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Recognition of NiCrAlY coating based on convolutional neural network

Rui Liu¹, Minghao Wang¹, Huan Wang², Jianing Chi², Fandi Meng¹, Li Liu¹✉ and Fuhui Wang¹

This paper established an eight-layer convolutional neural network to automatically recognize the characteristic phases of the NiCrAlY coating, the coating/substrate interface, and the oxide layer. Using this neural network, the Cr-rich phase, the coating/substrate interface, and the oxide layer, as the features of the NiCrAlY coating, were successfully identified and retrieved at different constant oxidation temperatures. Based on this achievement, the variations of the Cr-rich phase distribution and the changes of the oxide layer thickness calculated by the network were obtained, which are all consistent with the trend of the oxidation kinetic curves at different temperatures; the preliminary intelligent calculation of oxidation kinetics of the coating was carried out through the thickness of the oxide layer from the SEM images.

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INTRODUCTION

Nickel-based MCrAlY (M = Ni, Co) coatings are widely applied in some thermal protection fields, such as gas turbine and aero-engine components, due to their excellent oxidation resistance and thermal corrosion resistance^{1–3}. Al and Cr are essential components for the function of the coating as protection of the critical turbine components against oxidation and hot-corrosion attacks⁴. Generally, the requirement of high oxidation resistance needs high Al content. However, because of the limited Al content in the coatings and alloy substrates, suppressing elemental interdiffusion readily occurs between these two parts where they have composition difference⁵. To alleviate this bottleneck, inserting a diffusion barrier between alloy substrate and Al reservoir layer is a useful method⁶, and there have been many diffusion barriers such as AlN⁷, Al₂O₃⁸, W, Re, Cr^{9,10}, and NiCrO¹¹. Accordingly, a reliable criterion to estimate the variation of these characteristic phases is of great importance to accurately evaluate coating lifetime.

Images are one of the significant ways for humans to directly obtain information. Nowadays, image recognition technology has been widely applied in many fields, such as medical diagnosis^{12,13}, face recognition^{14,15}, unmanned driving^{16,17}, and remote sensing^{18,19}. Wen et al.²⁰ used the method of Photoluminescence Piezospectroscopy to measure the stress of the thermal barrier coating, and used regression and artificial neural network methods to predict the remaining life of the thermal barrier coating. However, traditional algorithms of machine learning are prone to problems such as over-fitting, difficulty in feature extraction, poor generalization capabilities, and low accuracy in the process of training models. With the rapid development of computer technology and the advent of the era of big data, deep-learning technology is about to take off. Convolutional neural networks trained by deep-learning algorithms perform well in image recognition and feature extraction. Compared with traditional neural networks, the processing of convolutional layer and pooling layer has been added to convolutional neural networks,

such as LeNet, AlexNet, GoogLeNet, VGGNet, and other convolutional neural network (CNN), resulting in very high accuracy in image classification and image recognition²¹. In the field of materials, some scholars have applied BP (Back propagation) neural network to identify the corrosion faults of in-service pipelines, identify circular holes, long strip defects, etc^{22–24}; some scholars have used full convolutional neural networks to extract weld features to improve the accuracy of automatic welding²⁵. It is expected that through image acquisition, image processing and image recognition²⁶, the type of material can be accurately identified, and the physical or mechanical properties of material can be effectively evaluated.

In this paper, image recognition is mainly applied to the MCrAlY coating, to obtain a model of the quantitative relationship and the dynamic variation law between the image feature and the service life of the coating, which could provide insights for the prediction of the service life of the coating. A convolutional neural network was built based on the Keras framework, and the characteristic phase, interface, and oxide layer of materials that affect the service performance of K38G/NiCrAlY coatings were identified. Based on this, the relationship between image information and oxidation kinetics was established, so that intelligent image recognition technology was applied to the service performance evolution of high-temperature coatings, which lay the foundation for the realization of intelligent life prediction methods based on image characteristics.

RESULTS AND DISCUSSION

Identification of oxidation characteristics of K38G/NiCrAlY

Considering that the Cr-rich phase is easy to distinguish in contrast in the SEM, the variation of the Cr-rich phase in the NiCrAlY coating is taken as one of the oxidation features. After oxidation, the cross-sectional SEM images were cut into 64 × 64 pixel images, and each image only contains one feature. These small images were treated as the dataset (3000 as the training set

¹Shenyang National Laboratory for Materials Science, Northeastern University, NO. 3-11 Wenhua Road, 110819 Shenyang, China. ²College of Information Science and Engineering, Northeastern University, 110169 Shenyang, China. ✉email: liuli@mail.neu.edu.cn

and 600 as the test set). Each characteristic (the Cr-rich phase, the interfaces of K38G/NiCrAlY, and the oxide layer of the coating) has 1200 images, and part of the dataset images are shown in Supplementary Fig. 1. After training, the three types of features in different cross-sectional SEM images are identified, as shown in Fig. 1. The characteristics of K38G/NiCrAlY at different oxidation temperatures are recognized. It can be seen that the neural network trained by the Adam optimizer with three layers of convolutional layers has high accuracy. Even if the oxide layer has certain bending and undulations, it does not affect the recognition of the oxide layer. Moreover, through the deep-learning process, the recognition accuracy rates of the CNN network for oxidation features at four different temperatures are all above 80%, as shown in Table 1. It means that the image information of

the NiCrAlY coating can be recognized and located at different service temperatures and times, by learning its basic oxidation characteristics. For example, the distribution of the Cr-rich phase varies during the oxidation progress; the changes in the thickness of the oxide layer also reflect the degree of oxidation. Obviously, the accurate retrieval of the interface and oxides is the premise of establishing the relationship between the change of coating micro-morphology and oxidation kinetics, which lays the foundation for the subsequent automatic calculation in the irregular coating.

Dynamic evolution of the distribution of the Cr-rich phase

Whether NiCrAlY coating is used as a simple cladding coating or a bonding layer, its morphology and composition are the important factors that affect the failure of the coating^{27–29}. During the isothermal oxidation process, the continuous diffusion of the Cr-rich phase to the outside of the coating and the inside of the substrate will cause the decrease of the Cr element content in the coating. Han et al.²⁹ found that the γ -Ni/ γ' -Ni₃Al phase was converted into β -NiAl/ α -Cr due to the depletion of Ni during high-temperature oxidation, indicating severe degradation of the coating occurred. When the protective elements in the coating are exhausted, the coating will no longer have the ability to generate a protective oxide film. Accordingly, the depth change of the Cr-rich phase from the interface with time can directly reflect the service life of the coating. Figure 2 shows the evolution of the cross-sectional image of the microstructure of the coating after oxidation at 950 °C from 10 to 150 h. At 10 h, the Cr-rich phase is small in volume and densely distributed, covering the entire coating. As the oxidation progresses, the volume of the Cr-rich phase increases, the density becomes sparser, and gradually segregates inside the coating. When the Cr-rich phase fills the entire coating, the depth from the outside of the Cr-rich zone to the interface is 24.55 μ m. At different oxidation temperatures, after retrieving the Cr-rich phase through eight-layer CNN, the automatically calculated depth from the outside of the Cr-rich phase to the interface is shown in Fig. 3. At 950 °C and 900 °C, from 20 to 150 h, the depth from the outside of the Cr-rich phase to the interface is linearly related to the oxidation time (Fig. 3a and b), and the distance from the Cr-rich phase to the coating/substrate interface drops to about 4 μ m after 200 h isothermal oxidation. At 850 °C, the Cr-rich phase fills the coating within 50 h of oxidation. From 50 to 150 h, the depth from the outside of the Cr-rich phase to the interface also decreases linearly with the oxidation time (Fig. 3c), but after 200 h of constant temperature oxidation, the distance from the Cr-rich phase to the coating/substrate interface is still about 12 μ m. It can be seen that the CNN can retrieve and intelligently find the evolution of the distribution of the Cr-rich phase, and establish the quantitative relationship between its distribution and time under different temperatures.

Dynamic evolution of oxidation kinetics

Figure 4 is the oxidation weight gain curve of NiCrAlY coating at 850, 900, 950, and 1000 °C. At different temperatures, there are two stages in the oxidation kinetic curve, namely the rapid oxidation stage and the steady weight gain stage. It shows that the higher the temperature, the greater the weight gain of oxidation. Among them, the oxidation kinetic curves from 900 to 1000 °C basically conform to the parabolic law (see Fig. 5), indicating that the oxide layer can play a very good protective role³⁰. Under the three temperatures, the parabolic constant K_p is calculated by Eq. 1 in the stable weight gain stage between 20 and 200 h, and the fitting results are shown in Table 2.

$$y^2 = K_p t \quad (1)$$

Fig. 1 Results of identification for three types features of K38G/NiCrAlY after different oxidation conditions. **a** 900 °C, 20 h; and **b** 1000 °C, 200 h.

Table 1. Picture identification accuracy of eight-layer convolutional neural network (Adam).

Temperature/°C	ImageNum	Succesed ImageNum	Recognition accuracy/%
1000	210	169	81
950	318	276	87
900	338	271	80
850	294	262	89

Fig. 2 Micro-morphology process of the NiCrAlY coating after oxidation at 950 °C. **a** After 10 h; **b** After 50 h; **c** After 80 h; and **d** After 150 h.

Fig. 3 Depth between Cr-rich phase and interface at different temperature. **a** 950 °C; **b** 900 °C; and **c** 850 °C. The error bars are the standard error.

where, y is the mass gain, K_p is the parabolic rate constant, and t is the oxidation time. By contrast, the oxidation kinetics curve for 10–200 h are linear, indicating that the coating cannot provide good protection performance at this temperature³¹. The oxidation rate constants at the four temperatures are shown in Table 2.

Dynamic evolution of oxide layer thickness

Associating the morphologies of NiCrAlY coating with oxidation kinetics is the basis for predicting its service life using the deep-learning method. The oxide layer, known as another oxidation feature whose thickness is mathematically related to the global oxidation rate or oxidation kinetics^{32,33}, was extracted from SEM images. The oxidation layer information in the cross-sectional

image is extracted by flood filling, binarization, and micro-hole filling technologies in sequence, as shown in Supplementary Fig. 2. Then the oxide layer position is retrieved through the CNN network and its thickness is calculated. It can be seen from Fig. 6 that the oxide layer thickness calculated by CNN has basically the same trend as the oxidation kinetic curve measured by the weight gain method, indicating that the dynamic evolution law of oxide layer thickness identified by CNN to establish the oxidation kinetic relationship has a high degree of credibility. At 1000, 950, and 900 °C, the square of the oxide layer thickness for 10–200 h has a linear relationship with time (see Fig. 7a, b, c), indicating that the change curve of oxide layer thickness with time also conforms to the parabolic law, which is consistent with the published literature³³. Moreover, at 850 °C, the change of oxide layer thickness with time also

Fig. 4 Oxidation kinetics of K38G/NiCrAlY at the temperature of 1000 °C, 950 °C, 900 °C, and 850 °C.

Fig. 5 y^2 vs. t of K38G/NiCrAlY at the temperature of 1000 °C, 950 °C, 900 °C, and 850 °C.

Table 2. The oxidation kinetics of K38G/NiCrAlY at different temperatures for 200 h.				
Temperature/°C	Oxidation duration/h	Fitting equation	Correlation coefficient	$K_p/(\text{mg}^2\text{cm}^{-4}\text{s}^{-1})$
850	10–200	$y = 0.0027t + 0.0972$	0.9088	—
900	20–200	$y^2 = 0.0025t + 0.0746$	0.9701	0.0025
950	20–200	$y^2 = 0.0021t + 0.1755$	0.9383	0.0021
1000	20–200	$y^2 = 0.0046t + 0.3012$	0.9594	0.0046

Fig. 6 Physical quantities of K38G/NiCrAlY at different temperatures. **a** 1000 °C; **b** 950 °C; **c** 900 °C; and **d** 850 °C.

Fig. 7 Fitting results of the oxide thickness for K38G/ NiCrAlY at different temperatures. **a** 1000 °C; **b** 950 °C; **c** 900 °C; and **d** 850 °C.

Table 3. The oxide thickness of K38G/NiCrAlY at different temperatures for 200 h.

Temperature/°C	Oxidation duration/h	Fitting equation
850	10–200	$H = 0.0133t + 0.3596$
900	10–200	$H^2 = 0.0555t + 0.5906$
950	20–200	$H^2 = 0.0301t + 3.5710$
1000	10–200	$H^2 = 0.0816t + 3.2641$

conforms to a linear law, which is similar to the oxidation kinetics at 850 °C (see Fig. 7d). At 850–1000 °C, the fitting mathematical model function expression of the oxide layer thickness is shown in Table 3. Therefore, the CNN with an eight-layer structure can effectively identify and retrieve the microstructure of NiCrAlY coating at different temperatures, and its intelligent calculation of oxide layer thickness can be consistent with the trend of oxidation kinetics curve, realizing the preliminary prediction of the service life of NiCrAlY coating.

In summary, a method to identify the characteristics of the NiCrAlY coating was proposed based on the understanding of the structure of the convolutional neural network. Using the eight-layer convolutional neural network, the characteristic phases of the coating, the coating/substrate interface, and the oxide layer were automatically identified and retrieved—the Cr-rich phase exhibits a dark grey area, the micro-voids at the coating/substrate interface are the discontinuous black dots, and the oxide scale is a

dark continuous layer. Then, dynamic evolution models of the Cr-rich phase distribution and the oxide layer thickness were built by the network. The trends of the oxide layer thickness at different temperatures are consistent with those of the oxidation kinetic curves. Therefore, the NiCrAlY coating image database at different constant oxidation temperatures was established, and the preliminary intelligent calculation of oxidation kinetics of the coating was carried out.

METHODS

Experimental materials

Using $\varnothing 15 \times 2$ mm K38G as the matrix material, of which the composition is shown in Supplementary Table 1. After being polished with SiC sandpaper 1000#, the surface of the alloy was shot blasted to increase the binding ability between the coating and the base. Subsequently, the sample was ultrasonically cleaned in a mixed solution of acetone and alcohol, and dried for later use. Using arc ion plating technology, NiCrAlY coating (Cr 27%, Al 11%, Y 0.5%, Ni balance) was prepared on the surface of the matrix when the vacuum degree was below 7.0×10^{-3} Pa and the Ar gas bias is 0.2 Pa. After 5 h of deposition, the coating thickness was 30 μm. The heat-treated samples were obtained after being annealed at 1000 °C in a vacuum heat treatment furnace for 4 h. The XRD results of the original deposited NiCrAlY coating and the annealed NiCrAlY coating are shown in Supplementary Fig. 3. The deposited coating is mainly composed of γ -Ni and β -NiAl phases. After annealing, the coating is mainly composed of γ/γ' and a small amount of α -Cr and β -NiAl.

Constant temperature oxidation experiment

The crucible containing the sample was placed in a Muffle furnace for constant temperature oxidation at 850, 900, 950, and 1000 °C,

respectively. The oxidation time was 10, 20, 50, 80, 100, 150, and 200 h. The discontinuous weighing method is used to measure the oxidation rate of metals in the isothermal oxidation kinetic curve. The size and the overall mass of the sample and the crucible had been weighed before the experiment started. After being oxidized for a certain period of time, the crucible with the sample was taken out and the overall weight change was measured with an analytical balance (Sartorius CF225D). There were three parallel samples in each group to reduce the experimental error.

The scanning electron microscope (SEM, Inspect F50, FEI) was used to observe the cross-section morphology of the sample at different temperatures and times. The back-scattering cross-section morphology of K38G/NiCrAlY oxidized at 900 °C for 20 h and 1000 h for 200 h are shown in Fig. 8. In Fig. 8, the dark gray areas in the coating are the Cr-rich phase (see Supplementary Fig. 3 and Supplementary Table 2), of which the distribution varies significantly after different oxidation period; the black dots at the coating/substrate interface are the microvoids, which will reduce the bonding force of the coating and are the source of peeling of the coating from the substrate and thermal stress³⁴; and the black continuous layer is the oxide layer, which is mainly composed of Al_2O_3 and directly relates to coating's service life. For thermal barrier coatings, it is usually composed of the outermost ceramic layer (TC layer), a thermally grown oxide layer (TGO layer), bonding layer (BC layer), and the substrate. The NiCrAlY coating is used as the BC layer. When the thermal expansion does not match between the coatings, internal stress will be generated due to the formation of Ni and Cr spinel oxides as the TGO layer gradually grows up. Therefore, the image of this kind of change shows that the oxide layer has the characteristics of bending and undulation, uneven thickness, and white particles embedded in it and even cracks.

Construction of the convolutional neural network

In order to accurately build a quantitative relationship model of the dynamic evolution law between image features and service life, in the first place, it is necessary to identify and retrieve the image features related to the service performance of the coating. The convolutional neural network is used to identify these features, and it is composed of the input layer, convolution layer, pooling layer, fully connected layer, and output layer, as shown in Fig. 9. Among them, the input layer is a 64×64 pixel picture using RGB channels. An eight-layer CNN network with three convolutional layers and 32 convolution kernels in each convolutional layer is selected to train the input image. Each convolutional layer is followed by a pooling layer. The maximum pooling method is adopted and a 2×2 sliding filter is used to improve the efficiency of data processing. In the fully connected layer, regularized Dropout random neuron inactivation is used, and SoftMax classifier is used for classification, thereby increasing the anti-interference ability of the network and reducing over-fitting.

The network extracts image information features on the Keras deep-learning framework. In the training process, the number of iterations is 100, the size of the batch is 20, the learning rate is 0.001, the dropout regularization coefficient is 0.5, the optimizer is Adam, and the excitation function is ReLU. The loss function is Categorical Cross-entropy, and the network is trained by cross-validation. For calculating

the thickness of the oxide layer, the binary image processing, and flood filling technology were used to select the appropriate threshold to extract the oxide layer from the SEM images. The change of the TGO was regarded as a continuous and uniform growth, and the pixel area occupied by the oxide layer could be obtained (10 μm corresponds to 213 pixels), then the oxide layer thickness was output automatically by the computer program. The source code of the convolutional neural network for recognition and retrieval is given in the Supplementary Methods.

Fig. 8 Sectional morphologies of K38G/NiCrAlY coating. **a** 900 °C, 20 h; and **b** 1000 °C, 200 h.

Fig. 9 Architecture of the convolutional neural network for recognizing the characteristic phases of the NiCrAlY coating after oxidation.

DATA AVAILABILITY

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also form part of an ongoing study.

CODE AVAILABILITY

The convolutional neural network was performed using Keras, an open-source artificial neural network library written in Python.

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AUTHOR CONTRIBUTIONS

R.L. and L.L. designed the research. R.L. and M.W. performed the experiment, analyzed experimental data, and wrote the manuscript. M.W. performed the experiment. M.W., H.W., and J.C. established the convolutional neural networks. J.C., F.M., and L.L. revised the paper.

COMPETING INTERESTS

The authors declare no competing interests.

ADDITIONAL INFORMATION

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Correspondence and requests for materials should be addressed to Li Liu.

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