CHEMICAL ENGINEERING TRANSACTIONS

VOL. 71, 2018

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Xiantang Zhang, Songrong Qian, Jianmin Xu

ISBN 978-88-95608-68-6; **ISSN** 2283-9216

DOI: 10.3303/CET1871130

Material Corrosion Classification Based on Deep Learning

Yi Zhao, Guodong Wang, Hanlin Zhang, Lin Li

College of Computer Science &Technology, Qingdao University, Qingdao 266071, China
zhaoyi2771@126.com

This paper sheds new light on the classification of material corrosion levels in an attempt to reduce the frequency of subjective judgment on it. Here, grounding grid material is taken as the study object, and the images of steel plates are collected. Based on the deep learning, the artificial bee colony algorithm is integrated to determine the best split point to carry out the corrosion area segmentation. In this way, the effectiveness of the deep learning algorithm can be improved. A material corrosion classification model is thereby built based on the SOM. The findings show that the corrosion levels can be divided into three classes, i.e. the blue part is the most severe corrosion area, the green part is the moderate corrosion area, and the red part is the least corrosion area. From the above test results, the staff can get across to what degree the relative corrosion of the grounding grid materials in the affected area reaches, then if necessary, carry out an emergency repair measures against the most severely corroded areas.

1. Introduction

We take the grounding grid material as an example. This kind of material readily initiates corrosion since it is often buried underground or under floor and subjected to soil, earth short circuit and other factors. If it is struck by lightning at this time, abnormal current is easy to occur. At this stage, people often detect the corrosion of grounding materials by manual judgment, which is subjective and time-consuming. It is better if there is a scientific and objective judgement method on the material corrosion to help people timely judge, dispose and protect severely corroded areas in order to prevent further corrosion and reduce the possibility of accidents.
Based on this, this paper collects the images about steel plate, and based on the deep learning, the artificial bee colony algorithm is integrated to determine the best segmentation point for the corrosion area segmentation, improving the effectiveness of the deep learning algorithm. Then, a material corrosion classification model is built by combining the SOM, an experiment is also conducted.

2. Literature review

Pidaparti et al. proposed a corrosion detection method. The main idea is to regard the grounding grid as a pure resistor network. All conductors in the network are converted into a resistor separately. The way of injecting current or voltage is to use underground leads and collect the current and voltage of the corresponding ports. This method mainly relies on the measurement of resistance. Usually, the layout of underground leads and the number of leads will affect the measurement results, so there are some limitations (Pidaparti et al., 2015). Jiménez-Come et al. put forward the electromagnetic induction method for corrosion measurement. By detecting the electromagnetic induction strength of the surface, they judged the corrosion situation. However, this method requires considerable experience and maturity of the inspectors, and considering the strong magnetic field interference around the grounding grid itself, it can be seen that this method is also imperfect (Jiménez-Come et al., 2015). Skal's'kyi et al. put forward the concept of deep learning algorithm and thought that if we deepen the layers of the neural network to make it have a certain depth, then the network would have a good performance of feature expression, and the expressed features would have a deeper description of the data, and further optimize the prediction and classification. As a result, layer initialization can greatly reduce the complexity of network training (Skal's'kyi et al., 2018). Roy et al. proposed an electrochemical detection method. However, corrosion measurements of conductor materials at non underground lead had not been taken into account (Roy et al., 2016). Sabir and Ibrahim mainly used the

Please cite this article as: Zhao Y., Wang G., Zhang H., Li L., 2018, Material corrosion classification based on deep learning, Chemical Engineering Transactions, 71, 775-780 DOI:10.3303/CET1871130

principle of electromagnetic induction to detect the corrosion of grounding grid. The sinusoidal excitation current with different frequencies was injected and extracted from the two leads of grounding grid. Then, the distribution of surface magnetic induction intensity above the grounding grid was measured. The surface magnetic induction intensity could reflect the corrosion thinning of the grid conductor below and the breakpoint fault. On this basis, a special sine wave excitation source with different frequencies and a signal acquisition and processing system capable of resisting various electromagnetic interference in substations could be developed (Sabir and Ibrahim, 2017). Chen and Lv used this method to get the location and grid structure of underground grid conductors. He Wei et al. of Chongqing University also put forward a diagnostic method of grounding grid based on inverse magnetic field problem, which could get the current distribution of each circuit in the grounding grid, analyze the changes of conductor resistance from the current distribution, and judge the corrosion state of grounding grid (Chen and Lv, 2013).

Najima et al. made the grounding grid equivalent to a pure resistance network, took the lead of each grounding grid as the accessible ports, measured the voltage changes of these ports, calculated the resistance changes of each conductor, and judged the corrosion and breakpoint of the grounding grid by the resistance changes (Najima et al., 2011). Taghipour et al. adopted grounding grid material electrodes as sensors. Polarization resistance was obtained by potentiostatic steady-state measurement method and corrosion rate was calculated to monitor the grounding grid corrosion status and grounding parameters (Taghipour et al., 2016). Abdelrahman et al. used damped Gauss-Newton iteration algorithm to fit the corrosion weak polarization curve of grounding material in soil. Although the corrosion current and Tafel constant can be obtained by fitting, the iteration algorithm had many processes and complicated calculation. The object of measurement was grounding material sample in laboratory environment, not intermediate grounding network ontology in actual environment (Abdelrahman et al., 2016). Cui et al. used constant current charging curve method to measure polarization resistance of grounding grid and developed a small hole current limiting sensor. But it is not enough to measure polarization resistance of grounding grid only. To get its corrosion current, it is necessary to know Stern-Geary constant B. If the empirical value is used to calculate, the corrosion system will not be formed because of environmental differences and also causes great errors (Cui et al., 2015). Shaukat et al. proposed that the existing grounding network corrosion detection methods should be used to obtain the grounding network corrosion defects and detect the severely corroded and fractured branches, and then the information of these corroded branches could be simulated by software to obtain whether the step voltage and contact potential could meet the safety requirements, and then the characteristic parameters of the grounding network coulc be improved. After testing and calculating, the corrosion parameters and grounding network characteristic parameters were analyzed by fuzzy analytic hierarchy process, and the weight was determined. Finally, the grounding network state was divided into six grades, and the grounding network state was evaluated. After the evaluation results were obtained, corresponding measures were taken (Shaukat et al., 2016). Illahi et al., in order to get the corrosion rate and degree of grounding grid, buried sensors near the conductor of grounding grid to monitor the corrosion information of grounding grid. At the same time, the grounding parameters of grounding grid, such as grounding resistance, step voltage and contact voltage, were analyzed and calculated by numerical method. The above corrosion information and grounding parameter information were used to evaluate the state of the grounding grid (Illahi et al., 2014).

In summary, the above-mentioned experts and scholars have little research on material corrosion classification, and there is no literature on the classification of grounding grid corrosion based on image processing methods. Especially the research on material corrosion classification based on deep learning algorithm is quite scarce. At the same time, the research on the combination of material corrosion and neural network is also insufficient. Therefore, based on the above research status, taking the grounding grid material as the research object, the pictures are collected, and the corrosion area based on the depth theory and artificial bee colony algorithm are divided to determine the best segmentation point. As a result, the effectiveness of the depth learning algorithm is improved, and the material corrosion classification model is established combined with SOM.

3. Principle and method

The machine learning mainly focuses on developing the computer in a more intelligent direction, in order to simulate and even implement human learning behaviors to an extreme extent, so that it can be allowed to acquire unknown knowledge. Such potential, once developed, will be able to restructure itself, refine its performance and achieve better goals in the discipline. The framework of traditional method for settling problems such as image treatment is shown in Figure 1.

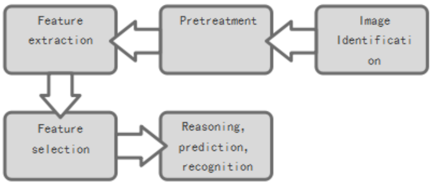

Figure 1: Traditional method framework for solving problems such as image processing

The deep learning includes two training processes, i.e. the unsupervised and the supervised learnings. First, this is the bottom-up unsupervised learning process. The neurons are constructed for each unit in a layer-by-layer manner, and each layeris tuned based on the wake-sleep algorithm. The algorithm includes two stages, i.e. cognition and generation: (1) cognition process. An abstract representation of each layeris generated by the underlying feature input and the upward cognition weight, and then reconstruction information is generated by the resulting generation weight. Therefore, the residual between the input feature and the reconstruction information can be available, and the downward generation weight between the layers is modified using the gradient descent. (2) generation phase. The state of the lower layer is generated by the concept of the upper layer and the downward generation weight, and then the cognition weight is used to generate an abstract situation whose residual is available using the sum of initial upper concepts. The upward cognitive weight between the layers is modified by gradient descend.
As a kind of neural network, the Convolutional Neural Network (CNN) has become a popular framework that allows deep learning in the field of speech analysis and image recognition. CNN is proposed to respond to minimizing pretreatment data. In the CNN, a little portion of the image is input as the underlying hierarchy. Information is transmitted to different layers once more, and in each layer, a digital filter can obtain the most significant features of observed data. The CNN is a multi-layered neural network, where each layer consists of multiple 2D planes, each composed of multiple independent neurons. The schematic diagram of the CNN is shown in Figure 2.

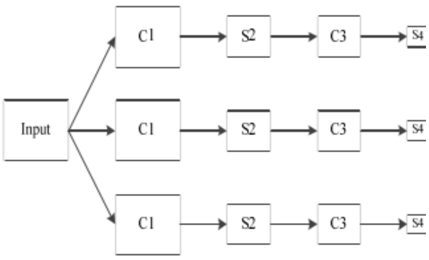

Figure 2: Example of a convolutional neural network

The Restricted Boltzmann Machine (RBM) is a bipartite graph of a directed acyclic graph used as a basic unit for building deep structures. This model consists of two layers, i.e. visible or data layer (v) and hidden layer, in each of which, there is no link between nodes, and all the nodes are random binary variables. A full probability distribution satisfies the Boltzmann distribution. The following is the RBM model.

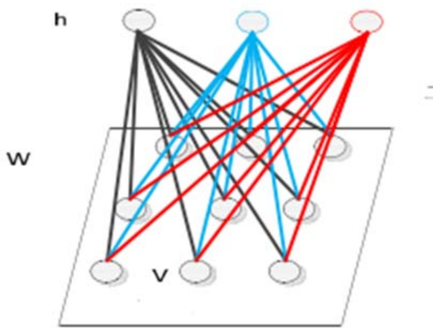

Figure 3: RBM model

This paper introduces a bilinear discrimination strategy based on the original DBN network. The structure chart of the algorithm is shown in Figure 4. A fully linked directional confidence network includes an input layer H1, hidden layers H2..., HN, and markup layer La on the top. The input picture is 50*50 pixels. There are 50*50 elements in the input layer H1, and its size is equal to the dimensions of the input feature. In this model, the pixel value of the set of samples is used as the original input feature. The top markup layer has C elements equal to the number of classesavailable as expected. How to find the mapping function from X to Y can be transformed into how to find the optimal parameter space θ* from the deep structure. The learning process of the improved DBN model is given as follows: (1) build a mapping relation using the bilinear discrimination projection strategy, and map original data into the bilinear discrimination subspace. (2) build an initial symmetry weight relation between adjacent layers based on initial assumptions for discriminant information. The size of the deep model structure is automatically determined based on the bilinear discrimination information. (3) After the structure of the next layer is determined, the RBM is used as a building module to extract the spatial parameter via layer-by-layer information refinement. (4) repeat the steps 1~3 until the parameters in the N-layer space are fully built. (5) In the “post-activation” phase, the whole depth model is fine-tuned to reduce errors based on the BP network.

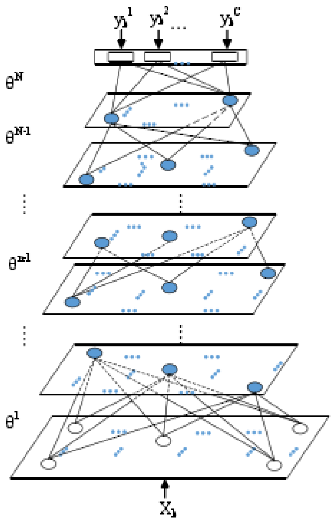

Figure 4: Structure diagram of the DBN algorithm

Parameter settings and training process for the corrosion classifier are given as follows: in the SOM neural network part, 1) the standard corrosion data sample containing three types of corrosion degrees is used as the initial weight class OW of the competitive layer. The purpose of this practice is to initialize theSOM neural network weight. The number of iterations is set to 80. 2) set up the initial learning rate, where n is the current number of trainings, N=8. 3) when the training reaches the number k, the winner neuron is found by computing the Euclidean distance between X and WK. 4) adjust the weight. 5) the topology neighborhood is updated, and then normalized.6) it is judged whether the number nof iterations exceeds N, and if n < N, go to Step 3; otherwise, the iterative process is ended. After initial training on the parameters set in the SOM network is performed, the K-means should be started. The SOM network classifies the samples and adjusts the weights, so that the classification of neuronsin the competitive layer is available, and then the K-means algorithm is used to perform secondary classification on the previous step. To choosethe standard vector of a certain class, the neurons in competitive layer are combined, which can increase the accuracy of classification.

4. Results and analysis

As shown in Figure 5, the test results of corrosion classification for steel plates in each period are listed.
The test results are obtained for the corrosion classification using the k-means classification model. The corrosion is divided into three classes, they are as follows: the blue part is the most corrosive part, the green part is the moderate corrosion area, and the red part is the least corrosion area. From the above test results, we can know the relative corrosion in the area of the grounding grid material. The emergency repair measures are taken for the most severely corroded areas to avoid accidents caused by corrosion; for other moderate corrosion, protection work should be done to avoid causing further severe corrosion.

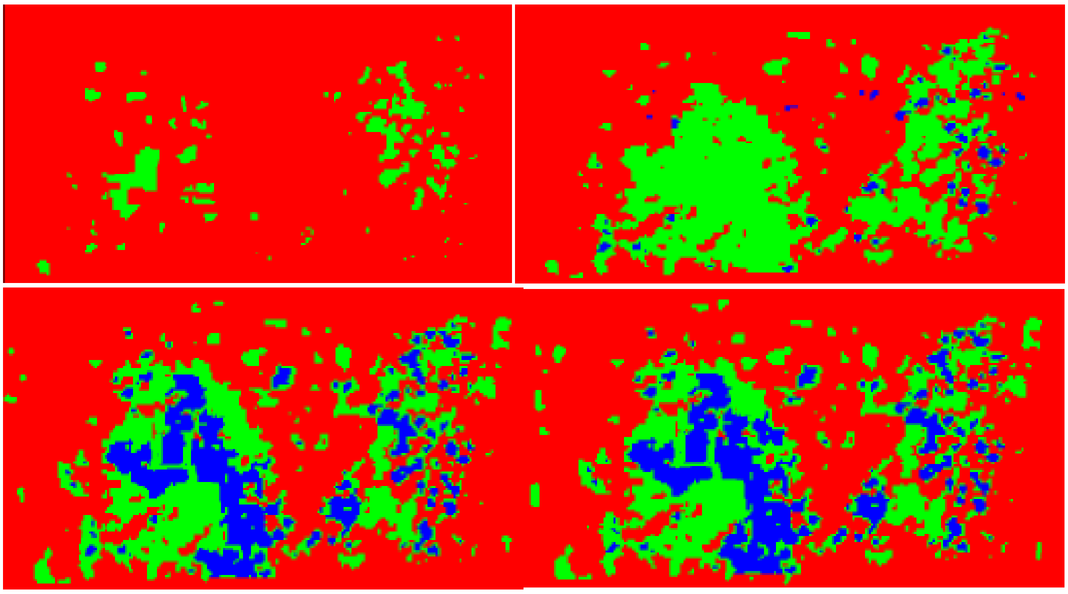

Figure 5: Experimental results of steel plate corrosion classification in each period

The rating is made for the overall appearance of the corrosion material, primarily involving the defects on the appearance of the specimen. Since the classifier has displayed the areas at three levels of corrosion of the test sample, the defected area can also be used for ratingoverall appearance of sample. Based on rich experience and the correspondence between corrosion areas, the appearance rating on the test results in Figure 5 in the previous section is performed, and the rating level are shown in Table 1 below.

Table 1: Appearance rating results

Serial number	Protection level	Stability	Grade
a	1	5.65	A
b	2	29.73	C
c	3	33.18	D
d	4	43.18	E

For the evaluation results of the protection and the appearance levels, it can be analyzed that the protection level of the steel plate is 6 in the first buried period, but drastically decreases from the second buried period. In this case, the occurrence of corrosion will be avoided by increasing the stability of the grounding grid material in the service environment. In the four buried periods, the appearance level of the steel plate changes from the level A of the first period to th e level E of the fouth period. It can be found that the appearance level changesonce every two periodsat a certain interval. On this basis, a more extensive study may be conducted on the corrosion law and rate.

5. Conclusion

This paper proposes to build the model using the image treatment method and allow it automatically learn the corrosion behaviors to classify them. According to the test results, we draw the following conclusions: (1) A kind ofartificial bee colony algorithm as improved is used to find the best segmentation point, and combined with the seed region growth algorithm to achieve the segmentation of the enhanced color image. According to the sampling sequence, typical corrosion samplesare manually selected to construct a typical corrosion region dataset containing three degrees of corrosion, each contains 50 images of the corrosion area. (2) A corrosion classification model that integrates the SOM neural network and K-means algorithm is established herein. Based on the SOM pre-classification, it classifies the corrosion levels again, which greatly improves the classification precision.

In the future work, there is still room for improvement in this field: the artificial bee colony algorithm is applied in the field of color image segmentation as improved in the paper. Although it has had its performance improved to some extent to get a good segmentation effect, the number of algorithm iterations is set manually depending on the experience. In order to further improve the operation efficiency of the algorithm, a model that can dynamically adjust the iterations presents a new trend of the study in the field.

Reference

Abdelrahman M., Elbatanouny M., Serrato M., Dixon K., Larosche C., Ziehl P., 2016, Classification of alkali-silica reaction and corrosion distress using acoustic emission, DOI: 10.1063/1.4940610

Chen Z.P., Lv J., 2013, Prediction of tank bottom corrosion classification based on fsvm, Applied Mechanics and Materials, 441, 4, DOI: 10.4028/www.scientific.net/AMM.441.590

Cui Z.Y., Li X.G., Xiao K., Dong C.F., Wang L.W., Zhang D.W., 2015, Exfoliation corrosion behavior of 2b06 aluminum alloy in a tropical marine atmosphere, Journal of Materials Engineering & Performance, 24(1), 296-306, DOI: 10.1007/s11665-014-1258-3

Illahi R.R., Nugroho F., Nurwantoro P., 2017, Spreading dynamics of corrosion on material surface using site percolation model, Materials Science Forum, 901, 69-75, DOI: 10.4028/www.scientific.net/MSF.901.69

Jiménez Come M.J., Turias I.J., Ruiz-Aguilar J.J., Trujillo F.J., 2015, Characterization of pitting corrosion of stainless steel using artificial neural networks, Materials & Corrosion, 66(10), 1084-1091, DOI: 10.1002/maco.201408173

Najima S., Morinaga M., Shirai H., 2011, Classification of corrosion behavior of water wall tube materials in simulated coal combustion atmospheres including h2s, Materials Science Forum, 696, 260-265, DOI: 10.4028/www.scientific.net/MSF.696.260

Pidaparti R.M., Jayanti S., Sowers C.A., Palakal M.J., 2015, Classification, distribution, and fatigue life of pitting corrosion for aircraft materials, Journal of Aircraft, 39(3), 486-492, DOI: 10.2514/2.2954

Roy J.M., Preston R., Bewick R.P., 2016, Classification of aqueous corrosion in underground mines, Rock Mechanics & Rock Engineering, 49(8), 3387-3391, DOI: 10.1007/s00603-016-0926-z

Sabir S., Ibrahim A.I., 2017, Influence of atmospheric pollution on corrosion of materials in saudi arabia, British Corrosion Journal, 52(4), 276-282, DOI: 10.1080/1478422X.2016.1274839

Shaukat A., Gao Y., Kuo J., Bowen B., Mort P., 2016, Visual classification of waste material for nuclear decommissioning, Robotics & Autonomous Systems, 75, 365-378, DOI: 10.1016/j.robot.2015.09.005

Skal's'kyi V.R., Nazarchuk Z.T., Ya Dolins'ka I., Yarema R.Y., Selivonchyk T.V., 2018, Acoustic-emission diagnostics of corrosion defects in materials (a survey). part. 2. corrosion cracking of metals, applied aspects of application of the method, Materials Science, 53(4), 431-443, DOI: 10.1007/s11003-018-0092-4

Taghipour M., Lashkaripour G.R., Ghafoori M., Hafezimoghaddas N., 2016, Evaluating the soil corrosion of bushehr, iran, based on a new classification system for corrosive soils, Anti-Corrosion Methods and Materials, 63(5), 347-354, DOI: 10.1108/acmm-01-2015-1489

Wang M.Y., Wang Z.Q., Zhao X., 2018, Development and Application of Corrosion Monitoring and Management System for Chemical Equipment, Chemical Engineering Transactions, 66, 979-984, DOI: 10.3303/CET1866164