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Methodology of analysis of casting defects

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Methodology of research

ABSTRACT

Purpose: The goal of this publication is to present the methodology of the automatic supervision and control of the technological process of manufacturing the elements from aluminium alloys and of the methodology of the automatic quality assessment of these elements basing on analysis of images obtained with the X-ray defect detection, employing the artificial intelligence tools. The methodologies developed will make identification and classification of defects possible and the appropriate process control will make it possible to reduce them and to eliminate them - at least in part.

Design/methodology/approach: The methodology is presented in the paper, making it possible to determine the types and classes of defects developed during casting the elements from aluminium alloys, making use photos obtained with the flaw detection method with the X-ray radiation. It is very important to prepare the neural network data in the appropriate way, including their standardization, carrying out the proper image analysis and correct selection and calculation of the geometrical coefficients of flaws in the X-ray images. The computer software was developed for this task.

Findings: Combining of all methods making use of image analysis, geometrical shape coefficients, and neural networks will make it possible to achieve the better efficiency of class recognition of flaws developed in the material.

Practical implications: The presented issues may be essential, among others, for manufacturers of car subassemblies from light alloys, where meeting the stringent quality requirements ensures the demanded service life of the manufactured products.

Originality/value: The correctly specified number of products enables such technological process control that the number of castings defects can be reduced by means of the proper correction of the process.

Keywords: Aluminium alloys; Neural networks; Images analysis; Cast defects

1. Introduction

To meet the customer requirements car manufacturers need to develop new technologies related to safety and comfort of travel. As a result the car weight and dimensions are increasing. At the same time the fuel consumption and exhaust emission are increasing too. Thanks to light materials such as aluminum alloys, car manufacturers may aim to reduce their weight. These alloys have become popular in automotive industry owing to their low weight and some casting and mechanical qualities [1,2]. The casting defects occurring during the technological process may be identified by various research methods including microscopy and defectoscopic methods such as X-ray method. The technological progress in material engineering causes the continuous need to develop product testing methods providing comprehensive quality evaluation. In material engineering it is the images obtained by various methods that have become the source of information about materials. The type of image being the subject of analysis depends on the selected registration method. Metallographic structures of images are obtained by light and electron scanning microscopy. These images are the source of information on material structure, ongoing processes and its properties. Images obtained by defectoscopic methods such X-ray and ultrasound methods provide information on material defects occurring at various stages of technological processes [3,4,5].

Also, the engineering works are frequently supported by various artificial intelligence methods including neural networks and genetic algorithms. In classical computer algorithms even a slight rotation or change in lightning can hinder the proper interpretation and alternation of variable input data. To eliminate this hindrance the programming can be converted by specifying such features of the structure element that remain most significant and affect the similarities of the analysed images. In neural network this particular feature needs not to be specified – if necessary, the neural network tracks it automatically [6,7,8].

2. Experimental procedure

This paper presents both the general assumptions for the application of selected methods of artificial intelligence and the statistical study of classification of defects by X-ray methods in aluminium alloy castings.

The purpose of the applied methodology was to identify the casting defects [11] that occurred during the casting process (fig. 1, fig. 2).

The research was carried on the images of automotive engine elements obtained by the X-ray defectoscopy. To specify the casting quality, the methods of analysis of image defects registered in castings by X-ray methods were applied. To enable the correlation between the morphology of defects registered in research, the scale of X-ray images presenting various sections of automotive engine elements were unified. The computer assisted methodology of providing information included in the images presenting various automotive castings of engine blocks and heads includes:

- unification of parameters describing casting images (size, scale),
- analysis of digital images presenting sections of automotive engines blocks and heads for the purpose of extracting castings defects from the images,
- calculating surface area, circumference, and geometrical parameters of casting defects according to formulas,
- calculating geometrical parameters of casting defects applied as independent variables for training neural nets.

The interval estimation was applied to estimate the interval which should comprise all the values of geometrical parameters describing the morphology of castings defects. In this way the image objects that become casting defects have been specified. The image analysis and calculation of geometrical parameters were applied. The confidence intervals for mean values were specified assuming that the tested values of geometrical parameters are of normal distribution N (μ,σ).

For determining the class of flaws developed in the material, 4.0F Statistica Neural Networks software was used. Neural networks input data were the geometrical parameters of casting defects respectively: defect circumference (L), defect surface area (S), horizontal Feret diameter (S_{Fx}), vertical Feret diameter (S_{Fy}), Feret coefficient (WF), nondimensional shape coefficient of the casting defect (BWK), circulatory coefficient of defect (R_{c1}), circulatory coefficient of defect (R_{c2}), Malinowska coefficient of defect (WM), centrality coefficient (C_t) [5,9].

Photos made using the X-ray flaw detection method of the transverse sections of the car cylinder blocks (Fig.3) cast from the EN-AC AlSi7Cu3Mg aluminium alloys with the chemical compositions shown in Table 1 [10] were the material for investigation.

Table 1.
Chemical composition of EN-AC AlSi7Cu3Mg aluminum alloy according to PN-EN 1706:2001

Mass fraction of the element, wt %							
Si	Cu	Mg	Mn	Fe	Ti	Zn	Ni
7.3	3.5	0.45	0.43	≤0.8	≤0.25	≤0.65	≤0.3

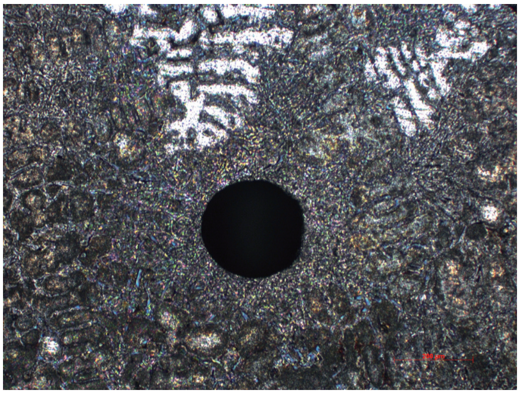


Fig. 1. Light microscope image of gas hole casting defect

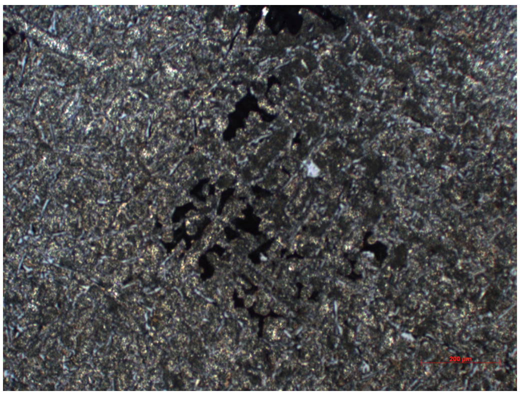


Fig. 2. Light microscope image of shrikage porosity casting defect

The obtained analysis is of considerable importance in proper extracting of casting defects from X-ray images. Another important coefficient is the quality of the X-ray images because poor quality images (eg. overexposed images) affect the correctness of the analysis. Thanks to the applied analysis of sections of images of automotive engine blocks and heads it is possible to prepare such image of casting that enables to detect the edges of objects on images and furthermore to extract those that qualify as casting defects.

The obtained results (table 2) indicate the significant dependence between the defect classes and values of selected geometrical parameters describing casting defects such as: circumference, surface area, Feret diameters, nondimensional shape coefficient, circulatory coefficients and roundness coefficient. Also the obtained results indicate the lack of dependence between defect classes and Feret coefficient and centrality.

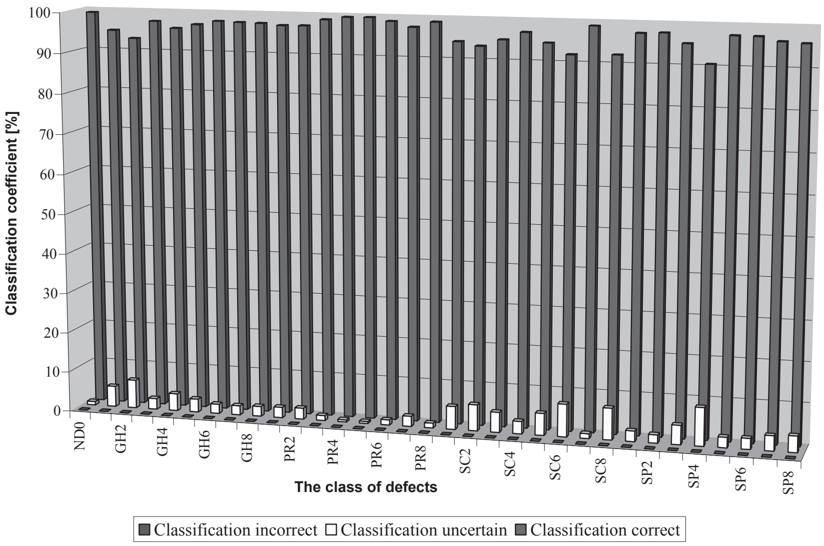
Fig. 3. The fragment of a pictures showing a section of car engine blocks

Table 2.
List of results of nonparametric tests of the significance of correlation for the defect class and calculated geometrical parameters of casting defects

Type of geometrical parameters	Size of N test	Correlation	t/Z test value	Significance level	Test result
		Gamma correlation			
defect circumference (L)	320	0.475531	12.51214	0.000	essential
defect surface area (S)	320	0.510874	13.43913	0.000	essential
horizontal Feret diameter (S_{Fx})	320	0.426672	11.19891	0.000	essential
vertical Feret diameter (S_{Fy})	320	0.438147	11.48111	0.000	essential
Feret coefficient (WF)	320	-0.041530	-1.09191	0.2748	inessential
nondimensional shape coefficient of the casting defect (BWK)	320	0.267082	7.026849	0.000	essential
circulatory coefficient of defect (R_{c1})	320	0.512155	13.47257	0.000	essential
circulatory coefficient of defect (R_{c2})	320	0.472165	12.42382	0.000	essential
Malinowska coefficient of defect (WM)	320	0.267082	7.026849	0.000	essential
centrality coefficient (C_t)	320	0.015748	0.414388	0.6786	inessential

Table 3.
Characteristics of neural network applied for the classification of casting defect

It.	Geometrical parameters of casting defects applied for training neuronal network	Network structure	Training method	Number of training periods
1.	defect area (S), horizontal Feret diameter (S_{Fx}), vertical Feret diameter (S_{Fy} circulatory coefficient of defect (R_{c1}), Malinowska coefficient of defect (WM)	MLP 5-15-15-33	Back Propagation, Conjugate Gradient Descent	583



Symbol	Defect type
GH	Gas hole
PR	Porosity
SC	Shrinkage cavity
SP	Shrinkage porosity

Fig. 4. The plot of defects and correct classifications in particular classes of MLP 5-15-15-33 network

The results of classification of defects obtained by applying multilayer perceptron (table 3). The neural net quality indicators applied in classification of casting defects obtained thanks to the prepared methodology are shown in fig. 4.

3. Conclusions

The developed computer system, in which the neural networks as well as the method of automatic image analysis were used, can ensure the automatic identification and classification of defects in Al-Si alloy casting, EN AC-AlSi7Cu3Mg type. It has become the way to support and automate the decision to eliminate the castings below the quality requirements thus reassuring the repetitiveness and objectivism of the results of the evaluation of the metallurgical value of these alloys. The correctly specified number of products enables such technological process control that the number of castings defects can be reduced by means of the proper correction of the process. Controlling the technological process on the basis of the computer generated information focused on the product quality, can enable the optimisation of this process and so the reduction of defective castings and in the result the reduction of expenses and environmental pollution.

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