An Early Warning Model for Intelligent Operation of Power Engineering based on Kalman Filter Algorithm

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***Abstract*—The accurate early warning of intelligent operation of power engineering can find the abnormal operation of substation equipment in time and ensure the safe operation of substation equipment. Thus, an early warning model for intelligent operation of power engineering based on Kalman filter algorithm is constructed. In this model, the noise elimination method of substation equipment inspection image based on particle resampling filter algorithm is introduced. After removing the noise information of operation situation inspection image of substation equipment, the gradient direction histogram feature, lab color space feature and edge contour feature in the image are extracted by the multi-feature extraction method for intelligent operation of power engineering based on multi-feature fusion. These features are combined to form the feature description set of equipment operation situation. The feature description set is used as the identification attribute set of the anomaly identification and early warning model for intelligent operation of electric power engineering based on Kalman filter algorithm to complete the anomaly identification and early warning of equipment operation situation. The test shows that when the model is used to observe the temperature change trend of the top layer of the transformer, the temperature error is very small, and the early warning accuracy for the abnormal temperature of the top layer of the transformer is very high, so the abnormal operation of the substation equipment can be found in time.**

Keyword—Kalman filter; power engineering; intelligent operation; early warning model; image denoising; feature extraction

I. INTRODUCTION

With the development of industrial revolution, electric power plays an important role in the development of human society. Problems in urban power supply system will cause serious consequences for people's daily activities and even the whole society. Therefore, ensuring the safe and stable operation of power system has become an extremely important part of the national strategic energy security system. To realize the safe and reliable operation of the power grid, it is necessary to continuously improve the automation level of the substation, so as to achieve the purpose of reasonable allocation of power supply equipment and effective supervision and management of the substation equipment [1].

The development of substation automation is mainly affected by the following aspects. First, the construction of substation automation system is inseparable from information technology. The development of information technology makes the information source and amount faced by power enterprises continue to grow. Therefore, enterprises also put forward relatively high requirements for the work efficiency and response speed of the processing system [2]. Secondly, the automation level of the substation mainly involves fault detection and fault isolation. On the one hand, the wide distribution of low-voltage substation has resulted in the large number and scattered nodes of low-voltage substation. Therefore, the staff must upload patrol inspection data in real time, accurately and efficiently. On the other hand, due to the long-term exposure of power equipment to the field, it often bears the effects of normal mechanical load and power load, as well as external forces such as lightning strike, pollution, strong wind, earthquake, flood, landslide and bird damage, and may even be endangered by the theft of power equipment by some criminals. These factors will cause aging, oxidation and corrosion of various components in the substation. If they are not found and eliminated in time, the existing hidden dangers will develop into faults, thus posing a threat to the security and stability of the power system [3]. Therefore, in order to fundamentally ensure the safe and stable operation of the power grid and the safe supply of power, it is necessary to carry out regular and irregular inspection of each substation, timely find hidden dangers, prevent them before they happen, and reduce the failure rate of power equipment to the lowest.

At present, the traditional manual inspection, video monitoring, comprehensive maintenance vehicle and other methods are mainly used for substation inspection in China's power system. For some enterprises, the cost is too high, the operation is difficult to implement, and it is not easy to promote. At the same time, it is difficult to eliminate the impact of human factors in the inspection work. Therefore, how to absorb the modern management experience of foreign advanced power enterprises and make full use of advanced mobile technology in the construction of intelligent inspection system for substation has become very important.

II. JOURNALS' REVIEWED

Xie, S studied the intelligent inspection technology of substation electrical equipment based on 5G. Based on 5G communication technology, intelligent patrol robots, video surveillance, AR glasses, mobile patrol APP and other terminals are integrated to realize all-round intelligent patrol of the substation, with poor early warning effect [4]. Yang Qiong designed an intelligent patrol inspection system for substation, which introduced GPS and PDA technology, and was characterized by the storage of equipment information in the upper management system and all management of equipment, defect information, historical data and patrol inspection. Patrol inspectors could complete the information collection of equipment only by arriving near the corresponding patrol inspection equipment. After the patrol inspection, the corresponding equipment information should be transmitted to the background database for storage through a certain communication mode. The comprehensive cost of this system was relatively high [5]. Zhang F. researched the inspection method combining PDA and RFID. This inspection method was a non-contact automatic identification technology, which could read and identify the electronic data stored in the card without contact. The reader / writer emitted energy in an area to form an electromagnetic field. When the RF tag passed through the area, it detected the signal of the reader / writer and sends the stored data. The reader / writer received the signal sent by the RF tag, decoded and checked the accuracy of the data to complete the identification, so as to achieve the purpose of patrol inspection [6].

Compared with other methods, RFID technology has the characteristics of non-contact identification, high-speed identification, multi-target simultaneous identification, and strong confidentiality. It is widely used in vehicle identification and production process control, but the immunity of radio frequency technology needs to be optimized. In order to discover the abnormal operation of substation equipment in time and realize the efficient and intelligent operation early warning of power engineering. On the basis of previous studies, this paper establishes an intelligent operation early warning model of electric power engineering based on Kalman filter algorithm, which is mainly used for intelligent patrol inspection of electric power engineering, in order to provide some help for timely early warning of abnormal conditions found in the patrol inspection process.

III. Early Warning Model for Intelligent Operation of Power Engineering

The early warning of intelligent operation of power engineering needs to be completed by using intelligent technology. At present, the application of intelligent inspection robot is no longer strange in the field of power engineering. The intelligent inspection robot has replaced the traditional manual inspection mode. The early warning model for intelligent operation of power engineering based on Kalman filter algorithm constructed in this paper belongs to one of the core technologies applied to the equipment of intelligent inspection robot. Before introducing the specific application technology of the model, the structure of the intelligent inspection robot is analyzed. The structure diagram of its operation mode is shown in Fig. 1.

The intelligent inspection robot system consists of a base station layer and a robot mobile station. The base station layer receives and processes patrol inspection data through its database, data processing and video monitoring modules, which is equivalent to a monitoring background. It also has the functions of image processing and pattern recognition, which can automatically identify equipment defects and automatically warn. The communication layer is divided into two modules: the wireless bridge base station and the wireless bridge mobile station. It provides data transmission channels for the base station and the robot mobile station through the wireless network transmission protocol. Wireless communication is used between the mobile robot and the monitoring background [7]. In addition, when the robot loses power, it can automatically return to the charging room for self-charging. The model in this paper is mainly installed on the intelligent inspection robot equipment to help the robot find the abnormal situation of intelligent operation of power engineering in real time and give real-time warning. The intelligent operation warning problem of power engineering studied in this paper is mainly to identify and warn the operation situation of substation equipment.

A. Noise Elimination Method for Inspection Image of Substation Equipment based on Particle Resampling Filter Algorithm

When the intelligent inspection robot performs the inspection task of operation situation of substation equipment, the collected infrared image is affected by external factors, so there is inevitably noise information, which directly affects the image quality [8]. For this reason, this paper uses the noise elimination method of inspection image of substation equipment based on particle resampling filter algorithm to remove the noise information of inspection image and optimize the image quality [9].

The particle filter algorithm uses the large number theorem to solve the nonlinear non Gaussian estimation problem in Bayesian estimation through Nonparametric Monte Carlo, which is applicable to any nonlinear non Gaussian random problem that can be expressed in state space [10]. The posterior probability density of noise particles is estimated through a group of observed random noise samples in the state space of noise particles in the inspection image, and the mean value of noise samples is used to replace the integral operation to obtain the minimum variance of noise filtering effect.

The infrared image state equation and noise observation equation of operation situation inspection of substation equipment are modeled as follows:

$$\begin{cases} y_h = g\left(y_h, u_h\right) \\ l_h = k\left(y_h, m_h\right) \end{cases} \tag{1}$$

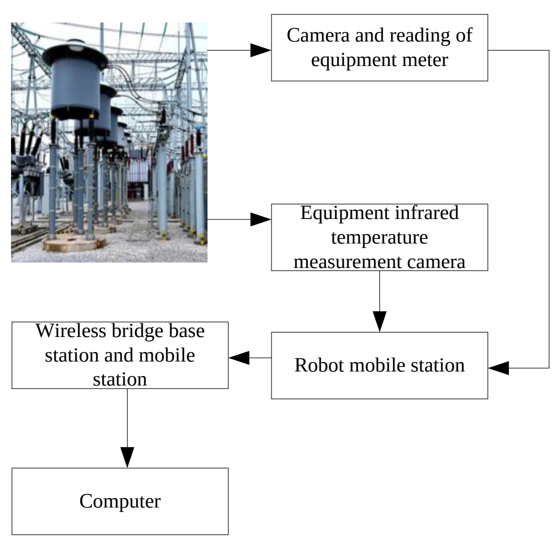


Fig. 1. Structure diagram of operation mode of intelligent inspection robot.

Where, u_h is the actual noise level during patrol inspection image acquisition; m_h is the measurement noise level of patrol inspection image; $g(\cdot)$ is the transfer function of patrol inspection image quality; $k(\cdot)$ is the measurement function of patrol inspection image quality. y_h is a group of filter state values of weighted particle with conditional distribution obtained by Monte Carlo simulation sampling at time h. Each noise particle uses its gray value at the patrol inspection image position as the characteristic value, and l_h is the observation value of noise particle filter at time h.

Through the probability density function $q\left(y_h \middle| l_{1:h-1}\right)$ of the spatial state of the noise particle swarm optimization system at time $h-1$ based on the Chapman-Kolmogorov equation, the state of noise information in the patrol inspection image of substation equipment's operation situation at time h is observed:

$$q\left(y_h \middle| l_{1:h-1}\right)=\int q\left(y_h \middle| y_{h-1}\right) q\left(y_{h-1} \middle| l_{1:h-1}\right) dy_{h-1} \tag{2}$$

Where, $l_{1:h-1}$ is the noise observation value from 1 to $h-1$.

The Bayesian formula is used to derive the prior probability $q\left(y_h \middle| l_{1:h-1}\right)$ and the posterior probability $q\left(y_h \middle| l_{1:h}\right)$ from the noise observation value at time h According to the law of large numbers, when the number of noise particles is very large, the particle filter is approximate to the posterior probability of the patrol inspection image quality state [11]. Namely:

$$q\left(y_h \middle| l_{1:h}\right) \approx \frac{1}{M} \sum_{j=1}^{M} \varpi_h^j \beta\left(y_h - y_{1:h}^{j(n,f)}\right) \tag{3}$$

Where M is the number of noise particles; ϖ_h^j is the weight of noise particle j at time h; β is a Dirac function; $y_{1:h}^{j(n,f)}$ is the j-th noise particle gray value located at the patrol inspection image (n, f) of operation situation of substation equipment from 1 to h. Generally, the noise particle set cannot be directly sampled from the posterior probability. The prior density that is easy to realize is selected as the importance density function, and the particles with uniform distribution are optimized through maximum likelihood estimation, so that the optimized particle distribution is closer to the posterior probability density. Only a small number of noise particles can achieve high estimation accuracy, thus reducing the amount of calculation [12]. Then the weight is updated to:

$$\varpi_h = \varpi_h^j q\left(y_h \middle| l_{1:h}\right) \tag{4}$$

Weight normalization:

$$\hat{\varpi}_h = \frac{\varpi_h^j}{\sum_{j=1}^{M} \varpi_h^j} \tag{5}$$

The optimal image quality of patrol inspection of substation equipment's operation situation is output:

$$\hat{y}_h = \sum_{j=1}^{M} \hat{\varpi}_h y_h \tag{6}$$

After several iterations of particle algorithm, only a small number of effective noise particles have non-zero important weights, and most of the important weights of noise particles tend to zero. Therefore, the noise cannot be effectively eliminated in the process of infrared image denoising. In order to prevent the weight degradation of noise particles, resampling method is adopted to reduce the impact of noise on the image quality of patrol inspection of substation equipment's operation situation to a certain extent [13].

The main idea of resampling is to remove the noise particles with small weight, retain and copy the noise particles with large weight, and sample the particles with large weight for many times, so as to increase the chance of noise elimination for the particles, and sample less for the particles with small weight [14]. Firstly, m uniformly distributed random numbers $\left\{\varepsilon_i; i=1,2,\ldots,\mathrm{m}\right\}$ are generated in the interval [0, 1], and then the weights of noise particles are accumulated:

$$d_h = \sum\nolimits_{j=1}^{h} \hat{\varpi}_h \tag{7}$$

Where, $h=1,2,\ldots,m$; d_h is the cumulative value of noise particle weight.

The resampled noise particles only account for a small part of the whole particle swarm. Such particles can no longer effectively describe the posterior probability distribution of patrol inspection image quality status. As each particle is sampled independently, the process includes cycle and comparison operations, which increases the computational complexity of particle filter for patrol inspection image of substation equipment's operation situation [15].

Resampling makes the noise particles with higher weight be sampled for many times, and the sampling results contain many repeated noise particles, thus losing the diversity of particles and reducing the filtering performance. In order to solve the problem of resampling dilution, the effective particle number threshold is used to optimize the filtering effect of patrol inspection image of substation equipment's operation situation.

Suppose $\left\{\hat{\varpi}_h^1, \hat{\varpi}_h^2, ..., \hat{\varpi}_h^M\right\}$ is the set of normalized weights of noise particles, and the sample variance of particle weights is:

$$U\left(\hat{\varpi}_h\right) = \frac{1}{M}\sum_{j=1}^{M}\left[\hat{\varpi}_h - mean\left(\hat{\varpi}_h\right)\right]^2 \tag{8}$$

Where $U\left(\cdot\right)$ is the variance function; $mean\left(\cdot\right)$ is the mean function.

Effective particle number threshold $M_{eff}\left(\hat{\varpi}_h\right)$ of the degradation degree of noise particles is measured:

$$M_{eff}\left(\hat{\varpi}_h\right) = \frac{1}{\sum_{j=1}^{N}\left(\hat{\varpi}_h\right)^2} \tag{9}$$

In this way, the effective noise particles are classified according to the weight value, which effectively reduces the complexity of the algorithm, and the random method increases the diversity of noise particles. In order to avoid too small noise particles in the patrol inspection image of substation equipment's operation situation, the lower limit of noise variance is set as $\alpha_{\min}$, and the maximum noise variance is set as $\alpha_{\max}$. The attenuation factor η is used to estimate the noise reduction rate. When the noise in the patrol inspection image of substation equipment's operation situation is small, a small number of particles can be used to describe the noise distribution. When the noise is large, the sampling range of particles is expanded and the number of particles is increased. Sigmoid function is used to express the relationship between the number of noise particles M_h and uncertainty measure o_h at time h.

$$M_h = \frac{2M_{eff}\left(\hat{\varpi}_h\right)}{1+\exp\left(-\eta o_t + \eta\cdot\eta_{\min}\right)} \tag{10}$$

Among them, the uncertainty measures $o_h = \theta_t^x\theta_t^z$, θ_t^x and θ_t^z are the actual noise and observation noise in the patrol inspection image of substation equipment's operation situation at time h. In this way, the noise particles with smaller weight are discarded and replaced by the noise particles with larger weight for multiple noise elimination. The noise particles with larger weight are erased after the patrol inspection image is resampled to complete the noise elimination of the patrol inspection image of substation equipment's operation situation [16].

B. Multi-Feature Extraction Method for Intelligent Operation of Power Engineering based on Multi-Feature Fusion

In order to identify the abnormal situation in the inspection process of substation equipment's operation situation, it is necessary to extract the image features of substation equipment's operation situation inspection after de-noising in Section IIIA. The image features of inspection are very important in the process of substation equipment's operation situation awareness. Therefore, this paper will comprehensively consider the edge, gradient and color features in the infrared image during intelligent inspection of substation equipment. A multi-feature extraction method for intelligent operation of power engineering based on multi-feature fusion is proposed. The feature description set of equipment operation situation is composed of gradient direction histogram (HOG) feature, lab color space and edge contour, which is used as the identification attribute set of the anomaly identification and early warning model of intelligent operation of power engineering based on Kalman filter algorithm.

1) Gradient feature extraction: The gradient of patrol inspection image of substation equipment's operation situation includes image edge contour and texture information, which can be used for image analysis and recognition. In the process of extracting the image features of substation equipment's operation situation inspection, this paper simplifies the calculation process of HOG features, improves the calculation efficiency, and can better describe the gradient features of substation equipment's operation situation. In the 5*5 cell, 9 bin histograms are used to calculate the gradient information of these 25 pixels. That is, the 360 ° gradient direction of the cell is divided into nine direction intervals, and each pixel in the cell is weighted projected in the histogram with the gradient direction. The weight is the gradient amplitude, and the amplitude of the histogram in each direction forms an eigenvector [17].

The gradient of all pixels in the patrol inspection image of substation equipment's operation situation after noise removal is calculated, and the gradient amplitude is:

$$F\left(x,y\right) = F_x\left(x,y\right) + F_y\left(x,y\right) \tag{11}$$

Where, $F_x\left(x,y\right)$ and $F_y\left(x,y\right)$ are the gradient amplitudes in direction x and y of each pixel in the inspection image of the substation equipment's operation situation after noise removal.

The gradient direction is:

$$\mu\left(x,y\right) = \tan^{-1}\frac{F_x\left(x,y\right)}{F_y\left(x,y\right)} \tag{12}$$

The weighted projection of each pixel in the cell within the uniform interval in the gradient direction $\left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$ is calculated as:

$$F_k\left(x,y\right) = \sum_{\mu(x,y)\in c_k} F\left(x,y\right) \tag{13}$$

Where, $F_k(x,y)$ is the cumulative value of gradient amplitude in different gradient directions in the cell; c_k represents the range of different gradient directions.

2) Color feature extraction: After de-noising, the component L in the lab color space of the inspection image of substation equipment's operation situation expresses the human eye's perception of brightness. The output color scales of components a and b are more uniform and balanced. Compared with RGB and CMYK color models, the lab space has a broader color gamut and is independent of physical equipment.

Therefore, in order to preserve the wide color gamut and rich colors as much as possible, and better quantify the colors, this paper uses the lab color model as the color feature, that is, the patrol inspection image of substation equipment's operation situation after noise removal is transformed into the lab color space model, and the lab color space is divided into three feature vector sets.

3) Edge profile features: The edge of the inspection image of substation equipment's operation situation after noise removal refers to the area where the local gray level of the image changes significantly. It is the most basic feature of the image and contains useful information for identification. Therefore, this paper extracts the direction, first-order and second-order differentiation of the image as the edge contour feature vector set of the de-noising patrol inspection image of substation equipment's operation situation [18]. Among them, the first-order and second-order differential are realized by Sobel differential operator.

To sum up, the extracted feature vectors of inspection image of substation equipment's operation situation after noise removal are used to form a feature descriptor. Each feature vector is a feature channel, and each feature channel is a matrix block with the same size as the image.

C. Anomaly Identification and Early Warning Model for Intelligent Operation of Power Engineering based on Kalman Filter Algorithm

The characteristic information of the patrol inspection image of substation equipment's operation situation extracted in Section IIIB is used as the identification attribute set of the intelligent operation anomaly identification and early warning model of power engineering based on the Kalman filter algorithm. The Kalman filter algorithm mainly includes two processes: prediction and correction, that is, observation and update. The observation process mainly uses the time updating equation to establish a prior estimate of the current substation equipment's operation situation, so as to calculate the current state variables and error covariance estimates in time, and construct a prior estimate for the next time state; In the correction process, a posteriori estimate of the current state of substation equipment's operation situation is established based on the prior estimate of the prediction process and the current measurement variables by using the measurement update equation through feedback. This process is called the prediction correction process.

In order to apply the Kalman filter algorithm to the intelligent operation early warning of power engineering, it is necessary to construct the description equation and measurement equation of substation equipment's operation situation based on the Kalman filter algorithm, and then establish the real-time optimal estimation model of substation equipment's operation situation [19]. Then the equation describing the operation situation of substation equipment is:

$$\alpha_{oil,h} = \Omega \alpha_{oil,h-1} + B_2 \begin{bmatrix} \alpha_{oil,h} \\ N \end{bmatrix} + V_{h-1} \tag{14}$$

Where, $\alpha_{oil,h}$ is the operation situation of substation equipment at time h; Ω is the characteristic information of patrol inspection image of substation equipment's operation situation extracted in subsection 2.2; B_2 is the gain of control input of substation equipment; V_{h-1} is the process excitation noise, which is generally considered to obey the normal white noise and does not change with time. It represents the observation error of substation equipment's operation situation between $h-1$ and h; N is the observation times of operation situation of substation equipment; $\alpha_{oil,h-1}$ is the operation situation of substation equipment at time $h-1$.

The observation equation of the operation situation of substation equipment at time h can be expressed as:

$$L_K = H_k \alpha_{oil,h} + W_K \Omega \tag{15}$$

Where, H_k is the gain of actual variable $\alpha_{oil,h}$ of substation equipment's operation situation to the observation variable L_K of substation equipment's operation situation; W_K is the change range of operation situation of substation equipment.

After determining the state equation and observation equation of the operation situation of the substation equipment, the Kalman filter algorithm estimates the operation situation of the substation equipment, which can carry out the two main processes of the Kalman filter: "time update (observation)" and "state update (correction)". Through repeated update and correction, the most accurate results can be obtained to realize the observation of the operation situation of the substation equipment. Firstly, it should establish the time update equation for the operation of substation equipment:

$$\hat{\alpha}^{-}_{oil,h} = \Omega \hat{\alpha}^{+}_{oil,h-1} + B_2 \begin{bmatrix} \alpha_{\mathrm{amb},h} \\ N \end{bmatrix} \tag{16}$$

$$Q^{-}{}_K = (1 - B_1)^2 \cdot Q^{+}{}_K + P \tag{17}$$

Where, "-" stands for a priori and "+" stands for a posteriori. $\hat{\alpha}^{-}_{oil,h}$ is the prior state estimation of step h when the operation situation of the substation equipment before step h is known, that is, the prior state estimation of time h using time $h-1$. $\hat{\alpha}^{+}_{oil,h-1}$ is a posteriori state estimation when the measurement variable L_K is known in the operation situation of substation equipment, and it is also the optimal estimation result of the state at $h-1$. $Q^{-}{}_{K}$ is the covariance of the error of prior estimation, and P is the process error of substation equipment's operation situation estimation. In the updating process, the state estimation is optimized by using the prior estimates and observations of the current state, which is called a posteriori state estimation. $Q^{+}{}_{K}$ is the covariance of the error of the calculated posterior estimate.

The verification equation for the estimation results of substation equipment's operation situation is:

$$\hat{\alpha}^{+}_{oil,h} = \Omega\hat{\alpha}^{-}_{oil,h} + F_h\left(L_K - H_k\hat{\alpha}^{-}_{oil,h}\right) \tag{18}$$

$$F_h = \frac{Q^{-}{}_{K}}{Q^{-}{}_{K} + S} \tag{19}$$

$$Q^{+}{}_{K} = Q^{-}{}_{K}\left(1 - F_h\right) \tag{20}$$

In Eq. (18) to (20), S is the variance of the operation situation estimation error of the measured substation equipment. A posteriori estimate $\hat{\alpha}^{+}_{oil,h}$ is composed of a linear combination between a priori estimate $\hat{\alpha}^{-}_{oil,h}$ and the observation variable L_K of substation equipment's operation situation; F_h is the Kalman gain, whose function is to minimize the posterior estimation error covariance $Q^{+}{}_{K}$ to ensure that the recursion can be carried out continuously. The magnitude of the residual value reflects the inconsistency between the observed value and the actual value. The greater the residual value is, the greater the inconsistency is. Otherwise, it is true. Eq. (17) to (20) constitute the five processes required for Kalman filter iterative observation. In the iterative process, equations (18) and (20) need to feed back the obtained posterior results to equations (17) and (18) in order to update the information of each step. In this way, the model can realize the real-time estimation of the operation situation of substation equipment and the real-time early warning of intelligent operation of power engineering.

The early warning program is mainly completed by the alarm device. The circuit of the alarm device is composed of high decibel active alarm. Because the driving ability of the single chip microcomputer is not enough, this circuit uses NPN triode to drive the alarm. The LED display circuit consists of two decoders 74l138, eight row drivers 4953 (each chip controls two rows), eight column drivers (each chip controls eight columns), and sixteen 1588 common anode diode lattice modules. Therefore, the LED display is a 1664 dot matrix. Four Chinese characters can be displayed at the same time. In normal state, the screen displays yellow "normal operation" and red "fault operation" in case of fault, accompanied by alarm sound [20]. The alarm flow of this device is shown in Fig. 2.

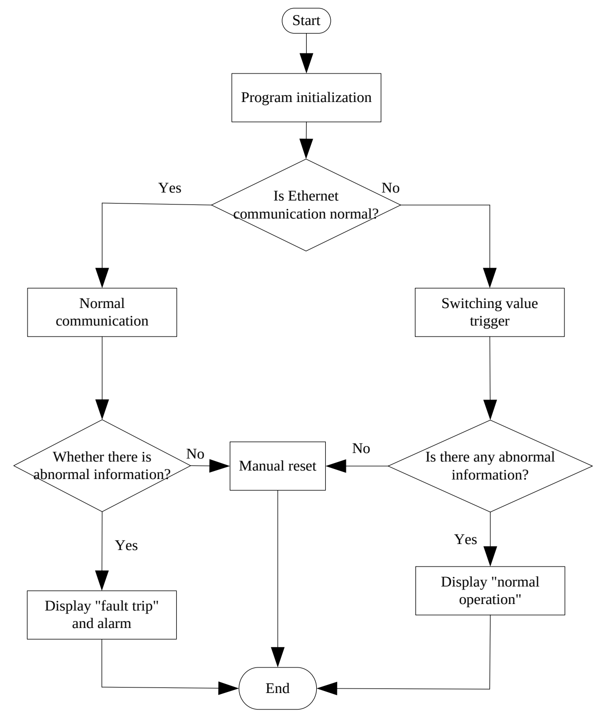


Fig. 2. Alarm process.

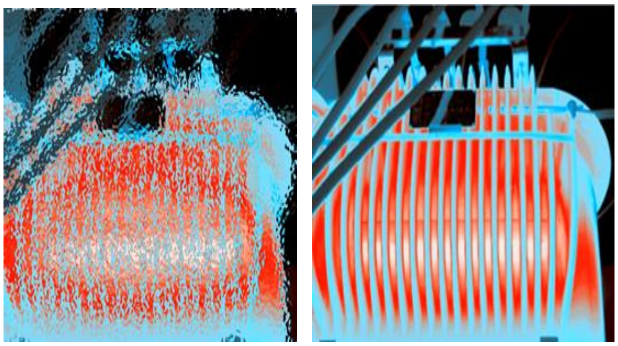
As shown in Fig. 2, the alarm device will first judge whether its Ethernet communication is normal. If the normal communication represents that the device can operate normally, it will judge whether there is any abnormal information touch device; if yes, it will display "fault operation" and sound light alarm. If there is no abnormality, it will display "normal operation" and reset manually.

IV. Results

The model is installed on an intelligent substation inspection robot to test the application effect of the model. The test content is mainly divided into the processing effect, situation recognition and early warning effect of intelligent inspection image of substation equipment's operation situation,.

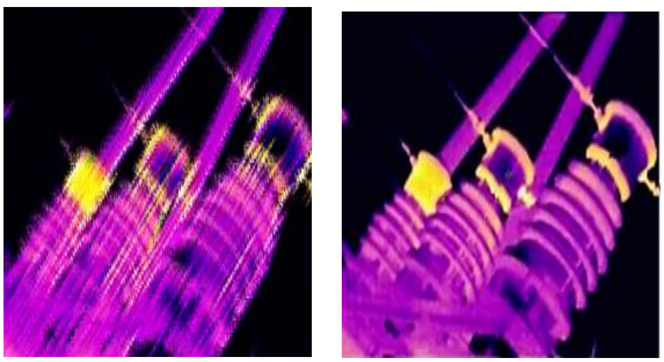
A. Analysis on Processing Effect of Intelligent Patrol Inspection Image of Substation Equipment's Operation Situation

As shown in Fig. 3(a) and Fig. 4(a), when the model in this paper inspects the operation situation of transformers and insulators in substations, there are different degrees of noise information in the captured intelligent inspection image of operation situation. The effect pictures of this model after noise removal are shown in Fig. 3(b) and Fig. 4(b).



（a）Before treatment （b）After treatment

Fig. 3. Intelligent inspection image of transformer operation situation.



（a）Before treatment （b）After treatment

Fig. 4. Intelligent inspection image of insulator operation situation.

From the analysis of Fig. 3 and Fig. 4, it can be seen that the model in this paper has a good denoising effect on the transformer and insulator images of the patrol substation when inspecting the operation situation of the transformer and insulator in the substation. From the visual point of view, the image definition after denoising is improved and the image details are more significant.

B. Abnormal Situation Identification and Early Warning Effect

The model in this paper is used to monitor the top temperature of the transformer shown in Fig. 3 in real time. The actual value of the top temperature of the transformer is shown in Fig. 5, and the ambient temperature is shown in Fig. 6.

The Kalman filter algorithm in the model of this paper can use the new patrol information to continuously observe and modify the new state estimates, so it can observe the top temperature in real time. The initial noise state of the state equation can be obtained from the statistical value of the variance function, and the variance of the observation error can be obtained from the statistical value of the temperature sensor error. The system state equation is used to optimally estimate the state variable, that is, the top temperature. The recognition results are shown in Fig. 7.

As shown in Fig. 7, the difference between the identification result of the transformer's top temperature and the actual value of the model in this paper is very small, which can well reflect the dynamic change of temperature. As long as the given system's initial value does not deviate too far from the real initial value, the Kalman filter algorithm can converge to the final value.

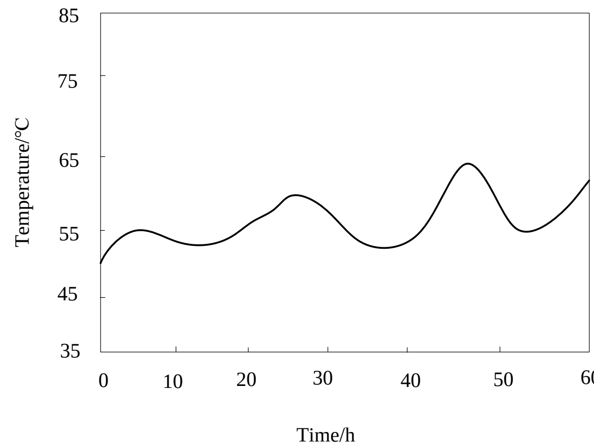


Fig. 5. Actual value of transformer top temperature.

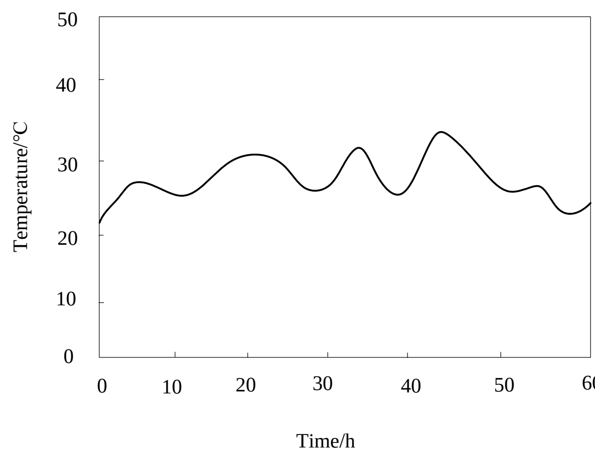


Fig. 6. Ambient temperature for intelligent operation of electric power engineering.

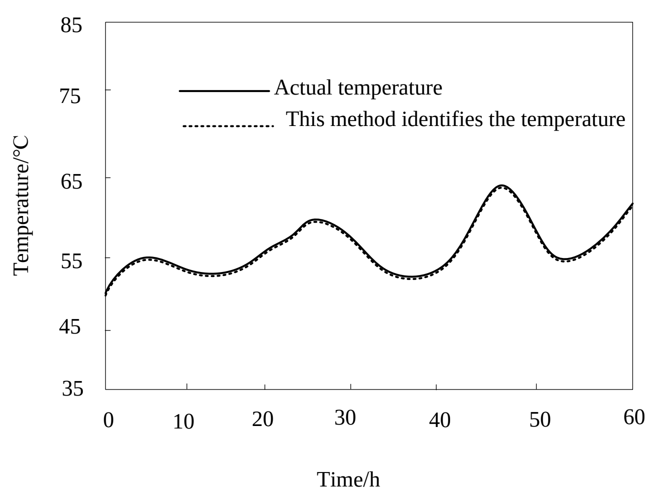


Fig. 7. The identification results of transformer top temperature by this model.

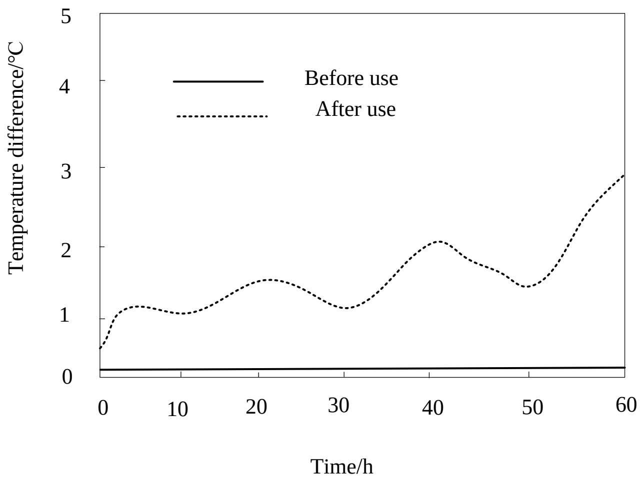


Fig. 8. The error variation of transformer top temperature identification results before and after the model is used in this paper.

Before and after the intelligent inspection robot uses the model in this paper, the error of the top temperature identification result of the transformer is shown in Fig. 8.

As shown in Fig. 8, when the model in this paper uses Kalman filter algorithm to observe the top temperature of transformer, the temperature error is less than 0.5°. When the model in this paper is not used, the observation error of intelligent inspection robot on the top temperature of transformer is more than 2°. This shows that the model in this paper has high observation accuracy on the top temperature of transformer. The reason is that the Kalman filter algorithm can continuously predict and correct the top temperature of transformer, and the observation error is minimized. Therefore, this model can be well applied to the abnormal identification of transformer top temperature.

The abnormal early warning effect of the model in this paper after identifying the top temperature of transformer is test, and the results are shown in Table I.

By analyzing the data in Table I, it can be seen that after the model identifies the top-level temperature of the transformer, there is only a 1-minute delay in the early warning time for the abnormal state of the top-level temperature of the transformer on February 2, 2022, but the number of early warnings is consistent with the number of abnormal occurrences. The model in this paper has verified the early warning effect of intelligent operation of power engineering and can accurately give early warning.

TABLE I ABNORMAL EARLY WARNING EFFECT OF TOP LAYER TEMPERATURE OF MODEL TRANSFORMER

Abnormal occurrence date	Abnormal occurrence time	Warning time	Number of exceptions	Warning times
2022/1/23	10:58	10:58	5	5
2022/2/2	9:20	9:21	1	1
2022/3/25	8:01	8:01	2	2
2022/4/14	12:36	12:36	3	3
2022/5/8	20:25	20:25	5	5
2022/5/13	2:36	2:36	4	4
2022/6/1	17:25	17:25	1	1
2022/6/3	13:33	13:33	1	1
2022/6/4	12:45	12:45	1	1

V. DISCUSSION

Based on the research content of this paper, at present, the intelligent inspection robot is mainly used in the intelligent operation inspection of power engineering. However, the intelligent inspection robot is not perfect, and it also has shortcomings in practical application:

1) Meter data reading: Patrol inspection robots are equipped with high-definition cameras that can be zoomed. According to the design idea, their advantages in reading meter data are far greater than the visual inspection of operation and maintenance personnel during manual patrol inspection. In the station, the installation position of some meters and meters is too high for manual vision to see the pointer, number and other contents in the meters and meters. In this case, the traditional inspection is conducted with the help of a telescope. The zoom camera of the intelligent inspection robot can not only shorten the meter interface several times the distance, save time and effort, but also save the meter interface as a picture for later analysis. However, in practical application, it is found that this advantage cannot be fully exerted, which is mainly manifested in that when the surface of the high-voltage meter in the station or the camera of the inspection robot becomes dirty due to the accumulation of pollutants and impurities in the air, the camera simply cannot obtain a clear meter image. In addition, the camera also fails to focus. For the problem that the camera surface of the inspection robot is polluted, a self-cleaning device similar to the automobile wiper can be added in the subsequent improvement to properly solve it. As for the phenomenon of surface pollution, the problem of non-inspection robot itself can only be solved by manual cleaning during each power outage and maintenance of power grid equipment. Focusing failure is caused by the camera algorithm or the auto focusing technology adopted. It is recommended to configure the camera with active auto focusing mode, which can greatly reduce the occurrence of focusing failure by combining the advantages of infrared ranging and ultrasonic ranging focusing methods and focusing mode based on image processing. At present, there are many researches and explorations on the research, development and application of inspection robot in the intelligent inspection system and the diversification of inspection functions, but the more advanced cutting-edge technologies are neglected in the hardware. High performance hardware equipment is more conducive to the advanced functions of the inspection robot.

2) Infrared thermometry: In the process of infrared temperature measurement, the layout of equipment in the station is complex and staggered, and the inspection robot is restricted by the fixed inspection path, positioning point and the traveling channel in the actual site designed in the system. It is unable to compare the maximum temperature and hot spot of the equipment from 360 ° directions flexibly like manual inspection, and there is inaccurate alignment. Therefore, the temperature information obtained is too large deviation from the actual situation, or even wrong. The problem of alignment and misalignment can be solved by optimizing the system and adding a distance monitoring unit. The function of the distance monitoring unit is to determine the reasonable distance between the tested equipment and the inspection robot. Only the equipment within a reasonable distance set in the system can be selected by the infrared camera, so as to effectively avoid the wrong selection of objects within the abnormal range such as the sum for temperature measurement in similar cases. However, in order to realize the full angle comparative temperature measurement like manual inspection, it is obviously impossible to realize it at the software level of the robot inspection monitoring system due to the factors such as the distribution of roads in the substation, the height of the inspection robot, the battery life and so on. Therefore, the infrared temperature measurement function cannot replace the accurate temperature measurement in the existing technical stage, and can only be used as a way of universal temperature measurement in a large area.

Therefore, the above two problems should be paid more attention in practical application.

VI. Conclusion

With the rapid development of China's economy, higher requirements are put forward for the safe operation of power transmission network, power plant facilities and other infrastructure. Major power companies have invested a lot of manpower and material resources in the inspection and maintenance of lines and facilities. However, due to the limitations of technical conditions, there are many deficiencies in the power inspection link, such as low inspection efficiency and difficult management. At the same time, the original manual records and reports also greatly limit the modernization of power operation management. Intelligent inspection of substation equipment is applicable to the power supply facilities management department of the power supply company. It helps to reduce the workload of inspection personnel and facilities management personnel and improve work efficiency. The research content of this paper is the early warning of intelligent operation of power engineering, which is simply the abnormal identification and early warning of substation equipment’s operation situation. In order to accurately identify and early warning the abnormal state of intelligent operation of power engineering, this paper constructs an early warning model of intelligent operation of power engineering based on Kalman filter algorithm, and verifies its application value in experiments. However, in the experiment, the model in this paper has a one minute delay in identifying the abnormal operation situation of substation equipment. In the future research work, the application effect of the model will be gradually optimized to provide effective assistance for power equipment monitoring.

Acknowledgments

The study was supported by “State Grid Gansu Electric Power Company Management science and technology project support (522709220008).”

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