual change significantly. Therefore, the errors are expected to be even smaller than those in the current tests. The observed errors are caused by: (1) lateral slippage of the wheels causes transverse displacement, affecting path closure and resulting in the maximum lateral deviation; (2) Sampling the attitude angles at intervals (four times per second) results in discontinuities in displacement and azimuth, leading to an increase in cumulative errors with distance; (3) Inertial navigation systems have an X and Y rotation angle accuracy of 0.001 ° and a Z-axis rotation angle accuracy of 0.1 °. Therefore, significant changes (such as the rotation of the traction head) in azimuth angle may result in cumulative errors; (4) if the traction head is not placed completely horizontally or its attitude angles are misaligned with the wheel travel direction, there will be coordinate calculation deviations. Further optimization will be conducted to improve the accuracy. In addition to the positioning experiments, pressure tests were conducted to evaluate the hardness of the traction head housing. The experimental setup is shown in Fig. 4, and the results are shown in Fig. 5.

Fig. 4. Pressure test setup

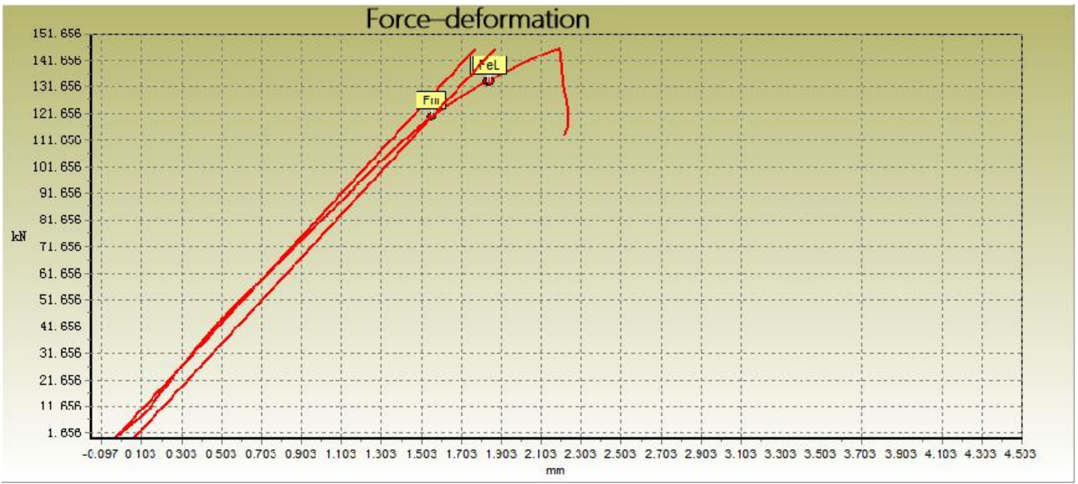


Fig. 5. Pressure test results

As shown in Fig. 5, after applying a pressure of 13 tons, the deformation of the traction head housing was minimal, at about 1.9 mm. The experimental results indicate that the housing hardness of the traction head meets the requirements of practical applications.

6. Conclusion

A compact and intelligent cable pulling system is proposed for underground power cable installation. Unlike conventional cable pulling systems that mainly rely on manual supervision, open-loop operation, and external monitoring devices, this system integrates traction force sensing, motion and attitude perception, visual environment awareness, and wireless communication into a highly compact traction head for confined concrete conduits. This integrated design can realize real-time perception, closed-loop control and automatic risk warning in cable pulling.

Combining an improved YOLOv9-based object detection model with an inertial navigation technology, the system can achieve environmental perception and three-dimensional cable trajectory reconstruction during traction, thereby improving the positioning accuracy and operational visualization. Compared with existing cable pulling solutions that typically lack path digitization and real-time trajectory awareness, this system provides a digital representation of the cable installation process, which is beneficial for construction assessment and subsequent maintenance. The hybrid “wired + wireless” communication architecture, as well as an adaptive retransmission mechanism can ensure continuous and stable data transmission under challenging underground conditions. In addition, the integration of mechanical sensors with a two-level warning strategy can more significantly enhance operational safety management than traditional passive protection methods.

The experiment was conducted in a laboratory environment with a limited pulling distance. The experiments are designed to verify the accuracy, reliability, and robustness of the sensing, trajectory reconstruction, and communication mechanisms under controlled conditions. Since the system architecture and sensing principles are independent of pulling length, this approach is applicable to longer and more complex conduit paths in practical engineering applications. Future work will focus on further mitigating inertial navigation error accumulation and enhancing system adaptability in complex underground environments, advancing intelligent cable pulling technology to higher precision, improved robustness, and broader application scenarios.

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