Neuro-fuzzy method for automated defect detection in aluminium castings

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Abstract. The automated flaw detection in aluminium castings consists of two steps: a) identification of potential defects using image processing techniques, and b) classification of potential defects into defects and regular structures (false alarms) using pattern recognition techniques. In the second step, since several features can be extracted from the potential defects, a feature selection must be performed. In addition, since the two classes have a skewed distribution, the classifier must be carefully trained. In this paper, we deal with the classifier design, i.e., which features can be selected, and how the two classes can be efficiently separated in a skewed class distribution. We propose the consideration of a self-organizing feature map (SOM) approach for stratified dimensionality reduction for simplified model building. After a feature selection and data compression stage, a neuro-fuzzy method named ANFIS is used for pattern classification. The proposed method was tested on real data acquired from 50 noisy radioscopic images, where 23000 potential defects (with only 60 real detects) were segmented and 405 features were extracted in each potential defect. Using the new method, a good classification performance was achieved using only two features, yielding an area under the ROC curve $A_z = 0.9976$.

Keywords: automated visual inspection, neuro-fuzzy methods, aluminium castings, ROC curves.

1 Introduction

Shrinkage as molten metal cools during the manufacture of die castings, can cause defect regions within the work piece. These are manifested, for example, by bubble-shaped voids, cracks, slag formations or inclusions (see examples in Fig. 1). Light-alloy castings produced for the automotive industry, such as wheel rims, are considered important components for overall roadworthiness. To ensure the safety of construction, it is necessary to check every part thoroughly.

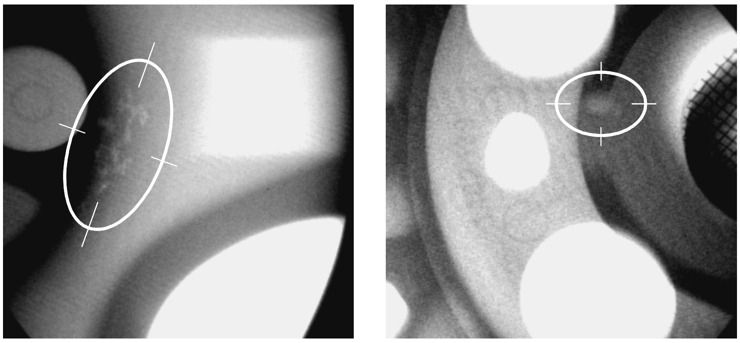

Fig. 1. Radioscopic images of wheels with defects.

Radioscopy rapidly became the accepted way for controlling the quality of die cast pieces through computer-aided analysis of X-ray images [1]. The purpose of this non-destructive testing (NDT) method is to identify casting defects, which may be located within the piece and thus are undetectable to the naked eye. The automated visual inspection of castings is a quality control task to determine automatically whether a casting complies with a given set of product and product safety specifications. Two classes of regions are possible in a digital X-ray image of an aluminium casting: regions belonging to regular structures of the specimen, and those relating to defects. In the computer-aided inspection of castings, the aim is to identify these two classes automatically. Data mining and image processing methods have been developed in a wide range of techniques for data treatment. Thus, it is possibly to apply several of these techniques for the defect detection task. Many approaches for automated defect detection in X-ray images have been used; these approaches included neural networks [2, 3], statistical classifiers [3], fuzzy clustering [4] and fuzzy expert systems [5].

Typically, the automatic process used in fault detection in aluminium castings, as shown in Fig. 2, follows a pattern recognition methodology that can be summarised in two general steps [3]:

a) Identification of potential defects:
- *Image formation*: An X-ray image of the casting being tested is taken and stored in the computer.
- *Image pre-processing*: The quality of the X-ray image is improved in order to enhance the details of the X-ray image.
- *Image segmentation*: Each potential flaw of the X-ray image is found and isolated from the rest of the scene.

b) Detection:
- *Feature extraction*: The potential flaws are measured and some significant characteristics are quantified.
- *Classification*: The extracted features of each potential flaw are analysed and assigned to one of the two following classes: ‘defect’ or ‘regular structure’.

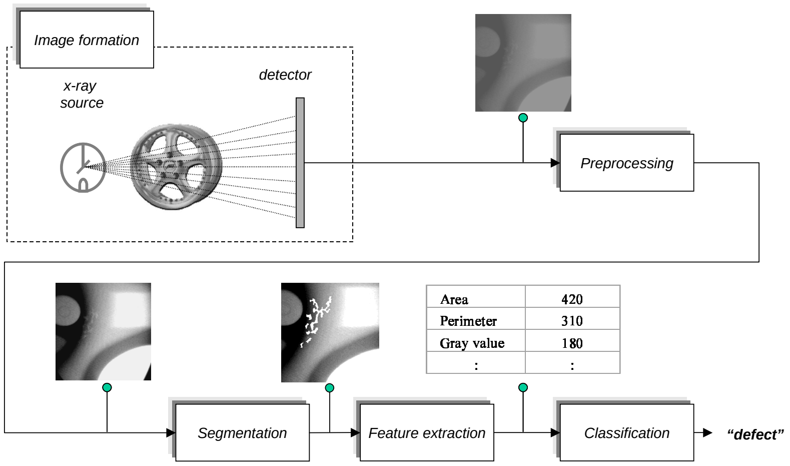

Fig. 2. Automatic process in fault detection in aluminium die castings [3].

In step a), the identification of real defects must be ensured. Nevertheless, using this strategy an enormous number of regular structures (false alarms) is identified. For this reason, a detection step is required. The detection attempts to separate the existing defects from the regular structures. In step b), since several features can be extracted from the potential defects, a feature selection must be performed. In addition, since the two classes show a skewed distribution (usually, there are more than 100 false alarms for each real defect), the classifier must be carefully trained.

In this paper, we deal with the classifier design, i.e., which features can be selected, and how the two classes can be efficiently separated in a skewed class distribution. A self-organizing feature map (SOM) approach is used for stratified dimensionality reduction for simplified model building [6]. After a feature selection stage, a neuro-fuzzy method based on an adaptive-network-based inference system (ANFIS) [7] is used for the classification. The advantage of neuro-fuzzy systems is the combination of both properties: non linear learning based on numerical data and handling uncertainties in data.

The rest of the paper is organised as follows: in Section 2 the pattern recognition using SOM and ANFIS is presented. Experiments and results on X-ray images are presented in Section 3. Finally, Section 4 gives concluding remarks.

2 Pattern recognition using SOM and ANFIS algorithm

As explained in Section 1, the automated visual inspection follows a pattern recognition methodology. This Section presents the steps of the proposed method using SOM and ANFIS algorithms applied to the automated flaw detection of castings.

2.1 Identification of potential defects

The X-ray image taken with an image intensifier and a CCD camera (or a flat panel detector), must be pre-processed to improve the quality of the image. In our approach, the pre-processing techniques are used to remove noise, enhance contrast, correct the shading effect and restore blur deformation [8].

The segmentation of potential flaws identifies regions in radioscopic images that may correspond to real defects. Two general characteristics of the defects are used to identify them: a) a flaw can be considered as a connected subset of the image, and b) the grey level difference between a flaw and its neighbourhood is significant. According to the mentioned characteristics, a simple automated segmentation approach based on a LoG operator was suggested in [9]. This is a very simple detector of potential flaws with a large number of false alarms flagged erroneously. However, the advantages are as follows: a) it is a single detector (it is the same detector for each image), b) it is able to identify potential defects independently of the placement and the structure of the specimen, i.e., without a-priori information of the design structure of the test piece, and c) the detection rate of real flaws is very high (more than 95%).

In order to reduce the number of the false alarms, the segmented regions must be measured and classified into one of the two classes: regular structure or defect. In the following sections, the detection of defects will be explained in further detail.

2.2 Feature extraction and feature selection

Features are used for representing original data in a lower dimension space. Features extracted can be divided into two groups: geometric features (area, perimeter, invariant moments, etc.) and intensity features (mean gray value, texture features, Karhunen-Lóeve coefficients, Discrete Cosine Transform coefficients, etc.) [3]. In order to build a compact and accurate model, irrelevant and redundant features are removed. The Correlation-based Feature Selection (CFS) method takes into account the usefulness of individual features for class discrimination, along with the level of inter-correlation among them [10].

2.3 Stratified dimensionality reduction using SOM

In the proposed approach, SOM is used for stratified dimensionality reduction for model simplification. Skewed class distributions can lead to an excessive complexity in decision boundaries construction, so to create a reduced representation of the original data is necessary. In the stratified dimensionality reduction approach, the idea is to have an economic representation of the whole dominant class without loss of knowledge of the internal relationships among features.

SOM is performed using neural networks. The approach transforms a high dimensional input space to a low order discrete map. This mapping has the particularity that it preserves input data topology while performing dimensionality reduction of this space. Every processing unit of the map is associated with an n-dimensional reference vector, where n denotes the dimension of the input vectors. Weight updating is done by means of a lateral feedback function and winner-take-all learning, and this information forms a codebook.

In this work a SOM codebook of the dominant class is used as new training data for the next stage of classification. Thus, SOM contributes to the stratified dimensionality reduction, but in addition, this approach introduces other benefits like computational load decrease and noise reduction [6].

2.4 Pattern classification using ANFIS

Pattern classification attempts to assign input data to a pre-defined class. In our approach, an ANFIS algorithm is used for supervised classification [11]. ANFIS is a hybrid network model equivalent to a Takagi-Sugeno fuzzy model, which means that a rule base can be expressed in terms of fuzzy 'if-then' rules like:

R_1: if x is A_1 and y is B_1 then $z_1 = f_1(x, y)$
R_2: if x is A_2 and y is B_2 then $z_2 = f_2(x, y)$

where A and B are fuzzy sets in the antecedent, and f_i is a crisp function of the consequent. In this type of controller the defuzzification stage is replaced by a weighted average of incoming signals from each node in the output layer. The resulting adaptive network can be viewed as shown in Fig. 3, where w_i is the output of each node in the second layer, which multiplies the incoming signals and outputs the product. This value actually represents the firing strength of a rule which is normalised in the next layer. Each node is a process unit which performs a function on its incoming signals to generate a single node output [11]. This node function is a parameterised function with modifiable parameters. If the parameter set in a node is non-empty, then the node is an adaptive node an is represented as a square. On the other hand, if the parameter set is empty, there is a fixed node, which is represented as a circle in the diagram.

In this paper, the ANFIS system is used for pattern classification into defects and regular structures. Fuzzy 'if-then' rules are extracted numerically from data

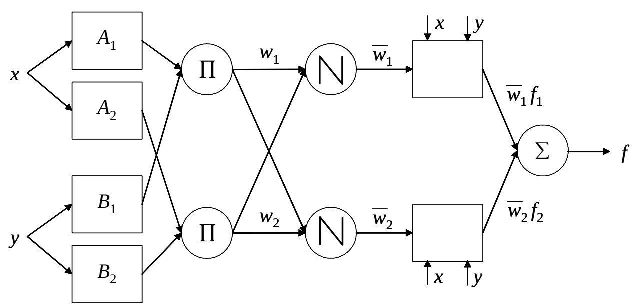

Fig. 3. ANFIS architecture [7].

and defines a mapping between extracted features from radiographic image data and decision boundaries for defect detection. These features become fuzzy sets and fuzzy numbers rather than crisp values, achieving robustness in the decision making process with an approximate reasoning based solution.

2.5 Evaluation basis

Once the classification is carried out, a performance evaluation is required. The area under the Receiver Operation Characteristic (ROC) curve is commonly used for classifier performance for two class problems [12]. This metric provides a scalar unit which represents overall mis-classification and accuracy rates, discarding unbalanced class distribution effect.

The ROC curve is defined as a plot of the 'sensitivity' (Sn) against the '1-specificity' ($1 - Sp$):

$$Sn = \frac{TP}{TP + FN}, \qquad 1 - Sp = \frac{FP}{TN + FP}, \tag{1}$$

where

TP is the number of true positives (flaws correctly classified);
TN is the number of true negatives (regular structures correctly classified);
FP is the number of false positives (false alarms, i.e., regular structures classified as defects); and
FN is the number of false negatives (flaws classified as regular structures).

Ideally, $S_n = 1$ and $1 - S_p = 0$, i.e., all flaws are detected without flagging false alarms. The ROC curve permits the assessment of the detection performance at various operating points (e.g., thresholds in the classification). The area under the ROC curve (A_z) is normally used as performance measure because it indicates how reliably the detection can be performed. A value of $A_z = 1$ gives perfect classification, whereas $A_z = 0.5$ corresponds to random guessing.

3 Experiments and results

In our experiments, 50 X-ray images of aluminium wheels were analysed. In the segmentation 22936 potential flaws were obtained, in which there were only 60 real flaws, i.e., the skew is 381:1. Some of the real defects were existing blow holes. The other defects were produced by drilling small holes in positions of the casting which were known to be difficult to detect (see examples in [9]). For each potential defect, 405 features were extracted. Detailed description of this data set can be found in [3].

The feature selection method evaluated 4009 subsets in a total space of 405 features. The selected features are intensity features obtained from 32×32 pixels containing the potential defect and neighbourhood: a) feature 37: first coefficient of Discrete Fourier Transform component of best 'Crossing Line Profile' [13]; and b) feature 360: coefficient $(3, 3)$ of Discrete Cosine Transform [3].

Table 1. Performance of ANFIS model evaluation for defect detection

Model	$TP/(TP+FN)$	$FP/(TN+FP)$	FP/image	S_n	$1-S_p$	A_z
Complete Model	57/60	199/22876	3.98	95%	0.87%	0.9968
Simplified Model	57/60	126/22876	2.52	95%	0.55%	0.9976
Threshold classifier [3]	57/60	230/22876	4.60	95%	1.01%	0.9961

The selected features are used for the complete and simplified ANFIS model building. The dominant class ('regular structures') has 22876 prototypes and the other class ('defects') has only 60 instances. The cmplete ANFIS model is performed using a training set with a sample (70%) of each class, and the other instances (30%) as a checking set for model validation. Classifier performance for this model (16055 training patterns and 6881 checking patterns) is $A_z = 0.9968$. Another training set is made using SOM codebook vectors from the dominant class. The simplified model uses SOM algorithm for reducing the 22876 instances from dominant class (100% of 'regular structures' patterns). The resulting codebook vectors and other 60 instances from the minority class (100% of 'defect' patterns) makes up the training set for this model. Classifier performance for this model (794 training patterns) is $A_z = 0.9976$. The false alarm rate $1 - S_p$ obtained with this method is 0.55080% of the total hypothetical flaws (2.52 false alarms per image), and defect detection S_p is 95% accurate. This result outperforms false alarm rate of 1.00279% (4.60 false alarms per image) reported in the literature with the same data [3], in which a threshold classifier was used. Table 1 summarises the results for complete and simplified ANFIS models in the radioscopic data and the results obtained in previous work.

4 Conclusions

Two-stage simplified model building outperforms classification performance of a complete ANFIS model. Although this improvement in classifying is not determinant, a simplified model improves results for computational workload and speed.

Sensitivity analysis using the CFS method had good results in classifier building with this data set. Although there are powerful wrapper learning schemes for attribute selection, a good trade-off between results accuracy, attributes interaction identification and computation time in large data sets handling is provided by this method. Results obtained are concordant with previous work using a Fischer discriminant for attribute selection [3], i.e., intensity features has better discriminant power for flaw detection than geometric features, so further research with this data can be done, including further intensity information, like wavelet components for the segmented images.

The main contribution of this research was the use of SOM for dimensionality reduction and the neuro-fuzzy method ANFIS for the pattern classification task. Neural networks have an inherent ability to recognise overlapping pattern classes with highly nonlinear boundaries. On the other hand, soft computing hybridizations provides another information processing capability for handling uncertainty from the feature extraction stage. Uncertainty handling of the feature space by means of fuzzy sets can be highly useful, even when no prior knowledge of data topology or expert opinions are available, but there is a need for a more powerful learning architecture for reduction of false positives. The best performance ($A_z = 0.9976$) was achieved using the simplified ANFIS model. That means, that only 2.52 false alarms per image are obtained in the identification of potential flaws (at $S_n = 95\%$).

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