

METAL'S MICROSTRUCTURE IMAGES CLASSIFICATION BY USING ARTIFICIAL NEURAL NETWORKS

Lect. Sura Abd Al-Zahra Muhsion Non. Metallic Department Materials Eng. / University of Babylon

Abstract

The objective of this study was to develop a back-propagation artificial neural network (ANN) model that could be distinguished the microstructure of metals instead of the traditional methods which are cost and need more time in addition some time give wrong results . Although the colour indices associated with image pixels were used as inputs, it was assumed that the ANN model could develop the ability to use other information, such as shapes that are implicit in these data. The 504x504 pixel images were taken in the field in standard situations and were then cropped to 10x10-pixel images depicting only one microstructure metal. The metals images with size 10x10 which is sufficient for recognizing by ANN. There are four images of different materials.

Keywords: Microstructure of metals Images, ANN, Back-propagation (Bp).

تصنيف البنى المجهرية للمعادن بوإسطة الشبكات العصبية الإصطناعية

الخلاصية

ان الهدف من هذه الدراسة لإنشاء نموذج الشبكة العصبية الاصطناعية (ANN) ذات الانتشار العكسي الذي يمكن أن تصنف المعادن النقية حسب بناها المهجرية بدلا من التقنيات التقليدية المكلفة و التي تحتاج الى وقت كثير و أحيانا تعطي نتائج غير دقيقة و لهذه السباب استخدمنا هذه التقنية.في هذا البحث يستخدم فقط مؤشرات ألون المرتبطة بالصورة (بكسل) كمدخل إلى الشبكة العصبية ' و ايضا في هذا النموذج (ANN) يمكن تطوير القدرة على استخدام المعلومات الأخرى ' مثل الأشكال المتضمنة في هذه البيانات. في هذا العمل سنأخذ صور بإبعاد 504*504 بكسل في هذا المجال بظروف قياسية ثم سنقوم باقتصاص الصور إلى 10*10 بكسل يكفي للتصنيف من قبل ANN و هنا سوف نأخذ

INTRODUCTION

It is obvious that the metallic materials have important role as an engineering materials in the industrial fields since they have a special characteristics in which depend on the microstructure constitution that takes a great part in the academic and industrial fields, Although of the importance of the microstructure constitution in which it controls the mechanical properties of metals, it is difficult to distinguish metals especially the pure ones according to their microstructure constitution.

Instead of using the various tests to knew the purity of metals or to recognize the kind of metal in a group of metals by applying the chemical analysis for metals that takes a long period and high costs, we can recognize microstructure constitution for metals through training neural network [**Scott**, 1991].

Significant progress in the development of machine vision and image processing technology has been made in the past few years in conjunction with improvements in computer technology equipment for machine vision and image processing has been reduced in cost, size, and weight, can be installed in most machines (e.g, tractors) and is accessible for civilian use. Machine vision and image processing are used increasingly in biology, materials science, photography, and other fields [Graupe, 2007].

Artificial Neural Networks (ANNs) are computational networks which attempt to simulate, in a gross manner, the networks of nerve cell (neurons) of the biological central nervous system. ANNs are an attempt to create machines that work in a similar way to the human brain by building these machines using components that behave like biological neurons, called artificial neurons. They are designed to emulate the structure of natural neural networks such as those of a human brain. For most ANNs, PEs in each layer are fully connected with PEs in the adjacent layer or layers, but are not connected to other PEs in the same layer. The PEs simulate the function of the neurons in natural networks, while the interconnections between them mimic the functions of dendrites and axons [Graupe , 2007].

ANNs are computational networks which attempt to simulate the networks of the nerve cell (neurons) of the biological (human or animal) central nervous system. This simulation is a grass cell by cell simulation[Fine , 1999]. It borrows from the neurophysiologic knowledge of the biological neurons and of networks of such biological neurons. It thus differs from conventional (digital or analog) computing machines that serve to replace, enhance or speed up human brain computations without regard to the organization of the computing elements and of their networking [Kocak , Seeber , Terzioglu,2003]. The primary significance for an ANN is the ability of the network to learn from its environment and to improve its performance through learning. The Back-propagation (Bp) algorithm is commonly used learning algorithm for Feed Forward Artificial Neural Networks. Bp algorithm is used in ANN learning process for supervised or associative [Su , Jhang , Hou , 2008].

The role of Artificial Neural Network (ANN) in the present world applications is gradually increasing and faster algorithms are being developed for training Neural Networks (NNs).For all these algorithms storage and computational requirements are different, some of these algorithms are good for pattern recognition and others for function approximation, but they have drawbacks in one way or another. Certain training algorithms are suitable for some types of applications only. It's difficult to find a particular training algorithm that is the best for all applications under all conditions [**Omandi**, **Rajapakse**, 2006].

The training of neural network is what has done in this research and it is achieved by training four kinds of microstructure constitution of four different metals at room temperature which can be recognized easily, also it enable as to recognize the metals of a huge number by putting the microstructure constitution in through using the train of neural network.

It is presently quite difficult to use machine vision to distinguish images from the main field in real time , due to the substantial computational resources and the complicated algorithms required. Artificial Neural Network (ANNs) can overcome some of these

difficulties by interpreting images quickly and effectively. AN Ns are composed of numerous processing elements (PEs) arranged in various layers, with interconnections between pairs of PEs. The function of the neuron is described by the following equations [Muthuramalingam, Himavathi, Srinivasan, 2008].

$$yj = fj(x) \tag{1}$$

and

$$x = \sum_{i}^{n} Pi \ Wij + bj \tag{2}$$

The basic structure of a neuron with 'n' inputs is shown in (Fig. 1).

Where P_i be the ith inputs of the system, W_{ij} is the weight in the ith connection and b_j is the bias. The output y_j for the computation unit (node j) is the result of applying a transfer function f_j to the summation of all signals from each connection P_i [Muthuramalingam, Himavathi, Srinivasan, 2008].

TRAINING ANN USING BP FOR METALS IMAGES

Three-layer ANN is used to do the classification on this paper for all datasets. The total number of neurons for every hidden layer is different depending on the classification problem. Number of input layer and output layer usually come from number of attribute and class attribute. However there is no appropriate standard rule or theory to determine the optimal number of hidden nodes. In this work, trial and error has been used to determine number of hidden neurons. The activation function used to calculate output for each neuron is sigmoid activation (transfer function equation) except input neuron. The color indices associated with image pixels are used as inputs, it is assumed that the ANN model could develop the ability to use other information, such as shapes that are implicit in these data, these color pixel images are taken from the material field, each image depicting only one microstructure of metal, either iron, zinc, lithium or titanium. A total of four types of metal images (iron, lithium, titanium and zinc image) as shown in (Fig. 2) are used for training purposes. After the Red-Green-Blue (RGB) color images (the original images four types of metal images of iron, zinc lithium and titanium image) were obtained with size 504*504 pixels and then converted to indexed images based on a black and white system (Gray Scale) and cropped to 10x10-pixel images depicting only one microstructure metal requirement the size suitable for training the ANN. they will be preprocessed with the Neural Network Toolbox v7.9 for MATLAB v7.9 (MathWorks R2009b).

SIMULATION RESULTS OF TRAINING ANN BP

The parameters of Back-propagation algorithm are set to the momentum coefficient α =0.9 and the learning rate η =0.54. The initial weights and biases are randomly generated between [-0.45, 0.45]. In the training process which are discussed in this work as shown in Fig.(3). During training, the ANNs were presented with binary output data. There are only two output variable in the training data set. An output variable value of (0,0) are assigned to iron , (0,1) output are assigned to zinc microstructure image , (1,0) output are assigned to lithium microstructure image , and a value of (1,1) output are assigned to titanium microstructure image . The performance of FNNBP on four images dataset with 50 hidden neurons is shown in Fig.(4).The accuracy of performance and the performance for FNNBP on four images dataset is shown in Figure (4) where the weights move towards best fitness. The parameters of training algorithm (BP) parameter the maximum number of iterations (epoch)=100 and MSE=10e⁻⁵. The simulation results of FNNBP for four metal's microstructures images training with 50 hidden neurons are shown in table (1).

RESULTS AND DISCUSSION

Referring to the objectives, the experiments are carried out to analyze the optimization algorithm called BP that is applied on FNN to explore the classification accuracy and convergence time compared with Back-propagation Neural Network. Based on the results. The ANN's ability to properly classify metal's microstructure images using the scheme 1 with 100 input 50 hidden neurons and 2 output, the one evaluation schemes is shown in Table1, the results show FNNBP, where it takes 1.8271e+003 seconds at iteration 1000 for overall learning process. FNNBP algorithms are converged using the minimum error criteria. For the correct accuracy percentage, it shows that FNNBP with 99.98 %.Table(1) shows that the FFANN blocks are robust enough in handling the image variations. During the classification phase, the Neural Network is explored for robust decision in the presence of wide variations. BP exhibits the most favorable performance, on account of the fact that it has the lowest overall training time, and the highest classification rates.

CONCLUSIONS

In this paper we have concentrated on describing issues to the development and use of artificial neural network-based intelligent systems for metal's microstructure image recognition at room temperature. Research in artificial neural network remains centered on technological issues and is mostly application succeed. However, in this research and experience suggests that the successful implementation of computerized systems and decision support systems in particular in the area of materials field on the successful integration of the technology with the organizational and social context within which it is applied. Therefore, ANN help us to classify the metals image without using the traditional ways that take long time, high cost and the same time it is inaccurate in some situations.

| Parameters | FNNBP |
|------------------------|------------------|
| Learning Iterations | 1000 |
| Error Convergence | 1e ⁻⁵ |
| Convergence Time | 1.8271e+003 sec. |
| No. of Initial Weights | 1 set |
| Accuracy (%) | 99.98 |

Table (1) Results of FNNBP of t case one.







Fig. (2) Original Images, (iron , lithium , titanium and zinc image)





Fig. (3) Training ANN Using BP



(a)





REFERENCES :-

A. Muthuramalingam, S. Himavathi, E.Srinivasan "Neural Network Implementation Using FPGA", Issues and Application, International Journal of Information Technology, Vol. 4, No.2, 2008.

A. R. Omandi and J. C. Rajapakse, "FPGA Implementation of Neural Network", Springer, ISBN: 10 0-387-28485-0, 2006.

David A.Scott, metallography and microstructure of ancient and historic metals, 1991.

D. Graupe, "Principles of Artificial Neural Networks", 2nd Edition, World Scientific publisher, ISBN: 13 978-981-270-624-9, 2007.

T. Kocak, J.Seeber and H. Terzioglu, "Design and Implementation of Random Neural Network Engine", IEEE, Transactions on Neural Network, Vol. 14, No. 5, pp.1128-1143, September, 2003.

T. L. Fine "Feedforward Neural Network Methodology", Springer publisher, ISBN: 0-387-98745-2, 1999.

T. Su, J. Jhang and G. Hou, "A Hybrid Artificial Neural Network and Particle Swarm Optimization for Function Approximation", International Journal of Innovative Computing, Information and Control, Vol. 4, No. 9, September, 2008.