Computer-aided shape analysis and classification of weld defects in industrial radiography based invariant attributes and neural networks

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Abstract

The interpretation of possible weld discontinuities in industrial radiography is ensured by human interpreters. Consequently, it is submitted to subjective considerations such as the aptitude and the experience of the interpreter, in addition of the poor quality of radiographic images, due essentially to the exposure conditions. These considerations make the weld quality interpretation inconsistent, labor intensive and sometimes biased. It is thus desirable to develop computer-aided techniques to assist the interpreter in evaluating the quality of the welded joints. For the characterization of the weld defect region, looking for features which are invariant regarding the usual geometric transformations proves to be necessary because the same defect can be seen from several angles according to the orientation and the distance from the welded framework to the radiation source. Thus, a set of invariant geometrical attributes which characterize the defect shape is proposed. The principal component analysis technique is used in order to reduce the number of attribute variables in the aim to give better performance for defect classification. Thereafter, an artificial neural network for weld defect classification was used. The proposed classification consists in assigning the principal types of weld defects to four categories according to the morphological characteristics of the defects usually met in practice.

Keywords: Weld defect, invariant attributes, principal component analysis, neuronal classifier.

1. Introduction

The welded joints radiogram often contain defects which the interpreter must identify and quantify, before he decides on their acceptability, by referring to non destructive testing standards and codes [1]. Once the radiographic segmentation was accomplished [2] providing a description in term of regions (defect and background), the problem is then to interpret their contents. It is thus question of determining effective attributes which permit to characterize these defect regions and even recognize them like class elements easily identifiable. In industrial radiography, we can obtain radiograms on which weld defects, if they exist, can have various sizes and orientations. For an example, a crack is identified as crack whatever its size and its orientation may be, and an inclusion is recognized as being an inclusion in spite of its position and its dimension. A major problem in the recognition of such defects is that these defects can be viewed from several angles and this, according to the orientation and the distance of the irradiated welded joint in regard to the radiation source. To characterize a given weld defect represented by its boundary or its region, the simplest attributes which be computed are the area and the perimeter [3]. The latter cannot be used because of their sensitivity to geometric transformations. For this reason, we will employ features which are invariant regardless geometric transformations of translation, rotation and scaling. A set of attributes satisfying the above conditions will be proposed in this paper. These geometric invariant attributes will follow from the calculation of geometric parameters (area, perimeter, etc.) and spatial moments. They will be implemented on binarized images issued from real radiographic films of welded joints [4].

The main idea behind the principal component analysis (PCA) is to represent multidimensional data with less number of variables retaining main features of the data. It is inevitable that by reducing dimensionality some features of the data will be lost. It is hoped that these lost features are comparable with the “noise” and they do not tell much about underlying population [5].

For this purpose, in this work, the principal component analysis technique will be used to reduce the number of the attribute variables.

When the expert knowledge is not explicitly defined or cannot be represented in terms of statistically independent rules, artificial neural networks (ANN) may provide a better solution than expert systems, and they can efficiently learn nonlinear mappings through examples contained in a training set, and conduct complex decision making [6]. Then, the ANN can be effectively updated to learn new features.

In this paper, a feed forward neural network trained by the backpropagation algorithm [7] will be used for the weld defect classification task [8]. This neuronal classification consists in assigning the usual types of weld defects met in practice to four categories according to their morphological characteristics.

Other work was the subject of the use of ANN in the radiographic testing area. Authors in [9] and [10] use ANN in the weld defect segmentation in edges and regions respectively. ANN were also used in the planer and volumetric weld defect classification using Hu’s invariant moments as features [9]. The authors in [11] combined the ANN with data mining for the weld defect detection.
2. Quantitative analysis of weld defect

2.1 Morphological attributes

For each weld defect, the geometric parameters: (Area \((A)\), perimeter \((P)\) \cite{12}, centre of gravity \(G(x, y)\), angle of orientation \((\alpha)\), principal axes of inertia, width \((W)\) and length \((L)\) of the surrounding rectangle, maximal diameter \((D_{\text{max}})\), radius of maximal inscribed circle \((R_{\text{max}})\), partial areas \((S_1, S_2, S_3, S_4)\), semi major and semi-minor axes \((a, b)\) of the image ellipse) are computed (see Figure 1).

![Figure 1. Illustration of the geometric parameters](image)

2.2 Geometric invariant attributes

The below definite geometric attributes are invariants regardless translation, rotation and scaling.

- **Compactness** (\(\text{Comp}\)): \[\text{Comp} = 4\pi A / P^2\] (1)
- **Elongation** (\(\text{Elong}\)): \[\text{Elong} = L / W\] (2)
- **Rectangularity** (\(\text{Rect}\)): \[\text{Rect} = A / (LW)\] (3)
- **Anisometry** (\(\text{Ani}\)): \[\text{Ani} = a / b\] (4)
- **Symmetry** (\(\text{Sym}\)): \[\text{Sym} = \text{Sym}H \times \text{Sym}V\] (5)

where \(\text{Sym}V\) and \(\text{Sym}H\) are given by this algorithm:

\[
\begin{align*}
\text{if} \ (S_4+S_3)<(S_1+S_2) \ \text{then} \quad \text{Sym}V &= (S_4+S_3) / (S_1+S_2); \\
\text{else} \quad \text{Sym}V &= (S_1+S_2) / (S_4+S_3); \\
\text{if} \ (S_2+S_3)<(S_1+S_4) \ \text{then} \quad \text{Sym}H &= (S_2+S_3) / (S_1+S_4); \\
\text{else} \quad \text{Sym}H &= (S_1+S_4) / (S_2+S_3); \\
\end{align*}
\]

**Lengthening index** \(\text{I}_a\): \[\text{I}_a = \pi \times D_{\text{max}}^2 / 4A\] (6)

**Deviation index to inscribed circle** \(\text{Ir}\): The indicia value is maximal (near to 1) for lengthened defects and minimal (near to 0) for round defects.

**Invariant moments** \((\Phi_1, \Phi_2)\): They gives measures in relation with the pixel spreading in comparison with the centre of mass.

\begin{align*}
\Phi_1 &= \eta_{20} + \eta_{02} \\
\Phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2
\end{align*}

where \(\eta_{pq} = \mu_{pq} / \mu_{00}^{1-p+q/2}\) \(p+q = 2, 3, ...\) are the normalized central moments \cite{13} and

\[
\begin{bmatrix}
\mu_{20} &= \sum(x^2) - \bar{x}^2 \\
\mu_{02} &= \sum(y^2) - \bar{y}^2 \\
-\mu_{11} &= \sum(x(y) - \bar{x}\bar{y}) \\
\mu_{00} &= \sum(y^2) - \bar{y}^2
\end{bmatrix}
\]

is the covariance matrix of the object.

We show in Figure 2 an example of a weld defect extracted from a welded joint radiographic film \cite{2,14}. The entire set of weld defects used as data for invariant attribute computation is illustrated in Appendix.

![Figure 2. A welded joint radiographic film with a defect](image)

2.3 Relationship between the proposed invariant attributes and weld defect types

- **Compactness** (\(\text{Comp}\)): Its value is included in [0,1]. It has little values for sharp defects (crack, lack of fusion) and big values for spherical defects (porosity, etc.).
- **Elongation** (\(\text{Elong}\)): It describes the occupied area in the bounding box of defect. Big values of this attribute characterize longitudinal defects (crack, lack of fusion, lack of penetration, elongated porosity, undercut, etc.).
- **Rectangularity** (\(\text{Rect}\)): Its value is included in [0,1]. It is equal to 1 for a rectangle. It characterizes rectangular defects (lack of penetration).
- **Anisometry** (\(\text{Ani}\)): It uses metrics from the equivalent ellipse image and is proportional to defect lengthening.
- **Symmetry** (\(\text{Sym}\)): Its value is included in [0,1]. The value 1 describes a perfectly symmetrical shape. An asymmetrical defect (slag inclusion, warm holes, etc.) can be related by little values of this attribute.
- **Lengthening index** (\(\text{I}_a\)): Big values of this indicia put in obviousness fine and rectilinear cracks.
- **Deviation index to inscribed circle** (\(\text{Ir}\)): The indicia value is maximal (near to 1) for lengthened defects and minimal (near to 0) for round defects.
- **Invariant moments** (\(\Phi_1, \Phi_2\)): They gives measures in relation with the pixel spreading in comparison with the centre of mass.

2.4 Invariance of the proposed attributes

In order to show the invariance performance of the proposed attributes, usual geometric transformations are applied on \(Df_{23}\) shown in Appendix.

![Figure 3. Df_{23} attributes and its geometric transforms](image)
Invariant attributes are computed and compared between those of original image and those of its transforms. The logarithm of $\Phi_1$ and $\Phi_2$ are taken to reduce the dynamic range. As shown in histograms (see Figure 3), the results for geometrically transformed images are in reasonable agreement with the invariants computed for the original image. The major cause of error can be attributed to the digital nature of the data.

2.5 Normalization of the attribute values

Because the different raw geometric attributes have values ranging from the order of 0 to 200, the features were rescaled to lie between 0 and 1, to avoid the effects of the larger features “swamping” those of the smaller features and possible numerical errors caused by a large range in values. This was done for each data using the maximum and minimum values for each attribute as observed in the data set, i.e.

$$\Gamma_j = \frac{A_i - \min(A_i)}{\max(A_i) - \min(A_i)}$$  \hspace{1cm} (9)

with $A_i$: compactness, elongation, ..., $\Phi_2$ and $\Gamma_j$: rescaled compactness, ..., rescaled $\Phi_2$

The choice of max and min values to use for scaling data is difficult. The most obvious choices are the maximum and minimum values observed over the entire data set. However, in this experiment we are attempting to train a classifier on one data set and test it on a completely unseen test set. Therefore, it should be made sure that the values max and min represent really the extreme cases of the attribute in question, and that they are related to a physical significance of the shape of the defects to characterize.

2.6 Dimensionality reduction of the attribute vector based PCA

With an aim of reducing the number of variables representing the attributes, the first result interesting to analyze is the correlation matrix of the attribute variables. However, it would be hazardous to use only the table of the correlations to eliminate the variables which presents a great correlation [15]. It can generate a loss of information. This is why, a set of the variable reduction methods are proposed in the literature. Let us add the fact that the number of measurement for each variable plays a significant role in the correlation calculation between the different attribute variables. In our study, PCA is used to extract dominant features (principal components) from the initial data set. This latter is formed into a column vector $\Gamma_n$, whose length $N$ is depending on the number of individuals (weld defect). For $M$ attribute variables, we will have an array matrix $\Gamma$ with the size of $M \times N$. Therefore, we have

$$\Gamma = [\Gamma_1, \Gamma_2, \cdots, \Gamma_M]$$  \hspace{1cm} (10)

The mean of the column vector $\Psi$ is defined by:

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i$$

The subtracted training set is represented as matrix:

$$\Phi = [\Phi_1, \Phi_2, \cdots, \Phi_M]$$  \hspace{1cm} (12)

The covariance matrix is calculated using

$$C = \Phi \Phi^T$$

The eigenvector of matrix $C$ as $\tilde{\Psi}_i$ with corresponding eigenvalues can be computed by

$$C \tilde{\Psi}_i = \lambda_i \tilde{\Psi}_i \hspace{1cm} (14)$$

Any weld defect can be identified as a linear combination of the eigenvectors. The principal components for any weld defect are defined by:

$$P = \Gamma \tilde{\Psi}_1^T, \tilde{\Psi}_2^T, \cdots, \tilde{\Psi}_L^T$$  \hspace{1cm} (15)

The matrix $P$ with the size of $N \times L$ represents the database into the axis corresponding to the eigenvector. The values of this matrix are the new features that can be used for classification and recognition purposes.

By examining the initial database eigenvalues (see Figure 4), we remark that the four first initial components gives more than 97 % of information on entire observations. Table 1 shows the new matrix where data are projected in the four principal axes. It is pointed out that these components are variables without physical meaning and are not directly observable.

![Figure 4. Eigenvalues and their cumulative variance](image)

3. Weld defect classification based neural networks

The proposed classification assigns the principal types of weld defects presented in Appendix to four categories, considering the shape characteristics of the weld defects usually met in practice. Initially, in the training phase, the weights are initialized with small random values and the network is trained with the feature vectors, representing the standardized invariant attributes or the four principal components resulted by PCA, and their corresponding weld defect categories, of which the selection criteria are developed in the next paragraph.

Each defect category is assigned to a distinct output class. A first set of weld defects is used as learning data in training by backpropagation. After the training stage is accomplished, testing consists simply in propagating the information presented at the input layer to collect the network decision on the output layer. The test set is made up on non learned or unknown defects.
3.1 Choice of the weld defect categories

The invariant attributes designed in § 2.2 characterize only the shape of the defects and cannot discriminate the defects on the basis of other parameters, like the defect image density, the defect position in the weld bead, etc. We associate to this category defects: inclusions, slag inclusions, worm holes, etc.). We associate to this category defects: porosities, tungsten inclusions, etc.).

First category: The defects of which the shape is spherical (exp. solid inclusion, lateral lack of fusion, etc.). We associate to this category defects: the defects of which the shape is irregular (non lengthened and non spherical) (exp. solid inclusion, lateral lack of fusion, etc.). We associate to this category defects: the defects of which the shape is lengthened, smooth and rectangular (exp. lack of penetration, elongated porosities, etc.). We associate to this category defects: Df_11 to Df_18 (see Appendix).

Second category: The defects of which the shape is lengthened, smooth and rectangular (exp. lack of penetration, elongated porosities, etc.). We associate to this category defects: Df_21 to Df_2_25 (see Appendix).

Third category: The defects with spherical shape (exp. porosities, tungsten inclusions, etc.). We associate to this category defects: Df_31 to Df_3_34 (see Appendix).

Fourth category: The defects of which the shape is irregular (non lengthened and non spherical) (exp. solid inclusions, slag inclusions, worm holes, etc.). We associate to this category defects: Df_41 to Df_4_43 (see Appendix).

3.2 Configuration of the used neuronal network

The number of neurons in the input layer corresponds to the feature vector components, used in classification and which is composed of

- the standardized invariant attributes in the one hand: 
  \( \Gamma_{\text{ATT}} = [\text{Comp } \text{Elong } \text{Rect } \text{Anis } \text{Ia } \text{Ir } \Phi_1 \Phi_2] \)

- or the four components representing the invariant attribute vector reduced by PCA, in the other hand: 
  \( \Gamma_{\text{ACP}} = [\text{Comp1 } \text{Comp2 } \text{Comp3 } \text{Comp4}] \).

The disadvantage of the multilayer networks is the lack of theoretical elements making possible to connect on the one hand the number of hidden layers and the number of neurons by layer and on the other hand the type and the complexity of the problem to be treated. There are heuristics [16] to determine the number of neurons in a hidden layer. However, a hidden layer with 10 neurons empirically proved sufficient in the case of our application. The output layer comprises four neurons, each one is affected to recognize one defect category. Before starting the network training, the neurons of the output layer are assigned as shown in Figure 5.

![Figure 5. Configuration of the used neural network](image)

3.3 Experimental results and discussion

Our neuronal classifier must answer to the following steps:

- Divide the data set into a training set and a test set.
- Its performance should be assessed by the classification error on an independent test set.
- Determine a decision boundary by minimising error of the training set.
- Determine the performance by computing the classification error of the test set.

Twelve defects: Df_11, Df_13, Df_14, Df_16, Df_21, Df_22, Df_1_25, Df_31, Df_3_2, Df_41, Df_4_2 and Df_2_42 (see Appendix), are chosen to constitute ANN data base in the training.

### Table 1. Database into the four principal axes

<table>
<thead>
<tr>
<th></th>
<th>Comp1</th>
<th>Comp2</th>
<th>Comp3</th>
<th>Comp4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Df_11</td>
<td>0.5733</td>
<td>0.2451</td>
<td>-0.6800</td>
<td>-0.0861</td>
</tr>
<tr>
<td>Df_12</td>
<td>0.5168</td>
<td>0.4168</td>
<td>-0.8955</td>
<td>-0.4078</td>
</tr>
<tr>
<td>Df_13</td>
<td>0.8332</td>
<td>0.5664</td>
<td>-0.7888</td>
<td>-0.1447</td>
</tr>
<tr>
<td>Df_14</td>
<td>0.7632</td>
<td>0.9038</td>
<td>-0.9075</td>
<td>0.2632</td>
</tr>
<tr>
<td>Df_15</td>
<td>1.8233</td>
<td>1.0398</td>
<td>-0.3081</td>
<td>0.1534</td>
</tr>
<tr>
<td>Df_16</td>
<td>1.9687</td>
<td>1.2552</td>
<td>-0.3071</td>
<td>-0.1325</td>
</tr>
<tr>
<td>Df_17</td>
<td>1.2339</td>
<td>0.2108</td>
<td>-0.0564</td>
<td>0.1093</td>
</tr>
<tr>
<td>Df_18</td>
<td>0.9533</td>
<td>0.7314</td>
<td>-0.8625</td>
<td>0.0847</td>
</tr>
<tr>
<td>Df_21</td>
<td>0.6098</td>
<td>0.5615</td>
<td>-0.8965</td>
<td>0.1331</td>
</tr>
<tr>
<td>Df_22</td>
<td>0.6603</td>
<td>0.9067</td>
<td>-1.1143</td>
<td>0.4951</td>
</tr>
<tr>
<td>Df_23</td>
<td>1.1658</td>
<td>0.6271</td>
<td>-0.5344</td>
<td>0.2795</td>
</tr>
<tr>
<td>Df_24</td>
<td>0.5784</td>
<td>0.5959</td>
<td>-0.9124</td>
<td>0.3593</td>
</tr>
<tr>
<td>Df_25</td>
<td>0.2365</td>
<td>0.7115</td>
<td>-1.1357</td>
<td>0.1815</td>
</tr>
</tbody>
</table>

### Table 2. Neural network training data

<table>
<thead>
<tr>
<th></th>
<th>Init. attributes</th>
<th>04 princ. comp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of iterations</td>
<td>4000</td>
<td>4000</td>
</tr>
<tr>
<td>Learning rate ( \eta )</td>
<td>0.6</td>
<td>0.6</td>
</tr>
<tr>
<td>Learning error</td>
<td>1.76.10^{-5}</td>
<td>5.27.10^{-5}</td>
</tr>
<tr>
<td>Execution time (sec.)</td>
<td>386,18</td>
<td>299,07</td>
</tr>
<tr>
<td>Number of weights</td>
<td>130 (4,95 Mo)</td>
<td>80 (2,44 Mo)</td>
</tr>
</tbody>
</table>
We deduce from Table 2 when the principal components are used as inputs that:

- firstly, the number of synaptic weights is less than the connections of the network trained with the initial attributes which consequently, more than 2.5 Mo in the storage memory are saved and
- secondly, the training stage takes less time of execution. Consequently, we imagine a considerable economy in execution time when bigger weld defect base will be used.

In the testing stage, we present to the neural network the learned defects and a set of non learned (unknown) defects shown in Appendix.

By examining the test results (see Table 3), we can note that all the learned defects correspond to the categories to which are assigned during the training with a precision exceeding:

- 97% for ANN with 9 invariant attributes as inputs
- 96% for ANN with 4 principal components as inputs

To test the non learned defects, we have assigned first to each category a number of weld defects from the testing set by taking in account the opinion of radiograph experts. The testing stage results (see column 2 of Table 3).

Therefore, a test is conclusive if the result of the classification of the non learned defect presented at the classifier corresponds to the class predefined by the radiograph experts. The testing stage results (see Table 6) show us that almost the entire defects presented to the neural network correspond to interpretations decided a priori by the experts, with a precision exceeding:

- 97% (except Df_12 with 84%) for ANN with 9 invariant attributes as inputs. By examining the shape of Df_12 shown in Appendix, we can remark that its rather significant width and pronounced asymmetric shape can relatively move it away from category C1 and bring it to category C2.
- 95% (except Df_45 with 67%) for ANN with 4 principal components as inputs. The precedent remarks are valid concerning the defect Df_12. We add in this case that the defect Df_44 is classified with the accuracy of 99.60% in the category C2 predefined by radiograph, nevertheless the ANN classifies it to the category C1 avec a precision of 40%. This can be justifiable in taking in account the defect shape which can be characterized by certain rectangularity. This last is a decisive attribute for the category C2.

Only one defect Df_23, defined by the experts as being a lack of penetration i.e. belonging to category C3, was classified by the neuronal classifiers in the category C1 i.e. in the category corresponding to cracks, undercut etc.. In fact, the more discriminating attribute between these two classes is the rectangularity. The category C1 is characterized by a weak rectangularity and inversely for C3. For this defect image, the circular shape in its right side and the gradual erosion of its surface influence considerably, among other things, its rectangularity. This shape can be caused by the presence of another weld defect (burn through) and the geometrical blur aspect due the radiographic exposure process. These considerations being taken into account, the defect Df_23 changes category during classification. This is why; a radiographic exposure under good conditions will contribute incontestably to the improvement of the radiographic image quality and consequently contribute to the classification accuracy.

### 4. Conclusion and further works

Concerning the quantitative analysis of the weld defect images thus extracted, the major problem remains how to build a set of attributes which characterize the most accurately possible these defect regions, while taking in account the specificities of the defects that they represent, the subjectivity and the risks of their interpretation. This is why, it may be that only one attribute plays a decisive role in the discrimination of two defect classes, really distinct, either by the cause of their occurrence or by the severity of the codes and standards in their interpretation.

The objective of quantitative analysis step is to research attributes which characterize the weld defect images according to two criteria:

- Maximal discrimination: Different defect shapes give different values of a given attribute.
- Minimal redundancy: An attribute don’t vary in the same way that another for a given defect shape.

### Table 3. Classification accuracy of weld defects

<table>
<thead>
<tr>
<th>Initial attributes</th>
<th>(04) principal comp.</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Df_11</td>
<td>98.08 1.78 0 1.69</td>
<td>97.73 2.85 0 0.36</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Df_13</td>
<td>99.98 0.31 0.01 0</td>
<td>100 0.12 0 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Df_14</td>
<td>97.98 2.05 0.7 0.25</td>
<td>97.55 2.49 0 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Df_16</td>
<td>100 0 0.02 0</td>
<td>100 0.01 0 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Df_21</td>
<td>2.76 96.93 0.02 0.01</td>
<td>3.24 96.07 0 0.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Df_22</td>
<td>0.01 99.93 0.2 0</td>
<td>0.02 99.87 0 0.01</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Df_25</td>
<td>0 99.89 0.11 1.54</td>
<td>0 98.11 0.01 3.24</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Df_31</td>
<td>0.1 0.01 99.78 0.03</td>
<td>0 0.03 99.70 0.16</td>
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</tr>
<tr>
<td>Df_32</td>
<td>0.08 0.01 97.79 2.05</td>
<td>0 0.03 97.83 2.17</td>
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<tr>
<td>Df_41</td>
<td>0.02 1.56 1.71 7.76</td>
<td>0.1 0 97.95 0</td>
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<tr>
<td>Df_42</td>
<td>0.03 0.73 1.33 98.37</td>
<td>0 0.66 98.64 0</td>
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<tr>
<td>Df_43</td>
<td>0.25 0.06 0.54 94.41</td>
<td>0 2.61 1.81 96.78</td>
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<tr>
<td>Df_12</td>
<td>84.83 0.76 0 24.79</td>
<td>95.49 0.09 0 28.13</td>
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<tr>
<td>Df_13</td>
<td>100 0 0.37 0</td>
<td>100 0.04 0 0</td>
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<tr>
<td>Df_14</td>
<td>100 0 0.02 0</td>
<td>100 0.12 0 0</td>
<td></td>
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</tr>
<tr>
<td>Df_15</td>
<td>99.94 1.42 0.06 0.99</td>
<td>99.99 0.2 0 0</td>
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<tr>
<td>Df_23</td>
<td>0.07 99.82 0.03 0.01</td>
<td>0.06 99.84 0 0.03</td>
<td></td>
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<tr>
<td>Df_24</td>
<td>0.19 96.98 0.01 0.69</td>
<td>0.12 98.13 0 1.22</td>
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<td>Df_25</td>
<td>0.09 0.03 99.87 0.01</td>
<td>0 0 99.75 0.08</td>
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</tr>
<tr>
<td>Df_33</td>
<td>0.16 0.01 99.83 0.01</td>
<td>0 0 99.75 0.11</td>
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<tr>
<td>Df_34</td>
<td>0.1 0.01 99.65 0.08</td>
<td>0 0 99.58 0.27</td>
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<tr>
<td>Df_41</td>
<td>1.75 0.06 0.09 98.46</td>
<td>0 17.92 0.58 95.31</td>
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<tr>
<td>Df_42</td>
<td>0.83 1.14 0.01 99.12</td>
<td>0.01 40.55 0.02 99.66</td>
<td></td>
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<tr>
<td>Df_43</td>
<td>0.03 0.41 3.43 97.84</td>
<td>0 2.57 4.22 67.06</td>
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variable reduction of these attributes must be done judiciously, by taking into account the number of individuals (defects) and the detailed analysis of the correlations between the various variables. The PCA technique permits to reduce the raw attribute vector to give a vector with four (04) non correlated components which present more than 97% of information and which are more suitable to use in the classification.

In the weld defect classification in shape categories, we try to classify the weld defects in four categories representing the principal shapes of defects usually met in practice. Thus, a comparative study is made between two neuronal classifiers using as input data:

- Firstly, nine standardized invariant attributes, and
- secondly, four principal components resulted from the application of PCA on the initial data base.

By the light of the obtained results, we remark that the performance of classification in the second case is as satisfactory as that of the first case.

However, the advantage of PCA utilization is that the reduction of the classifier input vector permits to lighten the network architecture and consequently, to have an irrefutable saving in execution time especially in the training phase and in the hard disk memory during the storage of synaptic weights. Currently, the increase of weld defect individuals representing the training and testing neural network data and the classification inside each morphological category based other types of attributes, such as weld defect position in the weld joint, defect gray level mean, etc., are under investigation.

5. References


6. Appendix