Application of Statistical Signal Processing Techniques to Ultrasound Signals for Automatic Microstructural Characterization and Classification

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Abstract
During the gas tungsten arc welding of nickel-based superalloys, the secondary phases such as Laves and carbides are formed in the final stage of solidification. But, other phases such as $\gamma''$ and $\delta$ phases can precipitate in the microstructure, during aging at high temperatures. However, it is possible to minimize the formation of the Nb-rich Laves phases and therefore reduce the possibility of solidification cracking by adopting the appropriate welding conditions. This paper aims at the automatic microstructurally characterizing the kinetics of phase transformations on a Nb-base alloy, thermally aged at 650 °C for 10, 100 and 200 h, through backscattered ultrasound signals at frequency of 4 MHz. For this, a decision support system was designed using statistical signal processing techniques. Indeed, three dimensionality reduction methods; Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) were independently applied on the Discrete Cosine Transform (DCT) coefficients. These dimensionality reduced features were fed to the k-Nearest Neighbor (k-NN) and Decision Tree (DT) classifiers to automatic microstructure characterization. DCT coupled with ICA and k-NN yielded the highest average accuracy of 95.5%. Thus, the proposed decision support system provides high reliability to be used for microstructure characterization through ultrasound signals.

Keywords: Decision Tree, Independent Component Analysis, k-Nearest Neighbor, Linear Discriminant Analysis, Microstructural Characterization, Non-Destructive Inspection, Principal Component Analysis, Ultrasound Signals

1. Introduction
Nowadays, Nb-bearing nickel-based superalloys, in particular Inconel 625, have found a great applicability in different industries including chemical, marine, aerospace, and specially in highly corrosive environments such as oil and gas industry [1-3]. Due to the excellent anti-corrosive properties of Inconel 625, this alloy is used widely in the offshore industry as the weld overlay of carbon steel pipes and also in the other equipment for transporting oil and gas. Nevertheless, it is worth to do further studies on this alloy to increase the overall knowledge about its properties.

During welding of an Inconel 625 alloy, there is an intensive microsegregation of some elements, such as niobium (Nb) and molybdenum (Mo), within the interdendritic regions, causing the supersaturation of the liquid metal with these chemical elements in its final stage of solidification, which results in the precipitation of Nb-rich Laves phase and MC primary carbides of type NbC [4,5]. This segregation and precipitation of the secondary phases can change the mechanical properties of the alloy and decrease its resistance to corrosion [6]. In addition, the Nb-rich Laves phase has a low melting point that causes an increase in the temperature solidification range, making the alloy susceptible to solidification cracking [7]. However, it is possible to minimize the formation of the Nb-rich Laves phases and therefore reduce the possibility of solidification cracking by adopting the appropriate welding conditions. Hence, there is a significant requirement to analysis the process of phase transformation.

Ultrasound testing has been used widely in order to evaluate this kind of material. For instance, these signals were captured to evaluate the mechanism of the spinodal decomposition on the UNSS31803 duplex stainless steel [8], to evaluate the influence of grain refiners on the mechanical properties in a CuAlBe shape memory alloy [9], and in order to evaluate of the phase transformations on a UNSS31803 duplex stainless steel [10], and also were used in many other applications [11-16]. In recent years, artificial intelligence methods have been used widely to characterize the microstructures. For example, procedures such as Multi Layered Perceptron (MLP) [17-19], Kohonen’s self-organizing neural network [20], Support Vector Machine (SVM), Optimum-Path Forest (OPF) classifier [21-23], and also a Probabilistic Neural Network (PNN) classifier with combination of the Linear Discriminant Analysis [25] were used to characterize the microstructures. Nevertheless, still there is a significant requirement to improve the classification accuracy when used for large database. This study proposed and evaluated the performance of an automatic decision support system to microstructurally characterizing the kinetics of
phase transformations on a Nb-base alloy, thermally aged at 650 °C for 10, 100 and 200 h, as well as in the as-welded condition.

It is obvious that the improved classification accuracy significantly impacts the costs. So, the aim of this study is the application of statistical signal processing techniques to design a more practical decision support system in terms of the accuracy. These techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) proved to be efficient methods for microstructural characterization and classification of ultrasound signals as they can reduce the redundancy in the feature set.

The paper is organized as the following way: section 2 presents the dataset used for the analysis. Section 3 describes the general methodology used along with brief description of different methods used. The experimental results and the interpretation of them are presented in section 4, and the paper ends with a conclusion in section 5.

2. Material Used
The database which was used in this study is based on the experimental works of Nunes et al. in [22]. Applied experimental procedures are summarized as follows:

After the welding, the coating was detached, so that the remained material was only the Inconel 625 alloy. Afterward, four samples were obtained from the coating. Three samples were submitted to heat aging treatments at 650 °C for aging times of 10, 100 and 200 h [24], and the remaining one was kept as the as-welded state (0h).

In order to evaluate the effect of aging on these samples, the backscattered ultrasound signal was used. This signal was obtained using a 4 MHz transducer [8,10,12,25] and applying the pulse echo and direct contact techniques [23]. Also, in order to transmit the ultrasound signals to a computer for subsequent processing, a sampling rate of 1 GS/s was used. The database consists of 40 signals with 500 points for each microstructural class, i.e. 160 signals. More information of these experimental procedures can be found in [22].

3. Methodology
Figure.1 shows the block diagram of the proposed decision support system used for the classification of ultrasound signals. In the first step, Discrete Cosine Transform (DCT) acts as a feature extraction method. In the second step, three different statistical techniques are used to reduce statistical redundancy and reveal discriminating features. These statistical feature reduction techniques include: Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA).

The ANOVA test was used to select only the relevant features. Then, these features were fed to the k-Nearest Neighbor (kNN) and Decision Tree (DT) classifiers for automatic microstructural characterization. The details of each of the methods used are explained in the following:

3.1. Discrete Cosine Transform (DCT):
The DCT of a given ultrasound signal which is a sequence of N=500 samples is computed as:
y = Cx

Where x = [x_1, x_2, ..., x_{N-1}] is the input ultrasound signal, y is the output of the transform and matrix C, the DCT coefficients matrix is defined as:

\[ C(n, k) = \frac{1}{\sqrt{N}} \quad , \quad k = 0, 0 \leq n \leq N - 1 \]  \hspace{1cm} (1)

\[ C(n, k) = \frac{\cos(\frac{2N}{2} \frac{2N}{2(n+1)k})}{\sqrt{N}} \quad , \quad 1 \leq k \leq N - 1, 0 \leq n \leq N - 1 \]  \hspace{1cm} (2)

Where C is an orthogonal matrix with real elements [27]. Indeed, the DCT technique extracts the frequency domain information to indicate the microstructural characteristics of an Nb-base alloy. In the next step, these DCT coefficients are independently subjected to dimensionality reduction using PCA, LDA and ICA.

3.2. Principal Component Analysis (PCA):
Principal Component Analysis is a statistical method that is used widely in dimensionality reduction and statistical pattern
recognition [28]. This method projects the data into the directions of highest variability and then selects a smaller number of components, called principal components. Thus, some of the data that are less significant will be discarded. The detailed procedure of computing the principal components is provided below: In the first step, the covariance matrix of the data is computed:

\[ C = (X - \bar{x})(X - \bar{x})^T \]  
(4)

Where \( X \) is the data matrix of DCT coefficients and \( \bar{x} \) is the mean vector of \( X \). \( X \) represents a 140 × 500 dimension matrix, each row of it is a 500 point training pattern (a total of 140 training patterns). Then, the matrix of eigenvectors \( V \) and diagonal matrix of eigenvalues \( D \) are computed as below:

\[ V^{-1}CV = D \]  
(5)

Afterward, the computed eigenvectors are sorted in decreasing order of eigenvalues. Finally, the data matrix \( X \) is projected to principal component domain by taking the inner product of \( X \) and the sorted eigenvector matrix as:

\[ pr(X) = [V^T(X - \bar{x})]^T \]  
(6)

Where \( pr(X) \) is the matrix of projected data into the principal components domain. Indeed, principal components are the elements of a projection matrix where are uncorrelated and ranked by the amount of statistical variance (energy) they retain from \( X \).

3.3. Linear Discriminant Analysis (LDA):
LDA technique is a statistical feature reduction method which projects the input data onto a direction that lead to the highest possible discrimination between different data classes [28]. Thus, this method can be used to reduce the dimensionality of input backscattered signals. The detailed procedure of LDA is explained below:

Step 1: Compute the within class covariance matrix (\( S_W \)) as follows,

\[ m_k = \frac{1}{N_k} \sum_{n \in C_k} x_n \]
\[ S_k = \sum_{n \in C_k} (x_n - m_k)(x_n - m_k)^T \]
\[ S_W = \sum_{k=1}^{K} S_k \]  
(7)  
(8)  
(9)

Where \( x_n \) is the DCT coefficients vector of the \( n \)th training pattern, \( N_k \) denotes the number of training patterns in class \( C_k \) and \( k \) is the number of available classes.

Step 2: Compute the between class covariance matrix (\( S_B \)) as follows:

\[ m = \frac{1}{N} \sum_{n=1}^{N} x_n = \frac{1}{N} \sum_{k=1}^{K} N_k m_k \]  
(10)
\[ S_i = \sum_{k=1}^{\kappa} N_k(m_k - m)(m_k - m)^T \tag{11} \]

Where \( m \) is mean of the all the data.

Step 3: Compute the projection matrix:
\[ W^* = \arg \max \left( (WSW^T)^{-1} (WSW^T) \right) \tag{12} \]

Step 4: Finally, compute the LDA coefficients by the dot product of the input DCT coefficients vector \( x \) with the projection matrix \( W^T \).
\[ y = W^T x \tag{13} \]

Where \( y \) presents the LDA coefficients vector. Indeed, \( y \) is the projection of DCT features vector onto a new direction that maximizes the discrimination between different classes.

3.4. Independent Component Analysis (ICA):

Independent Component Analysis is a statistical method that is used widely for separating the mixed signals into the independent sources. Since both of the mixing system and the initial signals are unknown, this problem can only be solved by using the mixed signals. The ICA model is defined as:
\[ x = A \cdot s = \sum_{i=1}^{n} a_is_i \tag{14} \]

Where \( s \) is the vector of source signals \( \{s_1, s_2, ..., s_n\} \), \( A \) is the weight matrix with elements \( a_{ij} \) and \( x \) represents the vector of mixed signals \( \{x_1, x_2, ..., x_n\} \), which is the only known parameter of this equation.

The purpose of ICA technique is the estimation of source signals \( s \). So, the source signal is expressed in terms of the mixed signals as:
\[ s = W^T x \tag{15} \]

Now, we need to find an estimate of \( W \) for computing the source signals. The FastICA algorithm was used to estimate the \( W \) [29]. After \( W \) is found from the FastICA algorithm, its inverse is computed to get the matrix \( A \).

3.5. K-Nearest Neighbors (k-NN)

The k-Nearest Neighbor classifier is a supervised learning method which uses the k-NN principal [28,30,31]. This technique searches among the training data and finds the closest neighbors to the testing data. Then, according to the class label of these k neighbors, a class label is assigned to the testing data. The k-NN search can be used with many distance based learning functions. The Euclidean distance function is used in this context.

3.6. Decision Tree (DT)

Decision Tree is a supervised method which uses the structure of trees for modeling a decision support system. This classifier uses a simple if-else rule to assign a class label to the each testing data [28,32]. Its tree structure consists of a root node which is divided to child nodes based on the information gain. For this purpose, a test property is defined for each node to select as much as possible pure data. But in terms of formalizing, defining impurity is more convenient rather than defining purity. Thus, the information impurity or deviance is used in this context:
\[ (N) = - \sum_j P_j \log_2 P_j \tag{16} \]

Where \( P_j \) is the ratio of number of patterns at node \( N \) that belongs to class \( j \) to the total number of patterns. According to this equation, a pure node has a deviance of \( 0 \) ((\( N \) = 0). And an impure node has a positive deviance ((\( N \) > 0). Thus, the test property is determined so that the deviance of node (impurity measure) decreases as much as possible and the process of splitting the nodes continues until the deviance of node becomes equal to zero. Once the rules are derived, the testing data is fed to the classifier and the patterns are classified.

3.7. Statistical Tests and Feature Selection:

The statistical ANOVA test computes the mean and variance of different classes and subsequently determine the F index of each particular feature to quantify the amount of discrimination provided by that feature. It means that a more discriminant feature lead to a higher F index. Thus, only the first 5 principal components, the first 3 LDA coefficients and the first 5 independent components were selected for the subsequent stages [33,34].
4. Results and Discussion

Most of the practical ultrasound inspection systems suffer from the low signal-to-noise ratio of ultrasound signals. It is due to the problems such as noise which is generated from acoustic and electronic sources [35]. Specially because of using the backscattered signals in this application (microstructural characterization), this issue is more vital. Therefore, there is an essential requirement to design a processing system which maximizes the efficiency of ultrasound inspection system. For this, the microstructural characterization was carried out using the proposed decision support system in section 3 on the backscattered signals.

The entire dataset is divided into ten sets. Nine sets consisting of 140 signals are used for training the classifier, and the remaining one set consisting of 20 signals is used for testing and performance evaluation of the classifiers. All the procedures were executed on a personal computer with an Intel core 2 Duo at 2.53 GHz and 4 Gb of RAM and windows 8 as the operating system, and using MATLAB 2014a.

In order to evaluate the performance of the classifiers, four common statistical indices [36] were computed in each Fold, Sensitivity (Se), Specificity (Sp), Positive Predictivity (Pp) and Accuracy (Acc):

\[
Se = \frac{TP}{TP + FN} \times 100
\]

\[
Sp = \frac{TN}{TN + FP} \times 100
\]

\[
Pp = \frac{TP}{TP + FP} \times 100
\]

\[
Acc = \frac{TP + TN}{TP + TN + FP + FN}
\]

Where,

\[TP = \text{True Positive} = \text{The number of samples correctly classified as belonging to a given class}\]

\[FP = \text{False Positive} = \text{The number of samples incorrectly classified as belonging to a given class}\]

\[TN = \text{True Negative} = \text{The number of samples correctly classified as not belonging to a given class}\]

\[FN = \text{False Negative} = \text{The number of samples incorrectly classified as not belonging to a given class}\]

These obtained results indicate the applicability of the proposed decision support system in accurate classification of microstructural classes.

Results of using the proposed decision support system in microstructural classification regarding the thermal aging at 650 °C is tabulated in Table. 1. This table provides the sensitivity, specificity, positive predictivity and the accuracy rate of classifying the microstructural classes on ultrasound backscattered signals at 4 MHz.

It can be observed from Table. 1 that the k-NN classifier which is fed from the ICA features, provides the highest sensitivity, and the DT classifier which is fed from the PCA features, provides the lowest sensitivity. Also, it can be seen that the k-NN classifier which is fed from the ICA features, and the DT classifier which is fed from the PCA features, provides the highest and the lowest specificity respectively. Figure. 2 shows the boxplot of accuracy for 10-Fold of different classifiers and different feature reduction techniques. It can be noted that k-NN classifier which is fed from the ICA features, provides the highest accuracy, whereas DT classifier which is fed from the PCA features, provides the lowest accuracy.

Considering these results, it can be seen that the signal processing chain of DCT, ICA and k-NN classifier provides the highest average performance with sensitivity of 95.0%, specificity of 98.3%, positive predictivity of 95.1% and accuracy of 95.5%.

It is worth to note that the lowest positive predictivities belong to the classification of 10 and 100 h classes. These results are verified by the experimental researches and microstructural SEM analysis which was conducted by Nunes et al. in [22]. Indeed, the microstructural SEM analysis showed that the time period between 0 and 100 h corresponds to the formation and partial dissolution of the Laves phases, and the time period from 100 to 200 h corresponds to the cuboidal precipitation rich in Ti and Nb, it means that two microstructure types were involved [23]. Finally, the delta-phases were completely dissolved in 200 h.

Based on the obtained results, the following inferences can be made:

1. Among the applied dimensionality reduction methods of this research, ICA performs better than LDA, and LDA performs better than PCA.

Based on the obtained results, the following inferences can be made:

Table. 1. Classification results (mean±SD)
provides the highest possible discrimination between different classes which can lead to a higher classification accuracy than PCA method. Besides, the PCA and LDA techniques explore the second order statistics and thus remove the statistical correlation between the DCT coefficients. But, the ICA technique uses also higher-order statistics and thus provides the statistical independency. In fact, the higher-order statistics can reveal more significant information of DCT coefficients and thus can lead to more discriminant features and subsequently a higher classification accuracy. All of these notions are verified by the experimental results of this research.

(2) k-NN classifier provides a higher classification accuracy than DT classifier. The obtained results showed the relative superiority of k-NN classifier than DT classifier. However, k-NN classifier requires more computations than DT classifier. Because the algorithm of k-NN search must compute the distance and sort all the training data at each prediction, which can be slow if there are a large number of training examples. But, by considering the intended application of this study which demands a high rate of accuracy, it is obvious that the k-NN classifier outperforms the DT classifier.

1. Conclusion
This article proposed and evaluated the efficiency of an automatic decision support system to microstructurally characterizing the kinetics of phase transformation on a Nb-base alloy, thermally aged at 650 °C for 10, 100 and 200 h, as well as in the as-welded condition, through the backscattered ultrasound signals at frequency of 4 MHz. For this, the frequency domain information (DCT coefficients) of ultrasound signals were subjected to the three different statistical techniques (PCA, LDA and ICA) to reduce the statistical redundancy and reveal discriminating features. In order to classifying these features, the k-NN and DT classifiers were used. The applied statistical techniques were able to reveal the underlying characteristics of microstructures.

Some of the significant notes of this study are as following:

<table>
<thead>
<tr>
<th></th>
<th>Se (%)</th>
<th>Sp (%)</th>
<th>Pp (%)</th>
<th>Acc (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>k-NN</td>
<td>54.8±3.1</td>
<td>60.8±2.3</td>
<td>57.3±2.2</td>
</tr>
<tr>
<td></td>
<td>DT</td>
<td>50.8±3.3</td>
<td>54.0±2.6</td>
<td>52.1±3.6</td>
</tr>
<tr>
<td>LDA</td>
<td>k-NN</td>
<td>90.6±2.3</td>
<td>96.7±2.6</td>
<td>87.8±1.8</td>
</tr>
<tr>
<td></td>
<td>DT</td>
<td>86.3±2.0</td>
<td>90.1±1.9</td>
<td>84.1±1.6</td>
</tr>
<tr>
<td>ICA</td>
<td>k-NN</td>
<td>95.0±0.0</td>
<td>98.3±1.3</td>
<td>95.1±3.9</td>
</tr>
<tr>
<td></td>
<td>DT</td>
<td>92.2±1.2</td>
<td>97.1±2.1</td>
<td>92.1±5.8</td>
</tr>
</tbody>
</table>

Figure 2. The boxplot of accuracy for 10-Fold of different classifiers and different feature reduction techniques (650 °C)
The applied statistical techniques (especially the Independent Component Analysis) were adequate to reveal the underlying characteristics of microstructural changes in the Inconel 625 alloy. Indeed, these techniques were able to detect the phase transformation kinetics considering the different thermal aging times and also the formation of secondary phases during the welding process.

It was shown that ICA with combination of k-NN classifier perform the highest average accuracy, sensitivity and specificity of 95.5%, 95.0% and 98.3% respectively. Besides, PCA did not have a successful performance in ultrasound signal classification.

It was shown in this study that the ICA technique is a useful method to reduce the statistical redundancy in the set of features and consequently is an efficient method for ultrasound signals compaction. Indeed, only five ICs were enough to extract discriminant information, which means a reduction of 100 times in DCT coefficients of backscattered ultrasound signals.

The procedure of classification was carried out using the k-NN and DT classifiers. The obtained results indicate that the k-NN classifier outperforms the DT classifier. High performance and accurate results showed that the statistical signal processing techniques are able to assess the aging conditions. Indeed, it was shown that the proposed decision support system is able to detect the best time of servicing, which significantly impacts the costs and maintenance time.

References


