Temperature extraction method for infrared image of high voltage power equipment

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Abstract. An infrared temperature prediction method for power equipment is proposed based on the radial basis function (RBF) network optimized by quantum genetic algorithm (QGA) and orthogonal least squares algorithm (OLSA). The modified compound algorithm was used to optimize parameters of the RBF network. A temperature prediction model was established through the fitting of pixels and temperatures of the infrared image of an equipment. After image matching, the infrared temperature at a position can be directly obtained from the visible image. Meanwhile, we can also directly read temperature values of different positions from the infrared image and identify the corresponding positions in the visible image. Experimental results indicate that the algorithm proposed has a better prediction performance than the RBF network optimized by OLSA alone and by adaptive genetic algorithm (AGA) and OLSA. It improves the generalization capacity of RBF network, resulting in a more stable input and a higher prediction accuracy. The algorithm proposed facilitates temperature analysis and condition-based maintenance for substations.

1. Introduction
Infrared thermography has found wide applications in the diagnosis of thermal faults of power equipments due to multiple advantages such as high efficiency, safety, non-contact temperature measurement, large detection range and rapid detection [1-3]. Electric power equipment usually operates under high voltage and high current, which is closely related to heat. Blackouts often occur due to local overheating of equipment, so the operating condition of main power equipments in the monitored substation is considerably useful for the prediction or diagnosis of potential faults and defects in the equipments. However, limited by working principle, external environment and the device itself, infrared images are less clear than normal images and the contrast between target equipment and background is weaker, which are unfavorable for fault analyses. Online monitoring systems based on infrared and visible images [4-7] have currently been piloted in developed regions and will be further promoted. But the infrared monitor market is almost occupied by foreign large companies, e.g. the US FLIR Systems. Due to industrial monopoly and blockade on new techniques, power companies have no choice but to purchase and use the built-in analytic software of equipments. Personalized requirements cannot be satisfied and the capability of diagnosing faults of power equipments in the substation can hardly be improved, bringing about potential risks for the safe and stable operation of smart grid. The key point of infrared thermography research is to determine the general relationship between temperature and image, namely, temperature fitting and prediction. At present, artificial neural network (ANN) theory has attracted great attention in the research of temperature prediction because of strong self-learning ability and fitting capability for complex nonlinear functions. Therein, radial basis function (RBF) network is able to achieve the global optimal approximation and give a better prediction. In this article, we optimized the RBF...
network-based infrared temperature prediction method for the substation's equipments by using quantum genetic algorithm (QGA) and orthogonal least squares algorithm (OLSA). The obtained infrared images were processed, and the pixels and temperatures of these images were fitted to establish an infrared temperature prediction model for the equipments. This model was then registered to visible images. Thus, the temperature of a position on an infrared image can be known by directly clicking on the corresponding place of the visible image; meanwhile, the infrared temperature can be directly obtained by clicking on the infrared image, which will also help find the corresponding position in visible image. Using experimental data, we made a comparison on the evolution situation of the fitness of QGA and adaptive genetic algorithm (AGA). Subsequently, the modified RBF algorithm was compared with OLSA-RBF and AGA-RBF algorithms, thus verifying the superiority and effectiveness of the former algorithm.

2. Temperature prediction algorithm based on modified RBF network

2.1. RBF network

RBF network is a traditional technique of multi-dimensional spatial interpolation, overcoming the defects of back propagation neural network such as local minimization and slow convergence. Composed of input layer, hidden layer and output layer, RBF network enjoys a favorable capability of global approximation and a self-adaptive structure. And its output is irrelevant to the initial weight [8]. The structure of RBF network is displayed in figure 1.

The hidden layer of RBF network has various basis functions of which the most common one is Gaussian kernel function

\[ R_j(X - c_j) = \exp\left(-\|X - c_j\|^2 / 2\sigma_j^2\right), \quad j = 1, 2, \ldots, p \]  

(1)

where \( X \) is an \( n \)-dimensional input vector \( X = [x_1, x_2, \ldots, x_n] \); \( c_j \) is the center of the \( j \)-th basis function, a vector with the similar dimension as \( X \); \( \sigma_j \) is a generalized constant of the \( j \)-th neuron, i.e., the variance of Gaussian kernel function; \( n \) and \( p \) denote the number of neurons of input layer and hidden layer, respectively. After determining the function of the hidden layer, the relationship between input and output of the RBF network is expressed as

\[ y_i = \sum_{j=1}^{p} w_{j,i} \exp\left(-\|x - c_j\|^2 / 2\sigma_j^2\right), \quad i = 1, 2, \ldots, m \]  

(2)

where \( m \) denotes the number of neurons in the output layer; \( y_i \) is the output value of the \( i \)-th neuron of the output layer; \( w_{j,i} \) is the weight of connection between the \( j \)-th unit of hidden layer and the \( i \)-th unit of output layer. To determine the structure of RBF network, three parameters need to be solved: the basis function center \( c_j \), variance \( \sigma_j \), and the weight from hidden layer to output layer \( (w_{j,i}) \).

The construction of a RBF network depends largely on the optional selection of basis function center, unit number in the hidden layer, and network weight [9]. But in traditional RBF network, the algorithm training is prone to local minimization in the adjustment of each parameter.

![Figure 1. Structure of RBF network.](image)

2.2. OLSA-RBF network
OLSA is a popular algorithm due to small computation amount, less occupation on storage space and rapid convergence [10-11]. OLSA can find the basis function center relatively accurately by introducing an error term:

\[
y_i = \sum_{j=1}^{k} w_{ij} \exp(-\| x - c_j \|^2 / 2\sigma_j^2) + e_i, i = 1, 2, \cdots, m
\]

(3)

It can also be expressed in the form of matrix:

\[
Y = BW + E
\]

(4)

where \( Y \in \mathbb{R}^{m \times 1} \) is the expected output vector of the neural network; \( B \in \mathbb{R}^{m \times q} \) is the regression matrix of each column of vectors; \( W \in \mathbb{R}^{q \times q} \) is the network weight vector and \( E \in \mathbb{R}^{m \times 1} \) is the vector of errors between actual and predicted values of the network output.

Through Gram-Schmidt orthogonalization, the regression matrix \( B \) can be decomposed into a set of orthogonal basis vectors:

\[
B = DA = [d_1, d_2, \cdots, d_q] \times \begin{bmatrix}
1 & a_2 & \cdots & a_q \\
0 & 1 & \cdots & a_q \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 1
\end{bmatrix}
\]

(5)

where \( A \in \mathbb{R}^{q \times q} \) is an upper triangular matrix and \( D \in \mathbb{R}^{m \times q} \) is an orthogonal matrix; \( d_i \) can be calculated through equation (6) and (7).

\[
D^T D = H = \text{diag}(h_1, h_2, \cdots, h_q)
\]

(6)

\[
h_i = d_i^T d_i = \sum_{a=1}^{q} a^2_i
\]

(7)

By combining the two equations, the expected network output \( Y \) is obtained as follows:

\[
Y = DAW + E = DG + E
\]

(8)

Gram-Schmidt orthogonalization can ensure that matrix \( E \) and \( DG \) are orthogonal to each other, so

\[
Y^T Y = G^T D^T DG + E^T E = \sum_{i=1}^{q} h_i g_i^2 + E^T E
\]

(9)

Thereby, the equal error rate (EER) of the k-th center is defined as

\[
\text{ERR}_k = \frac{h_k g_k^2}{Y^T Y}
\]

(10)

During continuous forward regressions of the RBF network, EER provides an effective standard for determining the network center. In each forward regression, when EER reaches the maximum an appropriate network center will be selected, and the regression will terminate at step q1 if the following condition is satisfied:

\[
1 - \sum_{i=1}^{q} \text{ERR}_i < 0
\]

(11)

In the construction of a neural network with OLSA, the selection of the initial \( \sigma \) value has great impact on the unit number of the hidden layer [12]. Hence, the parameter selection for OLSA-RBF network should be further optimized.

2.3. Modified OLSA-RBF network

We introduced QGA and optimized the initial \( \sigma \) value and the unit number of the hidden layer, to improve the efficiency of OLSA-RBF network.

QGA, firstly proposed by Ajit Narayanan and MarkMoore [13], is an optimized probabilistic searching algorithm combining quantum computational theory and evolutionary algorithm. It adopts quantum bit (qubit) to encode chromosomes and achieves evolutionary search by using the effect and updating of quantum gate. Compared with normal genetic algorithms, QGA has higher population diversity, faster convergence, and the ability of global optimization [14-15]. The steps of building a modified RBF network are described as follows.

2.3.1. Qubit encoding.
Quantum state is employed to encode information. Besides the two states, 0 and 1, a qubit can also represent any immediate state between 0 and 1. So the state of one qubit can be expressed as

\[ |\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \]  

(12)

where \( \alpha \) and \( \beta \) (possibly complex number) represent the probability amplitude of corresponding states and satisfy the following normalization condition:

\[ |\alpha|^2 + |\beta|^2 = 1 \]  

(13)

where \( |\alpha| \) represents the probability of \( |0\rangle \) and \( |\beta| \) represents the probability of \( |1\rangle \). Hence, a chromosome with \( m \) qubits can be expressed as

\[ q = [\alpha_1 \beta_1 | \alpha_2 \beta_2 | \ldots | \alpha_m \beta_m] \]  

(14)

2.3.2. Population initialization.

Suppose \( n \) is the population size (i.e., the number of chromosomes). In the initial population \( Q(t) = \{q_1^1, q_2^1, \ldots, q_n^1\} \), the qubits of all chromosomes were assigned the value \( 2^{\frac{1}{2}} \). This means that the state of each chromosome is the result of superposition of all possible states at an equal probability.

2.3.3. Adjusting strategy for quantum revolving gate.

Individual adjustment is realized through quantum revolving gate. In other words, the revolving gate in QGA is the final actuator of evolution. The working principle of revolving gate is as follows:

\[ \begin{bmatrix} \alpha' \\ \beta' \end{bmatrix} = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \]  

(15)

\[ \theta_i = S(\alpha_i, \beta_i) \Delta \theta_i \]  

(16)

Where \((\alpha_i, \beta_i)\) is the i-th qubit in chromosome; \( \theta \) denotes the revolving angle which controls the convergence rate of the algorithm; \( S(\alpha, \beta) \) and \( D\theta_i \) denote revolving direction and step size of the revolving angle, respectively. The delta in Table is a coefficient related to the algorithm's convergence rate, to which a reasonable value should be given. By referring to the idea of dynamically adjusting the quantum revolving angle [16], the coefficient can be determined with the following equation.

\[ \text{delta} = 0.05\pi \left(1 - \frac{k \cdot n}{\text{MAXGEN} + 1}\right) \]  

(17)

Where \( n \) denotes the current generation of evolution and \( \text{MAXGEN} \) is the final generation; \( k \) is a constant in the range of \([0,1]\). The convergence rate of the algorithm is raised in the early operation period because the grid searched is larger. In the late operation period, the searched grid narrows, thus realizing precise searching and facilitating the seeking of optimal solutions.

\[ \begin{array}{cccccc}
\hline
x_i & \alpha_i & f(x)& f(b_i) & \Delta \theta_i & \Delta \theta_i & S(\alpha_i, \beta_i) \\
\hline
0 \quad 0 & F & 0 & 0 & 0 & 0 & 0 \\
0 \quad 0 & T & 0 & 0 & 0 & 0 & 0 \\
0 \quad 1 & F & 0 & 0 & 0 & 0 & 0 \\
0 \quad 1 & T & 0.05\pi & \text{delta} & -1 & +1 & \pm 1 & 0 \\
1 \quad 0 & F & 0.01\pi & \text{delta} & -1 & +1 & \pm 1 & 0 \\
1 \quad 0 & T & 0.025\pi & \text{delta} & +1 & -1 & 0 & \pm 1 \\
1 \quad 1 & F & 0.005\pi & \text{delta} & +1 & -1 & 0 & \pm 1 \\
1 \quad 1 & T & 0.025\pi & \text{delta} & +1 & -1 & 0 & \pm 1 \\
\hline
\end{array} \]

Table 1. Methods for determining the revolving angle.

In Table 1, \( x_i \) and \( b_i \) represent the binary bit corresponding to the solution \( x \) and the i-th qubit of the current optimal individual \( b \), respectively; \( f(x) \) is the function of fitness. Guaranteed by the quantum revolving gate, the algorithm will rapidly converge to obtain the chromosome with a higher fitness. This study conducted a comparison between the evolution of QGA and AGA fitness, as shown figure
2. The result indicates that QGA has a great improvement in evolutionary efficiency and its best fitness is more ideal (2.3212 vs. 1.5944) compared with the AGA. The average fitness of QGA and AGA is 1.9191 and 1.4369, respectively.

![Figure 2. Infrared temperature prediction model.](image)

The model was established for the sake of power equipment analysis by relevant staff. They will be able to know infrared temperature by directing viewing visible images. This progress will reduce the difficulty in positioning thermal anomalies due to vague infrared images, thus improving positioning accuracy. Figure 3 shows the infrared and visible images which reflect thermal anomalies of the transformer in a substation.

It can be found from figure 4 that the upper and lower limits of each temperature bar of infrared images will adjust automatically due to the configuration of bundled software. And infrared images are generally different from each other, e.g. the infrared temperature range in figure 3 is 3°C~28°C and those in figure 4 are -6°C~7°C and -13°C~3°C. In this article, the upper and lower limits of temperature bars were manually input tentatively. This step can be improved using digital intelligent recognition in the future.

Preprocessing, registration and fusion were firstly carried out on visible and infrared images of the same scene. It was supposed that the infrared image was smaller than the visible image; if not, the former would be clipped. The image effect after preprocessing is displayed in figure 5.

Then, the pixel matrices of visible and infrared images were matched to realize that the location information can be acquired by directly clicking on the visible image, and the temperature on the infrared image can be known through the prediction of the modified RBF network. Similarly, when clicking on the infrared image, we can know the temperature of a target position immediately and be led to the corresponding area on the visible image. The flow chart of the model is shown in figure 6.

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3. Experimental results and analyses

Tests were conducted in the MATLAB environment. By setting points on the visible image, the coordinates of and RGB values at the corresponding positions of these points on the infrared image can be obtained automatically. Fifty sets of data were selected randomly as the input of the modified RBF network while the temperature on infrared image was taken as output. The output value was compared with those of OLSA-RBF network and AGA-OLSA-RBF network. See table 2 for the comparison result.
Table 2. A comparison between evaluation indices of each algorithm.

| Algorithm      | Average relative error | Maximum relative error |
|----------------|------------------------|------------------------|
| OLS-RBF        | 0.486425               | 1.819685               |
| AGA-OLS-RBF    | 0.141767               | 0.598378               |
| QGA-OLS-RBF    | 0.060528               | 0.240022               |

Figure 7 shows the predicted temperatures of the modified RBF network almost completely accord with actual temperatures, with little error.

Figure 7. Temperature prediction by the modified algorithm.

Figure 8. A comparison of prediction errors of each algorithm.

Figure 9. Interface of infrared temperature analysis result.

The distribution of relative errors of each algorithm is exhibited in figure 8, where the green, blue and red curve are the error curve of OLSA-RBF network, AGA-OLSA-RBF network and QGA-OLSA-RBF network, respectively. It clearly reveals that compared with the former two algorithms, our modified algorithm (QGA-OLSA-RBF network) performed better in temperature prediction and enhanced the generalization capacity of RBF network, with a stable input and a high prediction accuracy. The maximum relative error of the OLSA-RBF network was about 1.8, while that of the QGA-OLSA-RBF network was merely 0.24. As for the average relative error, the OLSA-RBF network was eight times that of the QGA-OLSA-RBF network and the AGA-OLSA-RBF network doubled the latter.

We designed a simple operation interface for the temperature analysis program using Matlab GUI. Taking the image of a transformer's thermal anomalies in a substation as an example, the specific interface is shown in figure 9. On the interface, one can separately analyze visible or infrared image, or simultaneously analyze both images. In Figure 9, we randomly selected a point on the visible image and obtained the infrared temperature value of 21.6°C for the target position, which is marked with a
red dot. We also selected a point on the infrared image randomly and obtained the infrared temperature value of 8.3°C for the target position, which is marked with a green dot. Its corresponding position on the visible image is marked with a yellow dot, with the coordinate of (123, 100).

4. Conclusion
An infrared temperature prediction method for power equipments in the substation was proposed by optimizing the radial basis function network with quantum genetic algorithm and orthogonal least squares algorithm. It overcomes many shortcomings of original infrared images of those power equipments, such as unclear picture, weak contrast between target equipments and the background, and the resultant inconvenience for fault analysis. The parameters of RBF network were optimized with the modified compound algorithm. Experimental results indicate that the algorithm modified in this article had a better prediction performance than OLSA-RBF network and AGA-OLSA-RBF network, whose maximum relative error was more than 7 times and twice that of our algorithm, respectively. Moreover, the average relative error has also been greatly lowered. These suggest that our algorithm has improved the generalization capacity of RBF network, leading to a stable input and an increased prediction accuracy. The algorithm proposed makes it more convenient to analyze the temperature of power equipments in substations and position the area of thermal anomalies, which is favorable for the condition-based maintenance in substations.

5. References
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