Surface Casting Defects Inspection Using Vision System and Neural Network Techniques

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Abstract

The paper presents a vision based approach and neural network techniques in surface defects inspection and categorization. Depending on part design and processing techniques, castings may develop surface discontinuities such as cracks and pores that greatly influence the material's properties Since the human visual inspection for the surface is slow and expensive, a computer vision system is an alternative solution for the online inspection. The authors present the developed vision system uses an advanced image processing algorithm based on modified Laplacian of Gaussian edge detection method and advanced lighting system. The defect inspection algorithm consists of several parameters that allow the user to specify the sensitivity level at which he can accept the defects in the casting. In addition to the developed image processing algorithm and vision system apparatus, an advanced learning process has been developed, based on neural network techniques. Finally, as an example three groups of defects were investigated demonstrates automatic selection and categorization of the measured defects, such as blowholes, shrinkage porosity and shrinkage cavity.

Keywords: Non-destructive testing, Machined aluminum die castings, Image processing algorithms, Vision system inspection, Neural network

1. Introduction

Since, the problem of surface defects identification of aluminium alloys is often problem that results casting rejection the authors focus on better understanding of the phenomena accompanying of their formation. The typical structural elements extremely sensitive to the quality of the joined surfaces include: handles of transmission systems, cylinder pistons and cylinder front faces in engine bodies (Figure 1). Their functionality and quality is a critical factor for the failure-free operation. The goal of the currently running project is to create a computerised system for the determination of quality of aluminium castings, which will also open new industrial and research capabilities. In the first step, a vision based system has been developed [1] and image processing techniques was utilized to identify deferent types of surface defects [2]. Also, as a results of this part of research three different techniques has been investigated to develop a guideline information that
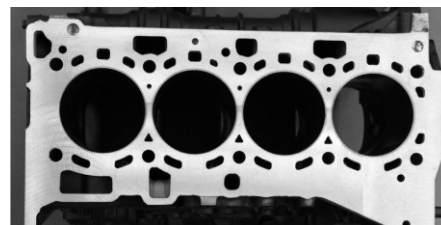

Fig. 1. Front face in engine body block.

enhance understanding and provide all process parameters necessary to make informed decisions in terms of inspection. This process lead authors to exploration of factors limiting the casting process of aluminium parts. Studies of this type will help future efforts for an early elimination of surface defects. Especially, the goal is to create a relatively easy system detecting the defects in castings after machining. thus eliminating their negative post-effect during operation and ensuring proper back flow of information on the presence and type of defects from the castings user to the manufacturer of the castings. Therefore, in the second step of the investigation, the authors proposed to examine and finally classify detected surface defects based on collected data and system learning process co-called neural network [3,4]. In recent years, various solutions were presented in the search for defects on the surface of cast aluminium such as: handles of transmission systems, cylinder pistons and cylinder front faces in engine bodies [5,6]. However, the commonly used solutions is still based on visual inspection, since the major limitation of the proposed methods [1,2] are offline analysis. As for the visual inspection, the method is well adapted to operate in the area of a large variety of products, but it is characterised by high costs, is slow, and the results largely depend on the human factor. Therefore, building an integrated vision system for an online control and inspection will make a basis for the development of industrial equipment. The use of this type of equipment can bring significant benefits through improvement of the quality and economics of a significant part of the engineering and automotive industry production.

2. Methodology

The research on identification of defects includes, first of all, the development and configuration of the experimental set-up. This combination of measurement devices and computational technique will constitute the essence of a solution leading to design and construction of a computerised vision system.
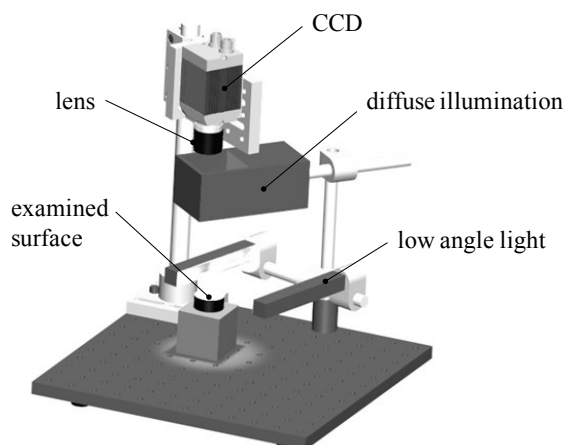

Fig. 2. Schematic representation of a developed vision system

It is expected to capture images of the examined surfaces jointly with the triggering of alternately operating lighting and

numerical processing of these images. The starting point for a computer-aided image analysis of casting quality will be the design of proper lighting system, allowing for visual distinction of casting defects on the machined surface. Hence, the proposed solution of a lighting system consists of the diffuse illumination in a direction perpendicular to the sample and low angle light (Figure 2). The picture of the examined surface with well visible pores and other on-the-surface objects passes through the lens to camera. The reason of the double illumination is the need to eliminate false signals, such as fine dirt and after-machining residues. Owing to the proposed solution in the form of an integrated vision system it will be possible to eliminate the interference in the visibility of the examined object falsifying the correct identification of surface defects.

Second, a numerical processing of the images to highlight the obvious defects in castings was performed. To summarise the subject of the numerical procedure for image processing, it is scheduled to make a single discrete convolution operation, thanks to a simplified form of notation of the combined Gaussian and Laplace (LoG) filters [7,8] at a specific σ value (determining the accuracy of the designation of defects - the first parameter). In the image processing procedure, the areas were identified, where the thus calculated function passes through a zero point and ultimately reject those areas where the average intensity values are smaller than the present value (the second parameter which determines the sensitivity threshold of the casting defect detection). The image processing results are presented in Figure 2, where one of the most representative type of defect for each category is selected and marked.

Finally, in addition to the developed numerical algorithm for image processing, an advanced learning process, based on the methods of computational intelligence (CI) was used, which allows to automatically categorize any of the inspected defects [9-13]. The preliminary investigation performed by the authors illustrates how a pattern recognition neural network can classify defects based on geometrical properties. The Neural Network Toolbox were used as a module of Matlab utilities to solve the problem of defects classification [14-15]. The standard network that is used for pattern recognition is a two-layer feed forward network, with sigmoid activation functions in both the hidden layer and the output layer (Figure 3). The default number of hidden neurons was set to 10. The number of output neurons is set to 3, which is equal to the number of elements in the target vector (the number of defect categories, see Figure 3).
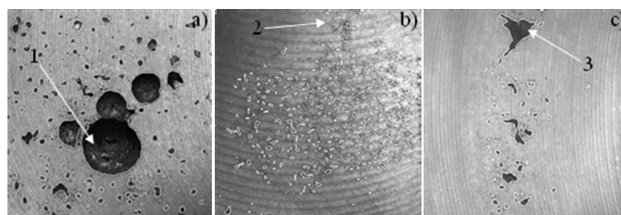

Fig. 3. The images present the results of numerical processing for the three types of defects: a) blowholes, b) shrinkage porosity, c) shrinkage cavity.

Eight attributes, described below, were selected to build a neural network:

- Area (the number of pixels in a blob),
- Perimeter (the total length of edges in a blob),
- Feret Elongation (a measure of the shape of a blob),
- Compactness (derived from the perimeter and area of a blob),
- Roughness (a measure of the roughness of a blob),
- Length (a measure of the approximate length of an object),
- Elongation and,
- Breadth (a measure of the approximate breadth of an object).

The input quantities are values of these eight attributes, while the output quantity are the correct detection of defect. The latter quantity is inherently of a discrete character (1 - the correct result of detection, 0 - invalid). Since, neural networks are very good tool for pattern recognition problems these technique can classify any data with arbitrary accuracy, however large number of elements (called neurons) are necessary to use. They are particularly well suited for complex decision boundary problems over many variables. Therefore neural networks are a good candidate for solving the defect classification problem. In order to organize data for a neural network two matrices of data the input and the target data were generated. Each column of the input matrix has eight known elements representing a defect geometry as shown on three specimens (Table 1). Each corresponding column of the target matrix has three elements, consisting of two 0 and 1 in the location of the associated defect. Next the three step calculation process is conducted, starting with training, validation – in the second step and testing in third step. All the samples are manually divided (typically 70%, 15%, 15%) into training, validation and test sets. The training set is used to teach the network. Training process continues as long as the network continues improving on the validation set. The test set provides a completely independent measure of network accuracy. If the network has learned to classify properly, the percentages indicating misclassifications should be very small. The overall percentages of correct and incorrect classification in the presented example is 90% to 10%.

Table 1.
Typical representation of the input attributes

Eight attributes [pixels]	Defect#1 blowholes	Defect #2 shrinkage cavity	Defect #3 shrinkage porosity
1. Area	4960	917	1
2. Perimeter	272.2	191.8	
3. Feret Elongation	1.092	1.276	1
4. Compactness	1.189	3.193	1.273
5. Roughness	1.05	1.213	1.257
6. Length	68.05	85.14	1
7. Elongation	1	7.905	1
8. Breadth	68.05	10.77	1

3. Application results

To verify the proposed methods for identification of defects in castings, preliminary studies have been conducted. For this purpose, recently developed vision system was used [2] to determine the feasibility of implementation of the detection and classification of the defects. The basis for analysis were images of the aluminium alloy samples and examining the possibility of identification of surface defects using the proposed numerical solution. The studies helped to demonstrate that image processing and the technique of lighting allow the identification of surface defects. Examples of sample with well visible defects is shown in Figure 4 together with the final results of image processing and defects detection. All the defects are surrounded by the border lines which indicate a defects shape. Finally, a probabilities of the three defect categories were measured by using the previously trained neural network. This calculation shows a sense of how well the network will do when applied to data from the real application. The network outputs are in the range 0 to 1, for each of the defect categories, where 1 is equal 100% of the probability. The accumulated probability (0.7) indicates that most of the defects are categorized as blowholes.
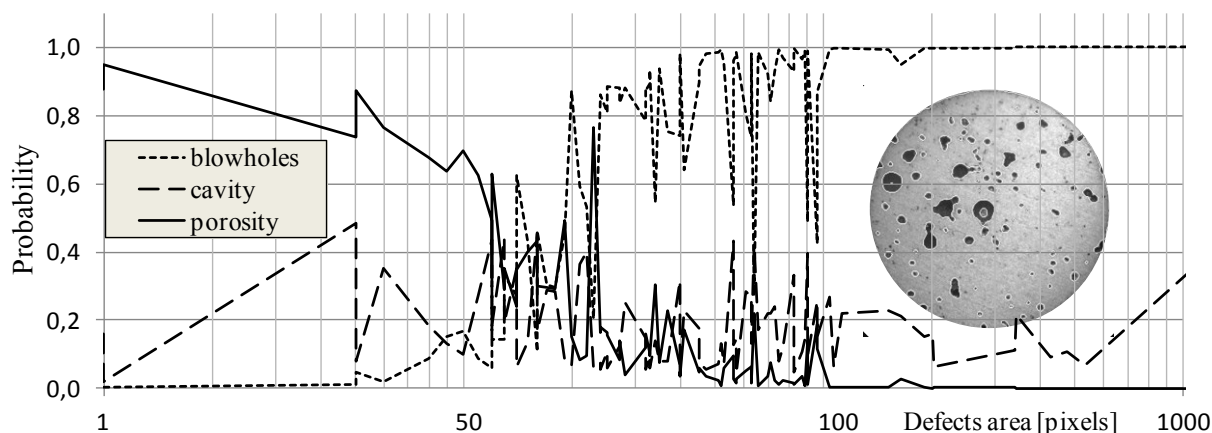

Fig. 4. The results of preliminary studies of the three types of defects categorization for selected surface

4. Conclusion

The scientific objective of the research was to develop and build computer based vision systems for online inspection of surface defects in products, especially discontinuities which appear in castings after machining. The essence of the research is to provide a method for obtaining and analysing images of the inspected surfaces, to allow an unmistakable and consistent finding of defects and specifying their type. In addition to the developed numerical algorithm for image processing, an advanced learning process, based on the methods of computational intelligence, was used. This process could be successfully used for automatic categorization. The new vision inspection system, image processing algorithm and learning system based on artificial neural network were successfully implemented to inspection of the surface aluminium die casting defects.

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