AUTOMATED DEFECT DETECTION IN ALUMINIUM CASTINGS AND WELDS USING NEURO-FUZZY CLASSIFIERS

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Abstract: In this paper we present the results obtained recently by inspecting castings and welds using Neuro-Fuzzy classifiers. The proposed approach to detecting defects follows a general pattern recognition scheme based on three steps: segmentation, feature extraction and classification. In the first step (segmentation), potential defects are segmented using an edge detector. In the second step (feature extraction), several features of the potential defects are extracted in order to characterise them. We investigate two groups of features: geometric and intensity features. In order to make a compact pattern representation and a simple decision strategy, the number of features is reduced using attribute sensibility analysis. Neuro-Fuzzy classifiers are implemented in order to establish decision boundaries in the space of the selected features which separate patterns (our segmented regions) belonging to two different classes (regular structure or defects). The results are compared with a statistical classifier and the performance analysis is evaluated using the area under the Receiver Operation Curve (ROC).

Introduction: The purpose of industrial non-destructive testing (NDT) method is to identify defects or flaws in industrial parts, which are difficult to detect for the human eye. X-ray testing is a traditional method for the evaluation and detection of defects in castings and welds, therefore digital image processing and computational intelligence can be used to automate this process. Automated visual inspection of industrial parts can be used as a quality control task to determine automatically whether a it complies with a given set of product and product safety specifications [1].

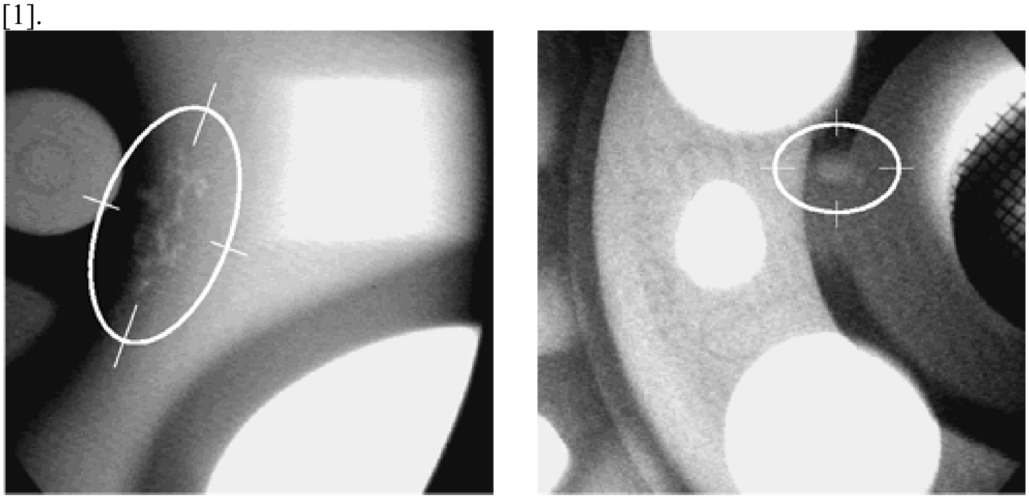

Figure 1: Radioscopic images of wheels with defects.

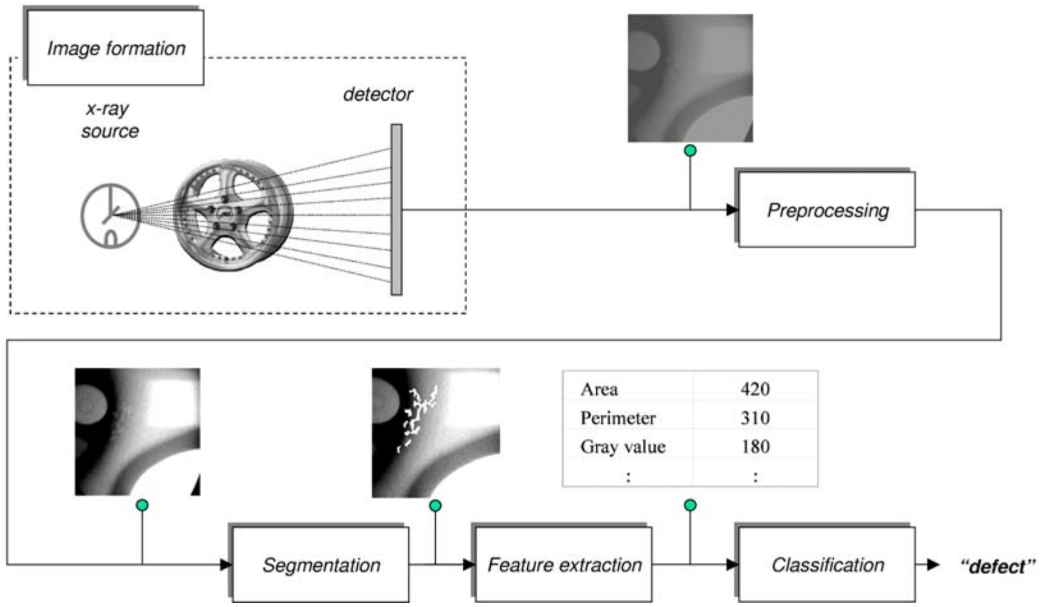

Figure 2: Automatic process in fault detection in industrial parts [3].

Two classes of regions are possible in a digital X-ray image of an industrial part: regions belonging to regular structures of the specimen, and those relating to defects. In the computer-aided inspection of industrial parts, the aim is to identify these two classes automatically. Computational intelligence 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 industrial parts, as shown in Fig. 2, can be summarized in two general steps [3]:

a) Identification of the potential defects:

- Image formation: An X-ray image of the industrial part 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 detail 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.

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 with. For this reason, a detection step is required. The detection attempts to separate the existing defects from the regular structures.

b) Detection:

- Feature extraction: The potential flaws are measured and some significant characteristics are quantified.
- Classification: The extracted features of each potential flaw are analyzed and assigned to one of the following classes: 'defect' or 'regular structure'.

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 have 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. After a feature selection stage, a Neuro-Fuzzy method named ANFIS [6] is used for constructing and training a fuzzy inference model that best classifies new data. The advantage of Neuro-Fuzzy systems is the combination of both properties non linear learning based on numerical data and handling uncertainties in data, but the fuzzy model identification is very sensitive to which attributes are presented and class distribution in the training data. Therefore a SOM based approach is used for stratified dimensionality reduction for simplified model building. Basically this approach attempts to reduce training patterns from the dominant class, without loosing information. This simplified model is compared to the complete model, which is done with stratified sampling for preserving original class distribution in the training data. As explained previously, the automated visual inspection follows a pattern recognition methodology. Figure 3 shows an overview of the tasks involved in simplified and complete model building. In following, the tasks will be briefly described.

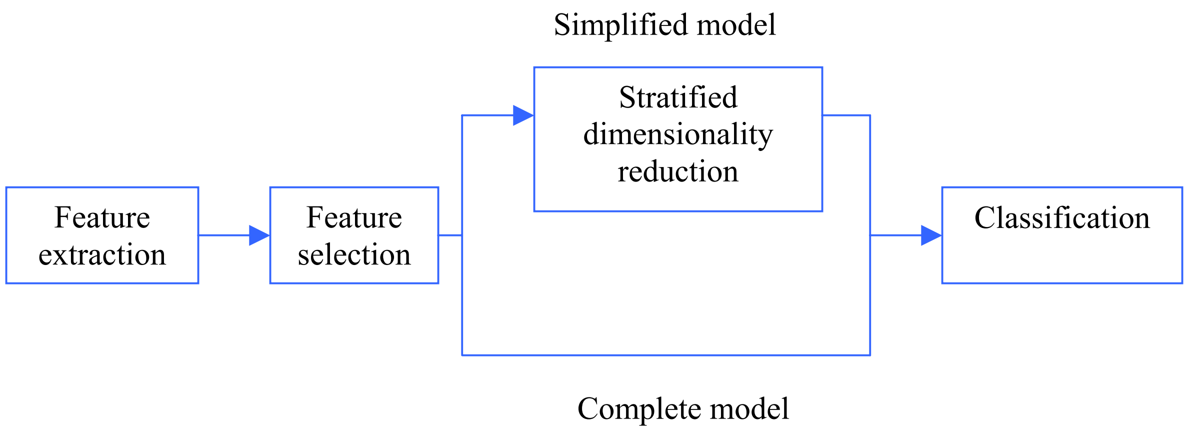

Figure 3: Overview of the pattern recognition tasks.

- Feature Extraction: 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 [7]. The segmentation of the 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 neighborhood is significant. According to the mentioned characteristics, a simple automated segmentation approach based on a LoG operator was suggested in [8]. 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 (approximately 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: 'non-defect' or 'defect'. Measures and descriptors 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-Lòeve coefficients, Discrete Cosine Transform coefficients, etc.) [3].
- Feature Selection: In order to build a compact and accurate model, feature selection is used for removing irrelevant and redundant features. There are many benefits associated with feature selection, like improving classification accuracy, reducing the number of features in real-time extraction and decreasing running time of the model. Usually feature selection methodologies involves two major tasks: a.) Search the feature subset space: When evaluation of all features combinations is prohibitive, heuristic search strategies and a stopping criterion are commonly used. b.) Feature evaluation: Some methodologies uses individual

attribute ranking as a baseline method and other methodologies uses features subsets evaluation, taking in account the usefulness of each individual feature in the subset, along with a low level of inter-correlation among them [9].

- Stratified dimensionality reduction: In the proposed approach, Self-Organizing Feature Map (SOM) is used for stratified dimensionality reduction for model simplification. Skewed class distributions can leads 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.

  Self-Organizing Features Maps (SOM) are neural networks, which transforms a high dimensional input space to a low order discrete map. This mapping has the particularity that 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 the SOM codebook vectors of the dominant class are 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 [10].

- Classification: Pattern classification attempts to assign input data to a pre-defined class. Labelled data is used to design a supervised classifier, but if there is no labelled data, classifier must be designed in an unsupervised way. In our approach, ANFIS algorithm is used for supervised classification. Adaptive-Network-Based Inference System ANFIS [11] is a fuzzy inference system represented as a neural network.

  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:

  - $R1: if\ x\ is\ A_1\ \ and\ y\ is\ B_1\ then\ z_1 = f_1(x, y)$
  - $R2: if\ x\ is\ A_2\ \ and\ y\ is\ B_2\ then\ z_2 = f_2(x, y)$

  Where A and B are fuzzy sets in the antecedent, and z is a crisp function of the consequent. In this type of controller the defuzzification stage is replaced by a weighted average of the output. The resulting adaptive network can be viewed as shown in Fig. 4, where $\overline{w}_i$ is the output of each node in the second layer, which multiplies the incoming signals and outputs the product. 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, the node is an adaptive node and 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.

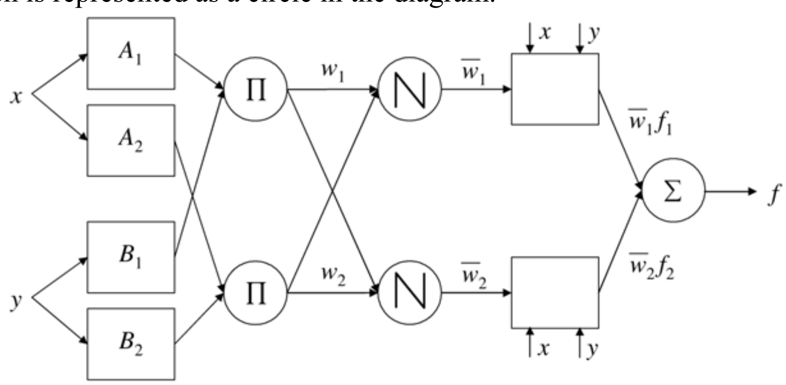

Figure 4: ANFIS architecture [7].

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

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' (S_n) against the '1-specificity' ($1-S_p$):

$$S_n = \frac{TP}{TP+SN} \qquad 1-S_p = \frac{FP}{TN+FP}$$

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 to 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.

Results: This section presents classification results using complete and simplified ANFIS algorithm models. These methods are tested using two radiographic images data sets with skewed class distributions ('defect' and 'non-defect').

<u>Experiments with synthetic data:</u> This data was generated to see how simplified model and complete model performs when class distribution is skewed. Consisted on 1000 patterns (991 instances from 'non-defect' class and 9 instances from 'defect' class) with non-linear relationships between classes and attributes. Table 1 shows classifier performance of the complete and simplified ANFIS models, and the quantization error (QE) [10] of the SOM in the simplified model:

Table 1. Performance of ANFIS Models for defect detection in aluminium castings.

Model	*TP(TP+FN)*	*FP(TN+FP)*	S_n	1-S_p	*QE*	A_z
Complete model	9/9	2/991	100%	0.2018%		0.9988
Simplified model	9/9	0/991	100%	0.00%	0.002	1.0000

<u>Experiments with castings:</u> This data set consisted of radiographic images of aluminium castings [3]. This data set contains 22936 patterns (22876 of 'non-defect' and 60 instances of 'defect' class) and 405 attributes. The Correlation-Based feature selection method (CFS) [9] is used for evaluation of the discrimination power of 4009 subsets (this number is optimally obtained by means of Best First [14] search strategy), and finally two attributes are obtained as the best features subset:

- Feature 37: Discrete Fourier Transform component of Best Crossing Line Profile [13].
- Feature 360: Coefficient (3,3) of Discrete Cosine Transform [3].

Complete ANFIS model uses 70% of each class total (16055 of 'non-defect' and 45 instances of 'defect' class) for training, and 30% of each class for checking. Simplified ANFIS model uses a Self-Organizing Map (SOM) for stratified dimensionality reduction in the dominant class. A new training set is made using the codebook vectors of the SOM (752 patterns) and 45 patterns of 'defect' class. Table 2 shows classifier performance of these models:

Table 2. Performance of ANFIS Models for defect detection in aluminium castings.

Model	*TP(TP+FN)*	*FP(TN+FP)*	S_n	1-S_p	QE	A_z
Complete model	57/60	199/22876	95%	0.87%		0.9968
Simplified model	57/60	126/22876	95%	0.55%	0.000	0.9976
Threshold classifier [3]	57/60	230/22876	95%	1.01%		0.9961

<u>Experiments with welds:</u> The second data set consisted of radiographic images of welding. This data set contained 1419 instances (1221 of 'non-defect' and '198' of 'defect' class) and 164 attributes obtained from texture features [15]. Information Gain filter [16] along with ranker search strategy is used for the feature selection task. Finally 3 features with the best scoring are used for model building:

- Feature 81: Texture feature (average of difference variance for co-occurrence matrix with a distance of 3 pixels) [15].
- Feature 82: Texture feature (average of difference entropy for co-occurrence matrix with a distance of 3 pixels) [15].
- Feature 142: Component (6,3) of Gabor Function [15].
- Feature 145: Component (6,6) of Gabor Function [15].

Complete ANFIS model uses 70% of each class total (855 of 'non-defect' and 139 instances of 'defect' class) for training, and 30% of each class for checking. Simplified ANFIS model uses a training set containing the codebook vectors of the SOM (168 patterns) and 139 patterns of 'defect' class. Table 3 shows classifier performance of these models.

Table 3. Performance of ANFIS Models for defect detection in welding joints.

Model	*TP(TP+FN)*	*FP(TN+FP)*	S_n	1-S_p	QE	A_z
Complete model	180/198	90/1221	90.91%	7.37%		0.9650
Simplified model	180/198	170/1221	90.91%	13.92%	0.021	0.9441
Polynomial classifier [15]	180/198	99/1221	90.91%	8.11%		0.9285

Discussion: Simplified model outperforms complete model in the first data set (aluminun castings), but this is not true in the welding data set. Simplified model performance can be affected by SOM quality, which is measured in terms of the resolution and the topology preservation of the training data. Topology preservation can be observed by means of the smoothness of the discretized surface of the SOM. Sammon's projection [10] of a SOM gives a very informative picture of the global shape and it's overall smoothness, and quantization error gives an overall measure of the performance of the SOM respect the training data.

Figure 5 and 6 shows non-linear projection of the input data space in each data set. Figure 5 (QE=0.00) shows better neighbourhood preservation capabilities than Figure 6 (QE=0.021). In this context, stratified dimensionality reduction can be more affected by quantization errors of the SOM in the welding radiographic images.

Conclusions: A new approach for detect detection in X-ray images based on stratified dimensionality reduction and the Neuro-Fuzzy classification is presented. This method outperforms prior results with the same data sets and since it follows a pattern recognition scheme, it can be used with a wide range of feature extraction and feature selection methods.

The best performance was achieved using the simplified model in the case of the aluminium castings (A_z=0.9976) and the complete model in the case of defect detection in welds (A_z=0.9659). Although this improvement in relation with prior work with the same data is not determinant, a simplified model improves results for computational workload and speed.

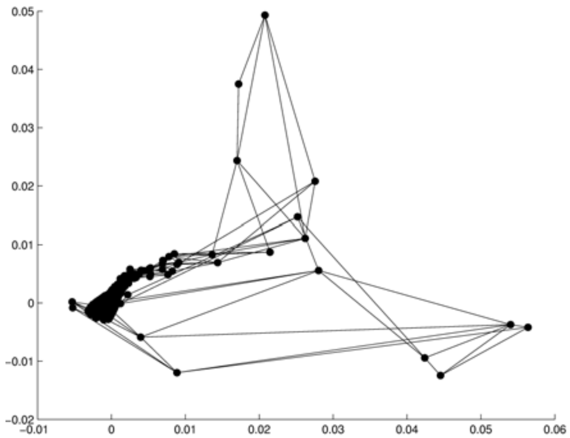

Figure 5. Sammon´s mapping of the SOM of 'non-defects' in aluminium castings images.

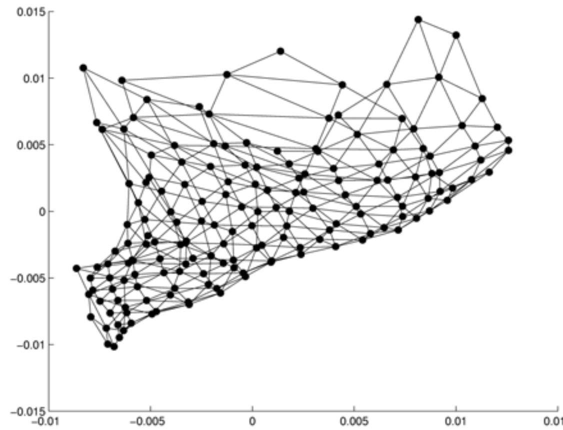

Figure 6. Sammon´s mapping of the SOM of 'non-defects' in welding images.

Neuro-Fuzzy classification provides a framework for handling uncertainty and non-linear boundaries in data. This can be very useful, due to the imprecision produced in the inherently noisy environment of the radiography testing, but in the other hand, there is a need for a more powerful learning scheme in these kind of systems.

Acknowledgments

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