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ON THE USING OF ARTIFICIAL NEURAL NETWORKS IN AUTOMATIC METALOGRAPHIC ANALYSIS

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ABSTRACT. This paper presents several considerations and preliminary results in implementing an automatic metallographic analysis system using artificial neural networks. The optical microscope images of special prepared samples of metals and alloys may be classified by a neural network trained with standards. We present some of the results and problems we encountered in our work. Our contribution mainly consist in analysis system design, images preprocessing and network training.

Keywords: *metallographic analysis, pattern recognition, artificial neural network, preprocessing.*

1. INTRODUCTION

One of the important investigation methods used by the physical metallurgy is optical metallography, which also concerns micrographic analysis using the optical microscope (magnifying rate up to 2000:1). The images obtained by microscope give direct indications on the chemical and structural composition, also indirectly informing on the physical and mechanical properties of the metallic alloys. One can as well get data on the structural changes occurred under the influence of various mechanical processing previously applied to the alloy.

When considering pure metals or monophasic alloys, micrographic analysis allows observing the size and the orientation of the crystalline grains, the particularities of the dendritic structure, even the repartition of the dislocations. As for polyphasic alloys, which present more complex structural aspects, one can determine the nature, quantity, shape, size and repartition of the various phases in the structure.

Microscopic analysis is an important information source. Its efficiency is partly influenced by the place where the samples are collected and the collecting manner, as well as the skills and experience of the specialist performing the analysis. Figure 1 presents images of samples taken from different materials.

It is to be noticed that the information is "coded" in graphical patterns-images (using gray tones or colors) that have to be interpreted by the person that does

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1998 *CR Categories and Descriptors.* I.5.1 [**Computing Methodologies**]: Pattern Recogniton – *Models*.

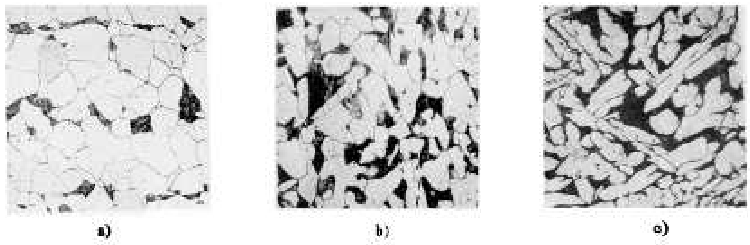

FIGURE 1. Metallic surfaces viewed through optical microscope: a) steel with 0.08–0.15% C, rolled at warm; b) steel with 0.16–0.25% C normalized at 880degC; c) bronze with biphasic cast aluminium. Source: [8].

the analysis. This operation is difficult, demanding a lot of time and experience. Therefore a very useful improvement would consist in the automation of these analysis by creating a system that is able to classify and recognize, possibly in real time, in the images obtained by microscope structures, flaws, previous processing.

2. Automatic Metallographic Analysis System

Our team, in collaboration with the industrial partner "SC SATURN SA"Alba Iulia, has started a project concerning the implementation of an automatic system for metallographic analysis (fig. 2), where the recognition and classification functions are performed by a neural network.

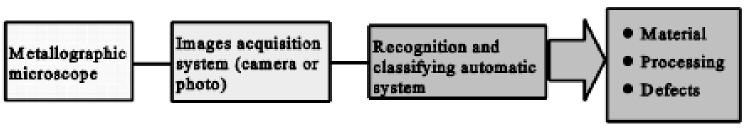

FIGURE 2. Automatic metallographic analysis system

During the current stage of the project, our attention has been focused on the interpretation and classification of the material samples images.

The interpretation of micrographic images is part of the larger area of pattern classifying and recognition. As it is shown by the example in figure 1, identifying rather simple patterns can require the interpretation of mega-dimensional databases, with complicated structure and unknown topological relations. In general there aren't known possible transformations that could simplify this structure and a multilevel hierarchy system of feature extraction becomes necessary.

Another general issue in model based pattern recognition consists in correct input image identifying, even when the image is a geometrically transformed version of the model. The invariant recognition can be achieved using, instead of the initial pattern, the result of a mathematical transformation, that necessarily assures a certain invariance (Fourier transform, Mellin transform etc.). Unfortunately this mathematical pattern preprocessing implies a great computing effort in electronic (hardware and software) implementations. Optical and optoelectronic systems can bypass this drawback due to the parallel computing.

In our case, for metallographic optical analysis, we can assume that the prototype (standard) images and those to be recognized and interpreted, will have the same scale factor, so that the system must be only translation and rotation invariant.

We intend to use for image interpretation a software simulated artificial neural network (ANN), therefore we have evaluated several ANN categories and several preprocessing techniques, in order to find an acceptable solution. The following section present some preliminary results of our work.

3. Neural Network Model

In our work we used two kinds of artificial neural ntworks: a recurrent network and then a feed forward neural network, trained with backpropagation method. The processing unit (artificial neuron) used in the two cases is displayed in figure 3.

In this figure $x_1, x_2, \ldots, x_n$ are neuron inputs, $w_1, w_2, \ldots, w_n$ are the interconnection weights, θ is the neuron threshold, $f()$ is activation function and y is neuron output.

We note: $x = [x_1, x_2, \ldots, xn]^T$ the input vector, $w = [w_1, w_2, \ldots, w_n]^T$ synaptic weights vector,

$$net = \sum_i w_i x_i = w^T x \tag{1}$$

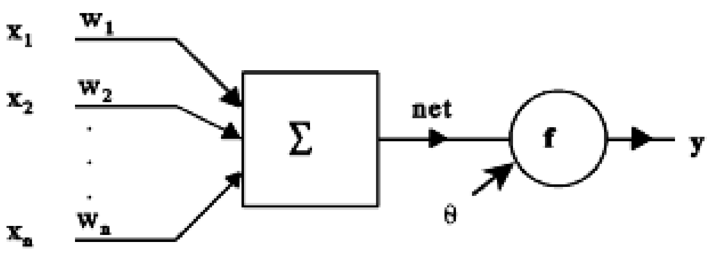

FIGURE 3. The processing unit used

Then the neuro output may be writen:

$$y = f(net - \theta) = f(w^T x - \theta) \tag{2}$$

A) For the recurrent neural network, the model is presented in figure 4. Let's consider the single-layer neural network built from totally connected neurons, whose states are given by $x_i \in -1, 1$, $i = 1, 2, \ldots n$, (fig.4).

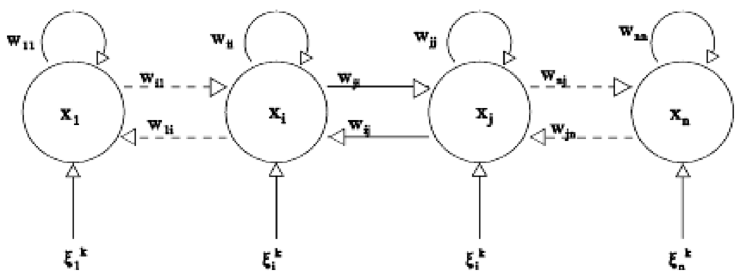

FIGURE 4. The recurrent network model

We denote: $W = [w_{ij} : 1 \leq i, j \leq n]$ the weights matrix, $\theta = [\theta_1, \ldots, \theta_n]^T \in R^n$ the thresholds vector, $x(t) = [x_1(t), \ldots, x_n(t)]^T \in -1, 1^n$ the network state vector.

The evolution in time of the network is described by the following dynamic equation:

$$x_I(t+1) = sgn\left[\sum_{j=1}^{n} w_{ij} x_j(t) - \theta_i\right], i = 1, 2, \ldots, n \tag{3}$$

with the convention:

$$\sum_{j=1}^{n} w_{ij} x_j(t) - \theta_i = 0, x_i(t+1) = x_i(t) \tag{4}$$

where:

$$sgn(x) = \begin{cases} 1 & \text{if } x > 0 \\ -1 & \text{if } x < 0 \end{cases} \tag{5}$$

Notes:

(1) We may consider networks where the neurons' state is not bipolar: -1,1, but binary: 0,1. A relation between the two representations can be easily found.
(2) In many situations we may give up the neural network threshold z_i and we'll do this whenever it doesn't affect the results.

For the autoassociative memory described in this paper, the weight matrix W will be built as follows: given a set of n-dimensional prototype vectors $X = [\xi^1, \xi^2, \dots, \xi^p]$, we establish the synaptic matrix W and the threshold vector θ, so that the prototype vectors become stable points for the associative memory, i.e.:

$$\xi^i = sgn(W\xi^i - \theta), i = 1, 2, \dots, p \tag{6}$$

where the sgn function is applied to each component of the argument.

Several classical rules for determining the weights matrix proved successful in time:

- the 'Hebb' rule
- the projection rule
- the delta projection rule (the gradient method)

B) In the second approach we used a feed forward network with three layers, trained with back propagation method. The number of neurons in the first layer is determined by the dimension of the input image. The number of neurons in the output layer depends on the number of classes in which the input images must be classified. In the hidden layer we tried several configuration and the final network used the best structure. For the neurons in hidden and output layer we used as activation function the sigmoid function.

4. Preliminary Results

Because of our industrial partner's interest in the metallographic analysis of cast iron (its field of production) samples, we've studied the synthesis of an ANN that could allow the recognition and classification of real samples reported to standards. Some standards used for these experiments are shown in figures 5 and 6.

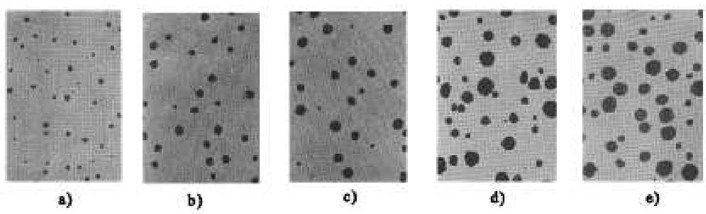

Figure 5. Standard structures of cast iro with nodule graphite: a) below 3%; b) 3–5%; c) 5–8%; d) 8–12%; e) over 12%. Source: [8]

Using samples taken from these standard images, we investigated the training methods for various types of ANN in order to perform micrographic images classification. The images used as prototypes have been preprocessed as to enhance their specific features (fig. 7).

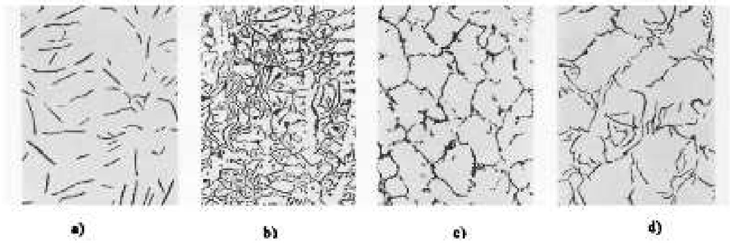

FIGURE 6. Stabdards for gray cast iron with lamellar graphite: a) isolated separations; b) agglomerations with low isolation degree; c) punctiform graphite net; d) lamellar graphite net. Source: [8]

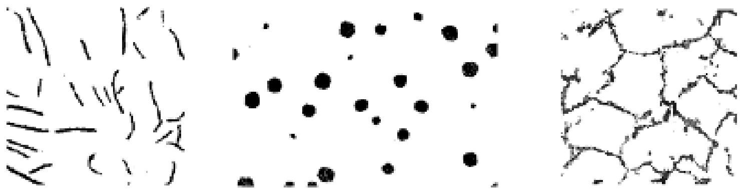

FIGURE 7. Some preprocessed prototypes

A. One first tested ANN category was a recurrent network used to implement an associative memory. We used as prototypes 32×32 pixels images randomly selected from the standard images. Rotation and translation invariance has been obtained by storing several images of the same prototype, randomly transformed [6]. The associative memory thus built has been verified with a great number of test images. The statistical results were very good in what noise contamination is concerned (up to 50% noise contamination). As for geometrical transforms invariance, the results were rather unsatisfactory; the correct recognition rate would be from 40% up to no more than 80%, depending on the prototype image.

B. A second simulation category consisted in the setup of a feed-forward ANN, trained with the same input data used in the previous approach. We investigated several feed-forward topologies, with 2 and 3 layers. Within the limits of available input data, the 3 layers structure provided acceptable results. We faced some difficulties when using 32×32 pixels images, therefore we had to work with 16×16 pixels images.

C. In order to obtain rotation and translation invariance, we also tried to use invariant moments, as presented in [1]. The difficulties we encountered in this approach are connected to the large computation volume and to the necessity for these descriptors to be different enough as to separate the different standard classes. For the 5 standards classes in fig. 5 and the 4 standard classes in fig. 6, the above mentioned descriptors are shown in fig. 8 and 9, respectively. One may notice a rather insignificant difference, which leads to difficulties and errors in data interpretation. We currently work on finding more efficient preprocessing, that could lead to stronger discrimination among invariant descriptors of different classes.

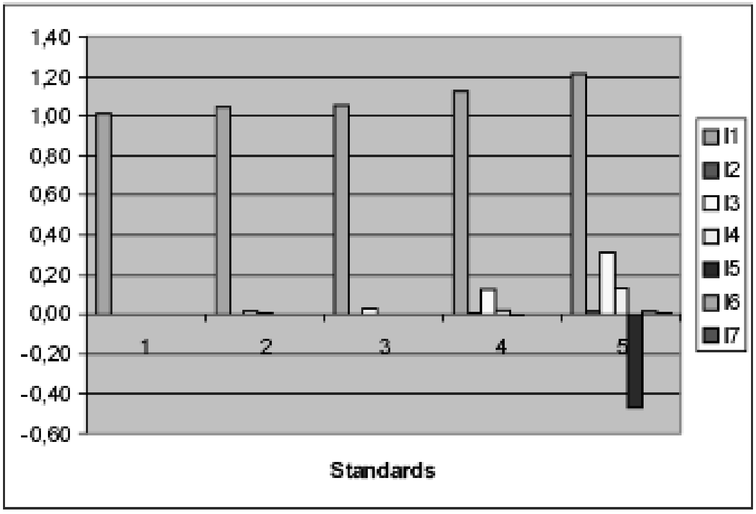

FIGURE 8. Moment invariants for images in fig. 3

5. CONCLUSIONS

The implementation of an automatic system for optical metallographic images analysis is an important objective for the laboratories where such tasks are performed. Moreover, such a system once implemented, it could be used in flaw analysis and even in biological tissue analysis.

This paper has presented some preliminary results obtained by our team in using ANN to perform the recognition and classification of optical micrographic images of material samples, as reported to standards.

The main difficulties we had to overcome were the following:

- The necessity of using relatively large images (over 32×32 pixels) in order to extract significant features out of the sample structure; consequently troubles in training and simulating the ANN were connected to the required memory space, as well as to the computation speed.

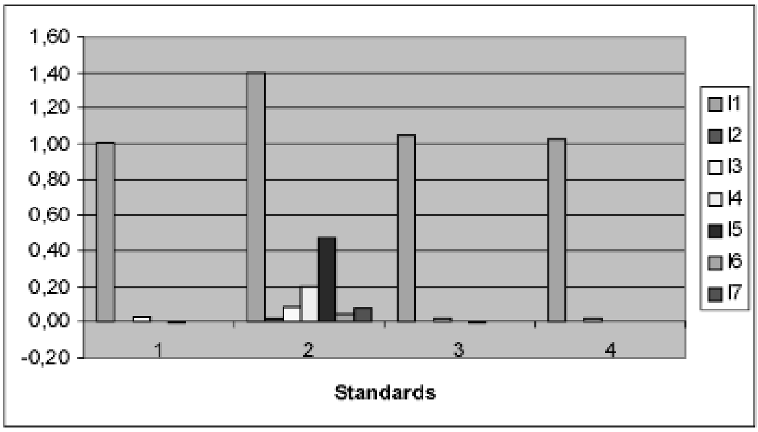

FIGURE 9. Moment invariants for images in fig. 4

- The necessity of recognition immunity, regarding the noise contamination of the images, and also their various geometrical transforms.

We investigated several methods to build a system that would accomplish these requirements and we may conclude that ANN do offer a realist perspective, if solving the above mentioned difficulties. The solutions we currently have in view partly refer to using a faster and more powerful computer for network training and simulation, and partly consist in using more efficient preprocessing methods for the input images.

REFERENCES

[1] Alastair, Mc. Aulay: *Optical computer architectures: the application of optical concepts to next generation computers*, John Wiley & Sons, Inc, 1991.

[2] Cojoc Dănuţ-Adrian: *Aplicaţii ale corelaţiei optice în recunoaşterea formelor*, Teză de doctorat, Universitatea "Politehnica", Bucureşti.

[3] Dumitrescu D., Hariton Costin: *Reţele neuronale. Teorie şi aplicaţii*, Ed. Teora, 1996.

[4] Jianchang Mao, Anil K. Jain: "Artificial neural Network for Features Extraction and Multivariant Data Projection", *IEEE Transactions on Neural Network*, vol. 6, Nr. 2, march 1995.

[5] Ileană Ioan, Iancu Ovidiu Corneliu: "Optoelectronic associative neural network for some graphical patterns recognition", *Proceedings of SPIE*, SIOEL '99, Volume 4068, p.733–739.

[6] Ileană Ioan, Iancu Ovidiu Corneliu, Joldeş Remus: "Recunoaşterea invariantă la translaţia, rotaţia sau scalarea formelor", *Annales Universitatis Apulensis, Series Economica*, Tom 1, 2000, p. 175–185.

[7] Nedevschi Sergiu: *Prelucrarea imaginii şi recunoaşterea formelor*, Editura Albastră, Cluj-Napoca, 1998.

[8] Rădulescu M., Drăgan N., Hubert H., Opriş C.: *Atlas Metalografic*, Ed. Tehnică, 1971.

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