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The measuring of spectral emissivity of object using chaotic optimal algorithm

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There exist a considerable variety of factors affecting the spectral emissivity of an object. The authors have designed an improved combined neural network emissivity model, which can identify the continuous spectral emissivity and true temperature of any object only based on the measured brightness temperature data. In order to improve the accuracy of approximate calculations, the local minimum problem in the algorithm must be solved. Therefore, the authors design an optimal algorithm, i.e. a hybrid chaotic optimal algorithm, in which the chaos is used to roughly seek for the parameters involved in the model, and then a second seek for them is performed using the steepest descent. The modelling of emissivity settles the problems in assumptive models in multi-spectral theory.

Keywords: spectral emissivity, radiation thermometric, chaotic optimal algorithm
PACC: 4450, 0200

1. Introduction

With the development of modern science and technology, a great progress in measurement and study of the radiant properties of materials has been made. However, the emissivity is determined by not only the inherent features of the measured object, but also the physical state of its surface, such as surface smoothness, material granularity, temperature, radiant angle, wavelength and so on. There exist great errors in the emissivity measurements by sophisticated methods because of the factors listed above. At present this problem has not been well solved.

In this paper, the authors establish a spectral emissivity model and design an optimize algorithm according to the chaos theory. With this model, the spectral emissivity and the true temperature of an object can be obtained by the chaotic optimization algorithm if the radiation information of object is available. Therefore, we can realize the discernment online. Chaotic steepest descent hunting algorithm can solve the problem of local minimum point which is caused by the steepest descent algorithm according to Ref.[1] and obtained the global optimum value of continuous spectral emissivity of the object.

2. Spectral emissivity neural network model

The variation of spectral emissivity of an object is caused by a number of factors, which are related not only to the material itself of the object detected, but also to the state of its surface, wavelength and ambient temperature. The large variation of emissivity is always an uneasily solved problem. We consider setting up a mapping relationship by using neural networks. As sample data of emissivity are unavailable in detection, we have to use other data to set up a new emissivity model. First, set up the mapping relationship between emissivity and wavelength by using neural networks: $\varepsilon = \varepsilon(\lambda)$, and combine thermometry theory with the neural networks theory. Second, set up a CNNE (Combinational Neural Network Emissivity) model to obtain the weight parameters of the mapping relationship. The detailed procedure can be found below.

2.1. Identification of the nonlinear relationship between wavelength and emissivity

It has been proved in theory that a forward neural network with one hidden layer can be approximated to any nonlinear curve defined in a compact set in

R^n to any accuracy. Since there exists a nonlinear mapping relationship between the spectral emissivity and the wavelength, a single hidden layer neural network is used to represent this relationship as shown in Fig.1. The network has a structure with one input and one output with k nodal points. The input signal is represented by λ, the output signal by ε, the hidden layer biases by $b1_1$, $b1_2, \ldots, b1_k$, and the output layer error by $b2$. According to the theory of neural networks, the activation functions $f(\cdot)$ of the output layer and hidden layer can be either the same or different on the assumption that both of the activation functions $f(\cdot)$ are a hyperbolic tangent function $f(x) = \dfrac{1+\exp(x)}{1+\exp(-x)}$. The relationship between the wavelength λ and the emissive ε can be obtained from Fig.1:

$$\varepsilon = \sum_{m=1}^{k} V_m f(S_m) + b2, \tag{1}$$

where $S_m = W_m\lambda + b1_m$.

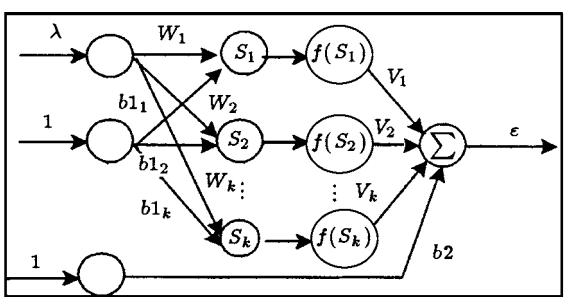


Fig.1. Structure of the neural network emissivity model.

As the sample data of wavelength and emissivity cannot be obtained in use of multi-spectral thermometry to measure temperature, the weights in the neural network above cannot be calculated either, which means that the network has to be improved. The brightness temperature of each spectrum can be measured, thereby a mathematical model for the best approximation to the weight of the model, thus the nonlinear mapping relationship between the emissivity and the wavelength can be constructed according to the brightness temperature. The neural network indicated below can serve this purpose .

2.2. Construction of CNNE model

Denote the number of channels of the multi-spectral radiation thermometer with n. Based on the theory of radiation thermometry, the relationships between the true temperature T of an object and the brightness temperature of the ith channel T_i $(i = 1, 2, \ldots, n)$, and between T and that of the jth channel T_j, where $j \neq i$, are given by Eqs.(2) and (3) respectively:

$$\frac{1}{T} - \frac{1}{T_i} = \frac{\lambda_i}{C_2} \ln \varepsilon(\lambda_i), \tag{2}$$

$$\frac{1}{T} - \frac{1}{T_j} = \frac{\lambda_j}{C_2} \ln \varepsilon(\lambda_j), \quad (i \neq j), \tag{3}$$

where C_2 is the second radiation constant, and $\varepsilon(\lambda_i)$ and $\varepsilon(\lambda_j)$ are the emissivities at the corresponding wavelengths of the object.

Subtracting Eq.(2) from Eq.(3) yields

$$\frac{1}{T_i} - \frac{1}{T_j} = -\left(\frac{\lambda_i}{C_2} \ln \varepsilon(\lambda_i) - \frac{\lambda_j}{C_2} \ln \varepsilon(\lambda_j)\right). \tag{4}$$

By substituting Eq.(1) into Eq.(4) and using $\hat{y}_{i,j}$ to represent the left side of the equation, we have

$$\hat{y}_{i,j} = -\frac{1}{C_2}\left(\lambda_i \ln\left(\sum_{m=1}^{k} V_m f(S_m)\right) + b2\right) - \lambda_j \ln\left(\sum_{m=1}^{k} V_m f(S_m)) + b2\right). \tag{5}$$

In Eq.(5), input signals λ_i and λ_j are the wavelengths of the two channels, and output signal $\hat{y}_{i,j}$ is the approximate value of $1/T_i - 1/T_j$. Since the brightness temperatures corresponding to the two channels are known, the difference between the reciprocals of the two brightness temperatures can be used as an expected output of the network. Thus, a set of sample data are obtained. By using these sample points, we can calculate the unknowns in Eq.(5) which are the weights and errors in Fig.1, and then set up the emissivity model of the object.

3. Chaotic steepest descent searching algorithm[2−6]

The word chaos first appeared in scientific and technical publications in 1975. Strictly speaking, chaotic phenomenon is a random behaviour of a system, which is an external random factor freely and completely determined. Actually, the chaotic phenomenon is a behaviour between regular behaviour and random behaviour.

Chaos is not a completely confused phenomenon, but has a fine and inherent structure. Chaotic motion can experience all states non-repeatedly according to its inherent 'regulation'. So if chaotic variables are

used to optimize the searching, the searching will no doubt be more superior to random searching.

In the optimization process, chaotic variables can be used for searching. This process follows the regulation of chaotic motion. The randomness ensures a long-rang searching ability, while the ergodicity ensures that the algorithm experiences all states non-repeatedly. Using the chaotic optimal algorithm to calculate the weight in the CNNE model will be easy and feasible.[2−7]

3.1. Idea of chaotic optimal method

Chaotic optimal algorithm is to make parameters confused in phase space, then to calculate and compare the points built up by parameters to obtain the optimal solutions. The important step is to seek for chaos. Seeking for chaos is to seek for oddness suction in the phase space.[8]

Logistic mapping equation is[9]

$$x_{n+1} = f(\mu, x_n) = \mu x_n(1 - x_n), \tag{6}$$

where μ is the control parameter, $\mu \in [0, 4]$, n is the iteration times, x is the optimizing parameter, which can be one-dimensional or multi-dimensional.

Iteration results are different for different μ. If $\mu = 4.0$, the iteration result is confused, and it is chaotic. The corresponding equation is

$$x_{n+1} = 4x_n(1 - x_n). \tag{7}$$

The final result is random numbers in (0, 1), and any two x are different, that is to say, Eq.(7) is ergodic in (0,1).

The basic idea of the chaotic optimal algorithm is to use the mapping method to introduce chaotic parameters into searching in order to obtain the optimum value. Because Eq.(7) is ergodic in (0, 1), it is necessary to map ergodicity range onto the span of optimizing variable.

The optimizing of the problem can be described as follows.

Search z, to obtain

min $f(z)$, Z=(z_1, $z_2, \ldots, z_m$),

$z_i \in [a_i, b_i] i = 1, 2, \ldots, m$,

map the chaotic variable x_n onto the space [a_i, b_i]; the mapping equation is

$$z_{i,n} = a_i + (b_i - a_i)x_{i,n}. \tag{8}$$

3.2. Steps of chaotic steepest descent hunting algorithm

3.2.1. Basic steps of chaotic optimal algorithm

Set maximum chaotic hunting times to be L.

Step 1 initialization: Give i initial values in (0,1) to Eq.(7), which are the same in measurement but different in mathematics.

Step 2 use Eq.(8) for making interval mapping.

Step 3 make the iterative search by using chaotic variables, seek for the solution to minimize $Z = (z_1, z_2, \ldots, z_m)$, i.e. $\min f(Z)$.

3.2.2. Steepest descent algorithm

The algorithm involves the following steps:

Step 1 Set the initial values of the error accuracy δ, the times of training N, the learning rate η, the momentum factor α, and the weights for the network.

Step 2 Let l=1, where l is the times of trainings to be undergone, and calculate the value of the energy function.

Step 3 If $E^l < \delta$ or $l \geq N$, stop the training; otherwise, go to Step 4.

Step 4 Calculate the gradient of $\nabla E(Z_n^l)$.

Step 5 Adjust the parameters Z_i according to equations $(Z_i^{l+1} = Z_i^l - \eta \nabla E(Z_i^l) + \alpha(Z_i^l - Z_i^{l-1})$.

Step 6 Recalculate E^{l+1}.

Step 7 $l = l + 1$, go to Step 3.

3.2.3. Chaotic steepest descent hunting algorithm

A chaotic searching can be seen as an inaccurate searching in a broad range. The purpose is to select a better initial value to avoid a local minimum in the steepest descent method. When the initial value is trapped in the local minimum, the selection would loop back to search for another better initial value. Because the chaotic searching's randomness is used to jump out of the local minimum and its ergodicity is utilized to avoid the repeating searching, the effectiveness and rapidity of the searching is guaranteed.

In order to obtain the global optimum value, a chaotic steepest descent algorithm is proposed.

Assume that the object function is $E = f(z_1, z_2, \ldots z_m)$.

Step 1 Initialization: iterative time n=1, the maximum iterative time is N, $x_i(0) \in (0, 1)$, $i = 1, 2, \ldots, m$.

Step 2 Interval mapping $x_i(0)$ using the equation $z_i(0) = a_i + (b_i - a_i)x_i(0)$, and let $\hat{z}_i(0) = z_i(0)\hat{Z}(0) = [\hat{z}_1(0), \hat{z}_2(0), ..., \hat{z}_m(0)]$.

Step 3 Use the equation $x_i(n) = 4x_i(n-1)[1 - x_i(n-1)]$ to calculate $x_i(n)$, make an interval mapping $z_i(n) = a_i + (b_i - a_i)x_i(n)$, let $Z(n) = [z_1(n), z_2(n), \ldots, z_m(n)]$.

Step 4 Calculate the object function and make a comparison, if $f[\hat{Z}(0)] \leq f[Z(n)]$, then $\hat{Z}(0)$ is unchanged, or, let $\hat{Z}(0) = Z(n)$.

Step 5 If $\hat{Z}(0)$ is unchanged for m times or $n > N$, then go to Step 6, or $n = n + 1$ go to Step 2.

Step 6 Take $\hat{Z}(0)$ as an initial value, and use the steepest descent to do iterative searching. If the optimum solution is found, then stop the training, or go to Step 2 for the chaotic searching.

4. Steepest descent hunting algorithm of CNNE model and simulated results

Let $d_{i,j} = 1/T_i - 1/T_j$ be the sample data. If the number of wavelengths is n, then the total number of inputs in the sample is $P = C_n^2$. The LMS (Least Mean Square) energy function is

$$E = \frac{1}{2}\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}(d_{i,j} - \hat{y}_{i,j})^2. \tag{9}$$

The chaotic steepest descent algorithm is used to obtain the weights W_1, $W_2, \ldots, W_K$, V_1, $V_2, \ldots, V_K$, the biases $b1_1$, $b1_2, \ldots, b1_K$, and the error $b2$ in Eq.(9), when E is the minimum.

Here E is also called the object function, $d_{i,j}$ is the expected output of the network, and $\hat{y}_{i,j}$ is the actual output.

Researchers in Europe and America usually choose the number of wavelengths to be from 6 to 8, up to a maximum of 35 for designing radiation thermometers. The larger the number of wavelengths, the better the approximation will be, but meanwhile the smaller the amount of radiation energy for each working band. For our high temperature thermometer, we choose 15 wavelengths to be used for testing the simulation results, giving a sample of C_{15}^2=105.

To verify the correctness of the CNNE model and the algorithm, we do some simulations. Steps are as follows:

1. Assume that the true temperature T of the object and the emissivity model are known. Then the brightness temperature of each channel can be calculated from Eq.(3).

2. Combine wavelength and brightness temperature of each channel to educe the sample number.

3. Use the known sample brightness temperature to train CNNE model with the steepest descent algorithm. When the training is over, the weight and bias in Eq.(1) are obtained, so the function is known and can be plotted.

4. Compare the assumed emissivity value with the simulation result to see whether this method is effective. On the contrary, if the model of emissivity and true temperature T are not known, then we cannot use the model to obtain the error in calculating the emissivity and temperature T in relative to the emissivity and true temperature obtained from the sample data of brightness temperature.

In practice, we should collect the brightness temperature of the object on-location, so that we can test the CNNE model on-line or off-line with the sample of these brightness temperature data. In training we can obtain the emissivity weight coefficient of the object, thus the relation between emissivity and wavelength.

As emissivities vary with properties of materials and their surfaces, the brightness temperatures are different, even if the true temperature is the same. We can train the CNNE model with the sample of brightness temperature data and develop different emissivity models.

We design three kinds of models. Assume that the true temperature T of the object is 1800K. Brightness temperature data is available. We can obtain a certain pair of sample data according to the wavelength and brightness temperature data. Take Model A as an example; then there will be 105 pairs of sample data with 15 wavelengths: they are

$$x_1 = (\lambda_1, \lambda_2)_1, \quad y_1 = (d_{1,2})_1 = \left(\frac{1}{T_{s1}} - \frac{1}{T_{s2}}\right),$$
$$x_2 = (\lambda_1, \lambda_3)_2, \quad y_2 = (d_{1,3})_2 = \left(\frac{1}{T_{s1}} - \frac{1}{T_{s2}}\right).$$

By using this as sample data, we can acquire simulation result from the CNNE model through the chaotic optimal algorithm.

Table 1. Data for the emissivity sample from the CNNE model.

ε \ λ	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10
A	0.50	0.53	0.55	0.57	0.60	0.62	0.65	0.67	0.70	0.73	0.75	0.77	0.80	0.83	0.85
B	0.75	0.70	0.65	0.63	0.65	0.70	0.75	0.80	0.83	0.85	0.83	0.81	0.78	0.76	0.74
C	0.85	0.83	0.80	0.77	0.75	0.73	0.70	0.69	0.70	0.73	0.75	0.77	0.80	0.83	0.85

With k, the number of hidden layer nodes for the neural network in Fig.1, set as 6, according to the prior knowledge of steepest descent parameter the interval is [–40, 40]. We use the chaotic steepest descent method to optimize E. For k=6, we have weight parameters $W_1, W_2, \ldots, W_6$ and $V_1, V_2, \ldots, V_6$, biases $b1_1, b1_2, \ldots, b1_6$ and the error $b2$, therefore, $i = 1, 2, \ldots 19$ in Eq.(8). We can see errors of the assumed emissivities and the simulated emissivities caused by using the chaotic steepest descent searching method to search for the proper values in Table 2. A comparison between the simulation emissivities and sample emissivities at different wavelengths is shown in Table 2. A comparison between the Gradient method and Chaotic Optimize Algorithm for Module A is shown in Table 3.

Table 2. Comparison between simulation emissivities and sample emissivities from the CNNE model.

model	T/K	$\Delta T=$ $\lvert T-T_c\rvert$ /K	$\Delta\varepsilon_\lambda = \varepsilon_\lambda - \varepsilon_{\lambda C}$													
			λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	λ_{10}	λ_{11}	λ_{12}	λ_{13}	λ_{14}	λ_{15}
			0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.0	1.05	1.10
A	1800	2	0.0049	0.0080	0.0013	0.0051	0.0013	0.0028	0.0028	0.0080	0.0030	0.0024	0.0019	0.0058	0.0006	0.0074	0.0046
B	1800	5	0.0463	0.0001	0.0046	0.0028	0.0057	0.0009	0.0025	0.0032	0.0046	0.0024	0.0019	0.0058	0.0006	0.0074	0.0046
C	1800	3	0.0189	0.0165	0.0060	0.0133	0.0231	0.0192	0.0063	0.0084	0.0049	0.0180	0.0243	0.0168	0.0083	0.0107	0.0051

Table 3. Comparison between the gradient method and the chaotic optimize algorithm for module A.

algorithm	calculation times	success times	probability of success/%	average iteration time/h
gradient method	30	11	36	5
chaotic optimize algorithm	30	28	93	10

As is shown in Table 2, the errors of sample data and simulation data are small. By using the improved CNNE model trained by chaotic steepest descent method, we can obtain expected results which do not rely on appropriate initial values. We can see that the probability of success for the chaotic steepest descent method is 93% but the probability of success for the steepest descent method is 36% because of the local minimum problem as indicated in Table 3.

In this paper we give a new emissivity model and design its optimal algorithm, the chaotic steepest descent. Simulation results show that this model and optimal algorithm can identify any object's continuous emissivity and true temperature by use of the detected brightness temperature. Its convergence rate is rapid and the approximation has a high accuracy, which establishes a foundation for commercial apparatus of Multi-spectral thermometry.

5. Conclusion

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