Fault Diagnosis of the LAMOST Fiber Positioner Based on a Long Short-term Memory (LSTM) Deep Neural Network Postprint

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Abstract

The Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) has been in normal operation for more than 10 yr, and routine maintenance is performed on the fiber positioner every summer. The positioning accuracy of the fiber positioner directly affects the observation performance of LAMOST, and incorrect fiber positioner positioning accuracy will not only increase the interference probability of adjacent fiber positioners but also reduces the observation efficiency of LAMOST. At present, during the manual maintenance process of the positioner, the fault cause of the positioner is determined and analyzed when the positioning accuracy does not meet the preset requirements. This causes maintenance to take a long time, and the efficiency is low. To quickly locate the fault cause of the positioner, the repeated positioning accuracy and open-loop calibration curve data of each positioner are obtained in this paper through the photographic measurement method. Based on a systematic analysis of the operational characteristics of the faulty positioner, the fault causes are classified. After training a deep learning model based on long short-term memory, the positioner fault causes can be quickly located to effectively improve the efficiency of positioner fault cause analysis. The relevant data can also provide valuable information for annual routine maintenance methods and positioner designs in the future. The method of using a deep learning model to analyze positioner operation failures introduced in this paper is also of general significance for the maintenance and design optimization of fiber positioners using a similar double-turn gear transmission system.

Full Text

Preamble

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Fault Diagnosis of the LAMOST Fiber Positioner Based on a Long Short-term Memory (LSTM) Deep Neural Network

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Abstract

The Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) has been in normal operation for more than 10 years, with routine maintenance performed on the fiber positioner every summer. The positioning accuracy of the fiber positioner directly affects LAMOST's observation performance—incorrect positioning not only increases interference probability among adjacent positioners but also reduces overall observation efficiency. Currently, during manual maintenance, the fault cause is only determined after positioning accuracy fails to meet preset requirements, resulting in lengthy maintenance times and low efficiency. To rapidly locate fault causes, this paper obtains repeated positioning accuracy and open-loop calibration curve data for each positioner through photogrammetric methods. Based on systematic analysis of faulty positioner operational characteristics, fault causes are classified. After training a deep learning model based on long short-term memory (LSTM), positioner fault causes can be quickly identified, effectively improving fault analysis efficiency. The collected data also provide valuable information for future annual maintenance procedures and positioner design improvements. The deep learning-based

approach for analyzing positioner operational failures introduced herein has general significance for the maintenance and design optimization of fiber positioners employing similar double-turn gear transmission systems.

Key words: telescopes – techniques: image processing – methods: analytical – techniques: spectroscopic

1. Introduction

1.1. Functions of the Fiber Positioner

The Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) represents the world's highest spectral acquisition efficiency astronomical telescope [?]. It employs a parallel controllable dual-rotation fiber positioning scheme, with 4000 optical fibers distributed across a 1.75 m spherical crown focal panel, enabling simultaneous acquisition of 4000 spectra [?]. The partitioned parallel controllable technology of the optical fiber positioner constitutes one of LAMOST's two key technologies, with the positioner serving as its core component [?]. The positioner consists of a central axis and an eccentric axis with equal arm lengths. This transmission mode maintains the transmission chain in a self-locking state, allowing the fiber to remain stable after positioning completion. The optical fiber is clamped at the end of the eccentric rotary shaft, achieving planar positioning through coordinated movement of the central and eccentric rotary shafts. The positioner features a two-stage transmission structure forming a double-rotation j- motion, with the central rotary axis operating over 0°–360° and the eccentric rotary axis over 0°–180° [?]. This movement can position the mounted fiber anywhere within the circular observation area. Both the central and eccentric rotary axes have gyration radii of 8.25 mm, yielding an effective motion range of Φ33 mm for each fiber end face, as illustrated in Figure 1 [Figure 1: see original paper]. With a center distance of 25.6 mm between adjacent positioners, observation areas overlap [?], yet no positioning blind spots are produced, as demonstrated in Figure 2 [Figure 2: see original paper].

This fiber positioning method achieves high accuracy and efficiency. Early Sloan Digital Sky Survey (SDSS) telescopes utilized perforated positioning, requiring pre-drilled holes in aluminum plates for each observation—a highly inefficient process [?]. The Subaru telescope initially employed a pendulum positioning method, controlling a piezoelectric actuator through zigzag voltage pulses to tilt the fiber-mounted mechanical structure to target positions. However, this approach suffered from insufficient light intake, defocusing issues, and inadequate positioning efficiency. New SDSS and Subaru projects have adopted positioning methods similar to LAMOST's dual-rotation scheme, substantially improving fiber positioning accuracy and efficiency [?, ?, ?]. The current Dark Energy Spectroscopic Instrument (DESI) telescope, with 5000 fibers, also employs this method for large-scale fiber positioning [?, ?, ?, ?].

1.2. Introduction to the Fiber Positioner Drive

The central shaft transmission structure is diagrammed in Figure 3 [Figure 3: see original paper]. The central driving motor connects to a motor interface plate, which is fixed to the fiber positioner with screws. The motor gear is secured to the motor shaft with a locking nut and rotates with it. This gear meshes with an internal gear that is fixed to the central shaft with set screws. The central rotary mechanism is driven by a stepper motor with a 1:1024 reducer through a two-stage spur gear system, driving the hollow shaft to perform central rotation within 0°–360°.

The eccentric shaft drive structure is shown in Figure 4 [Figure 4: see original paper]. The eccentric driving motor connects to a motor interface plate fixed to the positioner with screws. The motor gear, secured to the motor shaft with a locking nut, meshes with a helical gear tightly sleeved on an intermediate shaft. Another helical gear on this shaft meshes with the eccentric helical gear, which is fixed to the eccentric rotary shaft with a locking nut. The eccentric rotary mechanism employs a stepper motor with a 1:16 reducer through a two-stage single-tooth-multitooth helical gear reduction device for 0°–180° rotation.

The LAMOST fiber positioner uses an AM1020 stepper motor from the Faulhaber Group in Switzerland. When the central stepper motor operates with minimum pulses, the minimum drive arc length is 3.31 m; for the eccentric stepper motor, it is 1.687 m. Consequently, both central and eccentric rotary shafts operate with micron-level precision, guaranteeing overall positioner accuracy under open-loop conditions and providing future possibility for closed-loop control.

1.3. Diagnostic Method of the Operational Accuracy of the Fiber Positioner

Positioner accuracy directly affects LAMOST observation efficiency. When positioning accuracy is unacceptable, interference from adjacent positioners increases first, preventing effective convergence. Second, when the positioner installed in LAMOST's focal plane receives celestial light, it cannot accurately reach system-commanded positions, causing observation targets to be missed. When positioning error exceeds 40 m, the target cannot accurately fall on the fiber center; when error exceeds 100 m, the fiber cannot aim at the astronomical target. To ensure observation efficiency, we define fiber positioners with positioning errors greater than 40 m as unqualified during maintenance.

Since the fiber positioner comprises many complex parts, its failure rate increases with operational time. Frequent failures fall into two categories: central shaft failures and eccentric shaft failures. Central shaft faults include internal gear faults, anti-backlash spring plate looseness, motor gear looseness, and central shaft motor damage. Eccentric shaft faults include anti-backlash spring plate faults, gear faults, optical fiber bracket fixing screw looseness, and eccentric shaft motor damage [**?**]. These problems decrease positioner stability, reliability, and observation accuracy [?].

After more than ten years of normal LAMOST operation, annual summer routine maintenance is required. Currently, when maintaining positioners with unqualified accuracy, failure causes are analyzed through manual experience, followed by corresponding maintenance procedures. However, the unclear fault scope makes failure cause identification time-consuming, resulting in lengthy maintenance processes and low efficiency.

To address this problem, this paper proposes a new fault analysis and detection method. Section 2 describes how photogrammetry obtains repeated positioning accuracy and open-loop calibration curve data, systematically analyzing operational characteristics to classify observed faults. Section 3 applies deep learning-based LSTM model training for rapid classification and location of fiber positioner fault causes. Section 4 summarizes experiments and results.

2. Experimental Methods

2.1. Fiber Positioner Running and System Precision

Positioner accuracy is currently measured through a laboratory-built running and testing platform, depicted in Figure 5 [Figure 5: see original paper]. The system consists of five main components: the fiber positioner, a small focus panel, a control system, a measurement subsystem, and a light-guided fiber with light source. The small focus panel, fiber positioner, and complementary metal-oxide-semiconductor (CMOS) camera are installed on the same air-floating platform.

The small focus panel contains 276 holes processed in a honeycomb pattern for positioner clamping. As shown in Figure 6 [Figure 6: see original paper], each hole can accommodate one fiber positioner, with the focal panel perpendicular to the floating platform. The control host commands the camera, while the main node controls subnodes installed in the positioner via wireless communication. An integrating sphere provides uniform illumination for the optical fiber.

The measurement subsystem uses a CV50000 CMOS sensor from COMSIS with 7920×6004 pixels (4.6 m, 8T global shutter). The camera features a 3 mm full-frame optical format, temporal noise of 15.3 e^-, full well capacity of 16,000 e^-, and dynamic range of 60 dB. The lens has typical (maximum) optical distortion of $<0.08\%$ (0.20%) over its aperture, with an object-image relationship of 1 pixel corresponding to 18.6 m. We fully consider distortion factors from camera lenses in experimental measurements. Before data collection, we perform camera calibration using a polynomial calibration model to correct lens distortion. The calibration target is installed at the focal plane, and CMOS camera parameters are solved using this model. Since the calibration target lies in the same plane as the fiber-optic endpoint, the obtained camera parameters accurately capture positioner motion accuracy data.

Camera calibration is performed on the running and testing platform built at the University of Science and Technology of China. After calibration, the CMOS camera captures the calibration target with a residual distance of 4.6 m between actual and theoretical coordinates. This high measurement accuracy satisfies LAMOST's fiber positioning requirements. Currently, whether positioner accuracy meets preset requirements is determined through repeated positioning accuracy and open-loop calibration curve data, accurately obtained via the running and testing platform.

2.2. Fine Run-in and Experimental Process of the Fiber Positioner

During operation, the central and eccentric rotary axes are measured separately. We define one round as rotating the central shaft from 0° to 360° and the eccentric shaft from 0° to 180°. A set number of pause measurement points serve as index points in each round; after reaching full stroke, the system returns to the original position for the next measurement round. Index point count must be sufficient to reflect precise gear meshing accuracy and detailed positioner status, yet not so high as to excessively lengthen detection time. We select 210 division points to satisfy these requirements.

As visualized in Figures 7 and 8, when the central and eccentric shafts complete one round, the stepper motor running pulse is 63,000—300 pulses per step. To improve pixel coordinate accuracy at each index point, we repeat measurements ten times per point, with the CMOS camera capturing fiber position coordinates and recording them in the control host. This improves measurement accuracy and reduces errors. We typically run five rounds for each batch of positioner central and eccentric axes. Since positioners are still in the run-in stage initially, subsequent rounds become more stable. Therefore, we use data from rounds three through five for calculating fiber positioner motion accuracy.

The fiber positioner is driven by a permanent magnetic motor through a reducer and gear meshing transmission, achieving micron-level accuracy. Three-round measurement effectively reflects repeated positioning accuracy; additional rounds increase measurement time and decrease efficiency without significantly influencing repeated positioning accuracy evaluation. Thus, three-round measurement data satisfy positioning accuracy evaluation requirements.

2.2.1. Calculation of the Repeated Positioning Accuracy of the Fiber Positioner Each index point coordinate is measured ten times consecutively per round, with the average taken as the actual coordinate value for that round. After three rounds, we obtain the mean coordinate for each indexing point across all rounds. We then calculate the distance from each round's actual coordinate value to this three-round mean for all indexing points, determining the standard deviation (δ). Figure 9 [Figure 9: see original paper] displays typical repeat positioning accuracy for central and eccentric axes, where each colored curve represents the distance error between actual coordinates and the three-round average.

Experimental data analysis: Repeated positioning accuracy is based on multiple positioning rounds at the same positioner location. Stability and reliability can be qualitatively analyzed by plotting distances between each indexing point and the three-round average. Calculating the standard deviation quantitatively determines whether accuracy meets requirements. LAMOST requires that 3δ not exceed 40 m to satisfy positioning accuracy requirements [?]. In Figure 9, the central axis distance standard deviation δ is 1.6844 m, eccentric axis distance δ is 1.9566 m, and 3δ for both axes is far less than 40 m, indicating high repeated positioning accuracy that fully meets positioning requirements.

2.2.2. Fiber Positioner Calibration Curve Data Calculation We use the average of the last three rounds as calculation data, fitting the rotation center and two gyration radii of central and eccentric axes via least-squares method. We then calculate the actual rotation angle per step using positioner parameters through the cosine theorem.

Least-squares fitting method: Let (x, y) be rotation center coordinates, r the rotation radius, and (x , y) the ith division point coordinates. According to the circle definition:

$$(x - x_i)^2 + (y - y_i)^2 = r^2$$

where x and y are horizontal and vertical rotation center coordinates, x and y are horizontal and vertical coordinates of the ith division point, and r is the rotation trajectory radius.

From this we derive:

$$x^2 + y^2 - r^2 = 2x \cdot x_i + 2y \cdot y_i - (x_i^2 + y_i^2)$$

Let:

$$d = x^2 + y^2 - r^2$$

The following matrix can be obtained:

$$\begin{bmatrix} 2x_1 & 2y_1 & -1 \\ 2x_2 & 2y_2 & -1 \\ \vdots & \vdots & \vdots \\ 2x_n & 2y_n & -1 \end{bmatrix} \begin{bmatrix} x \\ y \\ d \end{bmatrix} = \begin{bmatrix} x_1^2 + y_1^2 \\ x_2^2 + y_2^2 \\ \vdots \\ x_n^2 + y_n^2 \end{bmatrix}$$

We solve for rotation center coordinates (x, y) and rotation radius r.

Actual step angle calculation: Let be the angle between the ith and (i+1)th division points, with triangle side lengths l , l__b, and l__c calculated from the planar distance formula. As shown in Figure 10 [Figure 10: see original paper], the cosine theorem yields:

$$\theta_i = \arccos\left(\frac{l_a^2 + l_b^2 - l_c^2}{2l_a l_b}\right)$$

where l , l_b, and l_c are side lengths of the triangle formed by the rotation center and ith and (i+1)th division points, and is the angle between l and l_b.

Experimental data analysis: As seen in Figure 11 [Figure 11: see original paper], the theoretical step angle for each central axis index point is 1.72°, and for each eccentric axis index point is 0.86°. However, actual calibration curves for both axes fluctuate near these theoretical values, indicating the relationship between pulse count and actual rotation angle is not simply linear.

2.3. Analysis of the Accuracy Error of the Fiber Positioner

Quantitatively, a fiber positioner with unqualified positioning accuracy has 3δ > 40 m; qualitatively, its repeated positioning accuracy curve and calibration curve exhibit large fluctuations. We classify common failure causes affecting positioner accuracy into four types:

1. **Looseness in eccentric shaft transmission component assembly.** This includes eccentric shaft anti-backlash spring looseness, eccentric shaft gear looseness, and optical fiber bracket set screw looseness—of which eccentric shaft gear looseness is most common. This fault causes backlash impact during eccentric shaft drive, resulting in unsynchronized eccentric shaft transmission and deviation from target points. As shown in Figure 12 [Figure 12: see original paper], the deviation increases residual error for each indexing point's fiber coordinates and amplifies step angle oscillation amplitude.

2. **Eccentric shaft motor damage.** When damaged, the eccentric shaft motor gear cannot drive stably, preventing the eccentric shaft from reaching exact required positions and causing unfixed fiber positions each round. As shown in Figure 13 [Figure 13: see original paper], jitter during driving results in unfixed position coordinates for each eccentric shaft indexing point, large residual errors, and high step rotation angles in the calibration curve.

3. **Looseness in central shaft transmission component assembly.** This includes central shaft internal gear looseness and anti-backlash spring looseness—primarily the former. When the central shaft runs, the motor gear meshes with the internal gear to drive it. Since the internal gear is not fixed to the central shaft, it cannot stably drive central shaft rotation, causing lost steps and large error distances between central shafts of different rounds. As demonstrated in Figure 14 [Figure 14: see original paper],

lost steps during central shaft transmission cause unfixed indexing point positions each round and large residual curve fluctuations.

4. **Central axis motor damage.** When the central shaft motor is damaged, the motor gear cannot drive stably, causing severe central shaft shaking and unstable indexing point positions each round. As plotted in Figure 15 [Figure 15: see original paper], severe jitter during central shaft driving creates large position errors for the same index point across rounds and violent residual curve fluctuations, with large fluctuations for each index point in the calibration curve.

During fiber positioner maintenance, we have accumulated extensive failure cause data. Analyzing 500 repaired positioners reveals that for 392 positioners (78.4%), failure cause was eccentric shaft transmission component looseness; for 257 positioners (51.4%), central shaft transmission component looseness; for 21 positioners (4.2%), central shaft motor damage; and for 19 positioners (3.8%), eccentric shaft motor damage. Since some positioners may have multiple simultaneous failure causes, probability sums may exceed 100%. These four fault types effectively cover all positioner failures encountered during annual maintenance.

3. Fault Diagnosis Based on an LSTM Deep Neural Network

3.1. Fault Diagnosis Method Selection

Existing fault diagnosis methods divide into traditional algorithms and deep learning-based algorithms. Traditional methods require manual feature extraction, selection, and classification, often employing time-frequency statistical analysis, fast Fourier transform, wavelet transform, and time-frequency map analysis to eliminate noise. Principal component analysis [?], independent component analysis [?], manifold learning, and other algorithms screen useful features. Finally, backpropagation neural networks or support vector machines achieve fault classification with good robustness [?]. While traditional algorithms have wide applications and can partially meet recognition rate requirements through appropriate classifier parameters, their feature extraction relies on manual extraction and expert knowledge, yielding insufficiently robust generalization. These methods have difficulty satisfying fiber positioner fault diagnosis requirements.

In contrast, deep learning-based fault diagnosis algorithms have emerged with strong robustness and extremely high accuracy, bringing new ideas to the field. These approaches automatically extract features from data without expert prior knowledge, achieving fault classification and effectively improving diagnostic accuracy and efficiency. Based on deep learning's unique advantages in automatic feature extraction and recognition, we select it for diagnosing fiber positioners with positioning accuracies that fail to meet requirements.

3.2. Data Analysis and Model Selection

Most existing deep learning-based fault diagnosis algorithms utilize vibration data. However, due to the LAMOST fiber positioner's complex mechanical structure, these methods are unsuitable for raw vibration signal analysis. Through precision running experiments, we obtain four sets of positioner parameters: central axis repeated positioning accuracy, central axis calibration curve, eccentric axis repeated positioning accuracy, and eccentric axis calibration curve data. These parameters correspond one-to-one with positioner failure characteristics. Each data group contains time series data that is one-dimensional with strong contextual correspondence.

For one-dimensional data, one-dimensional convolutional neural networks (CNN) can extract features effectively but lack memory capability, wasting data time features [?]. Recurrent neural networks (RNN) provide time memory but traditional RNNs implement backpropagation through time (BPTT) during training [?]. With long time series, residual errors decrease exponentially, causing slow network weight updates and lacking long-term memory capability. The LSTM model employs a special hidden layer cell structure [?], as shown in Figure 16 [Figure 16: see original paper]. Each neuron's input includes both current moment training data and previous moment neuron state, providing powerful context memory that solves gradient disappearance and explosion problems. This enables excellent sequence data feature extraction and has been widely applied in text learning and speech signal processing [?]. Therefore, we select the LSTM network to extract fault features and build a classification model based on given data and accuracy metrics, using error curves from different faulty positioners as training data.

Figure 16(a) shows the LSTM forward propagation model schematic. x $_1$, x , and x $_1$ represent previous, current, and next moment data, respectively. A is the trainable LSTM neuron. h $_1$, h , and h $_1$ represent neuron states at previous, current, and next moments. Figure 16(b) shows internal neuron structures. When training neuron A, three data parts are input: h $_1$ (previous moment state), C $_1$ (previous moment output), and x (current moment input). The forget gate f , update gate i , and state gate o process input data according to equations (7)–(9). σ is the sigmoid nonlinear activation function commonly used in deep learning networks, as shown in equation (6). W_f, W_i, and W_o are weight data for various parts; b_f, b_i, and b_o are offsets for different parts. After processing via equations (10) and (11), we obtain current moment output C and neuron A state h . The model trains for multiple epochs until each neuron obtains appropriate weights for successful failure data classification.

3.3. Concrete Model Construction

As displayed in Figure 17 [Figure 17: see original paper], the detection framework processes 4×210-dimensional positioner running and accuracy data sent to the LSTM model for feature extraction. Each data group has time length

210 with four features per moment. The LSTM model contains three hidden layers with 500 nodes each. After LSTM feature extraction, a fully connected layer linearly maps the 500-dimensional high-dimensional feature vector to four dimensions, where the maximum direction indicates the predicted feature. We use cross-entropy to calculate the loss function, employ BPTT gradient back-propagation, update model parameters with the ADAM optimization algorithm, and obtain a converged model.

3.4. Data Preparation and Preprocessing

Through long-term LAMOST fiber positioner maintenance, we find that failures classify into four categories: eccentric shaft motor damage, eccentric shaft part looseness, central shaft motor damage, and central shaft part looseness. We therefore use four double-turn positioners, each broken according to one fault type, inserted into the test platform for calibration and running, obtaining 2000 data rounds per fault. As shown in Table 1 , we divide data into training and test sets at a 4:1 ratio—1600 training and 400 test samples per fault type, with labels 0–3 corresponding to the four failure modes.

3.5. Training Results

We set training rounds to 100, randomly shuffling training data in batches of 500. After 100 rounds, the model converges, achieving over 98% accuracy on the test set and over 97% on the validation set, demonstrating excellent fault data identification capability. Figure 18 [Figure 18: see original paper] shows accuracy and loss function changes during training. The loss function decreases with training rounds while accuracy gradually exceeds 98%. Figure 19 [Figure 19: see original paper] visualizes final trained model classification results, showing the LSTM model accurately distinguishes all four fault types with effective feature extraction.

3.6. Validation Experiments with Actual Data

During dual-turn positioner precision running at the LAMOST site, we obtained substantial failure data. We selected 200 fault data points (50 per fault type) and input them into our diagnosis model to verify generalization effectiveness. As shown in Table 2 , the constructed model successfully diagnoses LAMOST field positioner fault data. In follow-up maintenance, we will continue updating fault models for rapid diagnosis. The considerable annual maintenance data will further optimize and enhance model generalization.

4. Conclusions

This paper proposes a method for obtaining fiber positioner repeated positioning accuracy and calibration curve data through photogrammetry, systematically analyzing causes of positioner failures that fail to meet LAMOST operational requirements. The deep learning model classifies failure data and accurately distinguishes failure causes, providing an efficient classification and diagnosis method that greatly reduces labor and time costs while accumulating reliable data for future positioner design, processing, and assembly. This approach effectively reduces adjacent positioner interference probability, improves convergence speed, and enhances LAMOST observation efficiency. The maintenance and design optimization methodology for this double-turn gear transmission fiber positioner system has general significance for future instruments. Similar fault diagnosis processes will be implemented during operation of fiber-optic positioners with double-turn mechanical structures such as DESI and SDSS-V, serving as valuable references. Future fiber positioners will be smaller than 10 mm, with simpler, more efficient transmission chains pushed to conventional processing limits, increasing failure rates. Tracking and analyzing positioning accuracy error causes during operation will be essential for implementing next-generation miniaturized fiber positioners.

Currently, the LSTM model training sample size is insufficient. Subsequent applications must continue accumulating data to improve generalization. Future research will focus on using large amounts of practical positioner data that fails to meet precision requirements, dividing fixed optical fiber positioner faults into more detailed failure causes to provide data support for subsequent design, manufacture, and processing.

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Data Availability

The data underlying this article will be shared upon reasonable request to the corresponding author.

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Note: Figure translations are in progress. See original paper for figures.