Support Vector Machines Applied to the Identification of Carburized HP Steels Using Ultrasonic Non-Destructive Testing

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Abstract. Pyrolysis furnaces are used for hydrocarbon cracking in the petrochemical industry. The chemical composition (Fe-Ni-Cr) guarantees resistance to high temperatures even with the reduced thickness of the tube. Unfortunately, the high temperatures are very aggressive to the tubes that operate inside those furnaces and due to the carburization phenomenon the level of chrome dissolved in the alloy reduces drastically at very high temperatures. This implies on severe reduction of both the creep resistance and the weldability. These factors encourage the development of studies in the area of non-destructive testing to ensure the integrity of those components. Magnetic non-destructive techniques are traditionally used on the monitoring of the furnace tubes. The production of chrome carbide in the carburization process modifies the magnetic properties in the metallic alloy. However, those methods are essentially empiric and only provide qualitative information about the carburization condition. Non-destructive testing using ultrasonic waves is widely applied in the industry in problems such as the analysis of corrosion effects and weld inspections. Ultrasound testing appears as an interesting alternative to magnetic analysis in the quantitative characterization of thermal damages in furnaces tubes, as it may provide detailed information on the possible extent of the damage. For proper ultrasound evaluation it is required to obtain the backwall echo. In this work Support Vector Machines (SVM) and the Discrete Fourier Transform were applied to pulse-echo ultrasound signals in order to predict the condition of samples with different levels of thermal damage obtained from pyrolysis tubes. The presence of thermal damages in the samples was confirmed by optical microscopy analysis. Feature selection techniques were employed to reduce the dimensionality of the data and increase the system efficiency. Initially is presented a method using SVM for the case of two classes separated by a kernel mapping. As a second approach, SVM was used for the case of multiclass data sets (considering multiple damage levels). The proposed technique presented high efficiency in the discrimination of the level of damage.
Introduction

Pyrolysis furnaces are tubular reactors connected together by means of bends and heads. These equipments are frequently exposed to high temperatures and low pressures causing to produce unsatured hydrocarbons such as ethylene. The furnaces have in their composition many stainless steel tubes (from type HP) made of Fe-Ni-Cr [1].

There are many ways of damaging the furnaces: creep, strain, erosion, corrosion and overheating caused by eventual misoperation. Due to the high operation temperatures, the chrome content in the metallic alloy highly decreases. This phenomenon is known by carburization. The consequence is not only a considerable reduction in the resistance to fluency, but also ductility and weldability losses. All these factors would contribute to the development of studies in the area of nondestructive testings with the purpose of controlling these components’ integrity [2,3].

Magnetics nondestructive testing techniques are traditionally used on these furnaces monitoring. The creation of chrome carbides in the carburization process modifies the metallic alloy magnetic properties. However, these methods are essentially empirics, and only return qualitative information about the alloy’s carburization level [1].

The aim of this work is to design an automatic classifying system fed from ultrasonic nondestructive testing signals to identify different levels of carburization in HP steels. To that end, it will be applied the Discrete Fourier Transform for signal pre-processing and a Support Vector Machine (SVM) for pattern classification.

1. Fundamental Background

1.1 Ultrasound nondestructive testing

Ultrasound nondestructive testing (UT) is widely used in the industry. This type of testing makes possible to identify corrosion, to detect laminar defect and to perform weld evaluation [2]. Acoustic waves in frequencies higher than the audible range are applied to the test object and the analysis of the received echoes allow to characterize the material internal characteristics [3].

Ultrasound nondestructive testing often uses piezoelectric materials such as lithium and quartz for the transducers. In this case, the vibration of the piezoelectric crystals produces ultrasound waves when they are connected to an AC electric source [4,5].

UT presents some benefits when compared to other nondestructive testing procedures (such as radiographic testing or penetrating liquid) due to its high penetration, which allows finding deep discontinuities and a simply and human-safe execution procedure [4,5].

1.2 Fourier Transform

The Fourier Transform (FT) technique is widely used to access frequency-domain characteristics of signals originated in ultrasound testing. The Discrete Fourier Transform (DFT) is a discrete-time version of FT and may be given by the Equation 1 [3].

\[ X[m] = \sum_{n=0}^{N-1} x[n].W^{mn} \]  

for \( m= 0,1,...,N-1 \), \( x[n]=x(nT) \) for \( n=0,1,...,N-1 \) \( e W = e^{\frac{-j2\pi}{N}} \). Let be \( X[m] = X_d(\omega_m) \).

Besides, \( \omega_m = m \frac{2\pi}{NT} \) with \( m \) called frequency index.

The Fast Fourier Transform (FFT), which is an efficient computational implementation of the DFT, was applied in this work.
1.3 Support Vector Machines

The Support Vector Machine (SVM) has the capacity to solve multidimensional data classification problems among two or more classes using optimal hyper-plane separation. A hyper-plane that divides data and maximizes the distance between the hyper-plane and the class data clusters is called an optimal hyper-plane [5].

The SVM, as any other classifier, may be related to a function f that receives an input x and returns a prediction y. Generally, an induction process is used in the training procedure obtaining possible solutions from the set of examples [1,6,7].

Considering the problem of separating the data x into two classes:

\[ D = \{ (x^1, y^1), \ldots , (x^l, y^l) \}, x \in \mathbb{R}^n, y \in \{-1,1\}, \]

using the canonical hyperplane (Eq. 3):

\[ \min_{||w||} \{ (w, x) + b \} = 1 \]  

To be defined as separating hyperplane, it has to satisfy the following constraints [7]:

\[ y^i ((w, x^i) + b) \geq 1, \quad i = 1, \ldots, l. \]  

The distance \( d(w, b; x) \) between the hyperplane \( (w, b) \) and the point \( x \) may be defined as:

\[ d(w, b; x) = \frac{|(w, x^i) + b|}{||w||} \]  

The optimal hyperplane maximizes the margin, \( \rho \), subject to the constraints of Eq. 4. The margin may be defined as [7]:

\[ \rho (w, b) = \min_{x,y=-1} d(w, b; x^i) + \min_{x,y=1} d(w, b; x^i) \]  

Therefore, the hyperplane that optimally separates the data minimizes \( \phi \) [7]:

\[ \phi(w) = \frac{1}{2} ||w||^2 \]  

In case of the classes that are not divisible by hyper-planes, it is common to use Kernel functions to map the dataset and model the hyper-plane in a way that the classifier may fit in different data cluster organizations. These functions map the input dataset into a feature space of higher dimension in which it usually turns easier to perform linear separation of the classes of interest [8,9,10].

In this work were used three different kernel functions: linear, quadratic and polynomial. Depending on the chosen function different results were obtained.

The dataset was divided in two groups: train and test. The training stage adjusts the classifier parameters to return a good generalization capacity. Training is the process of induction of a classifier based on a specimen. In the testing stage, it is inserted a subset of data with different samples to verify the classification performance [2,5,6]. The validation samples are used during the training procedure to avoid overtraining.

2. Methodology

2.1 Microstructural Analysis

Three samples were extracted from the tubes for optical microscopy analysis. After extraction they were polished and etched with acqua regia. The samples were observed with 300X of magnification from the inner to outer tube wall. Both the morphology and volume fraction of the precipitates were analyzed in order to establish their carburization degree.
2.2 Ultrasonic and Signal Processing Inspection

The data acquisition by pulse-echo ultrasound inspection was the first step. It was made in a way to collect only the background echo from each component. The specimens correspond to the sample of tubes from different carburization levels and it is displayed on Table 1.

It has been collected 200 signals from each class (level of carburization) with 2500 points per signal (by a sampling rate of 100Ms/s), which sums 600 signals to be classified. Past the acquisition, it will be started the digital processing of the data. All steps of signal analysis, extraction, selection and classification were made with the aid of Matlab.

<table>
<thead>
<tr>
<th>Tubes</th>
<th>Thickness (mm)</th>
<th>Diameter (mm)</th>
<th>Level of carburization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tube 1</td>
<td>7,9</td>
<td>6,9</td>
<td>Not carburized</td>
</tr>
<tr>
<td>Tube 2</td>
<td>7,2</td>
<td>6,20</td>
<td>Low carburization level</td>
</tr>
<tr>
<td>Tube 3</td>
<td>7,0</td>
<td>6,19</td>
<td>High carburization level</td>
</tr>
</tbody>
</table>

The classifier input data will be contained in two approaches. The first one uses the untreated signal on the time domain. The other one uses the Discrete Fourier Transform and then remove irrelevant information. The classifying system used was the SVMs for both binary and multiclass cases. The classifier parameters were adjusted in a way to return best performance.

3. Results

3.1 Microstructural Analysis

Figure 1 shows the microscopy of the three tubes. In Figure 1a the carburization doesn’t appear. In Figure 1b, the volume fraction of the precipitates increased, denoting the presence of a moderate carburization. In figure 1c, the coalescence of the precipitates and a higher volume fraction denotes a severe degree of carburization.

![Microscopy images](image_url)

**Fig.1** - Microscopy images from samples extracted of the three tubes: a) No carburized; b) Low carburization and c) High carburization.
The available data set was split into training and validation/testing sets (using 70% and 30% of the signatures, respectively). An attempt to classify the data using time domain (raw) information was initially made. As shown in Fig.2, for typical signals, it was not possible to identify the differences among the classes of interest by analyzing the time domain signals.

![Figure 2: Typical signal in time domain: (a) Tube 1, (b) Tube 2, (c) Tube 3](image)

Considering this, frequency-domain information was used to feed the automatic classifiers. Initially, to determine the number of DFT coefficients to be used in the classifier, the FFT algorithm was applied. The typical frequency spectrum for different classes is shown in Fig. 3. Note that the biggest amount of energy is concentrated in the first 200 coefficients.

![Figure 3: Typical spectrum for all classes: (a) Not carburized sample, (b) Low carburization sample, (c) High carburization sample.](image)

Due to superposition of information, it is very plausible that it is not possible to unbundle classes only by analyzing its frequency spectrum as shown in Fig.3.

3.2 Binary Classifier

Two ways were used to measure the classifier performance in splitting classes: confusion matrix and efficiency product.

The efficiency product (EP) is defined by the geometric mean from the efficiencies \( E_{fi} \) for each class as shown in the Equation 8.

\[
PE = (E_{f1} \times E_{f2} \times \ldots \times E_{fn})^{1/n}
\]  
(8)
The confusion matrix elements \((c_{ij})\) means the quantity (usually in \%) of signals from class \(j\) identified by the classifier as belonging to class \(i\). Thus, the main diagonal symbolize the efficiencies \((c_{ii} = E_i)\) and the elements out of the main diagonal show the classifying mistakes. When the maximum efficiency is reached, the confusion matrix turns to a diagonal matrix.

A Kernel function has such an important role in the classifier performance. Thereby, in the testing stage, different Kernels were applied in the binary machine in order to check their performances. As mentioned before, 200 DFT coefficients were used in the classifier input. The Table 2 shows the mean values of efficiency for each class considering different Kernels.

<table>
<thead>
<tr>
<th></th>
<th>Polynomial</th>
<th>Linear</th>
<th>Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not carburized x others</td>
<td>83,31%</td>
<td>83,13%</td>
<td>89,11%</td>
</tr>
<tr>
<td>Low carburization x others</td>
<td>90,19%</td>
<td>92,73%</td>
<td>92,92%</td>
</tr>
<tr>
<td>High carburization x others</td>
<td>91,00%</td>
<td>91,93%</td>
<td>93,41%</td>
</tr>
</tbody>
</table>

From Table 2, it is clear that the kernel function that achieved the highest efficiency was the quadratic.

In order to properly define the number of input DFT coefficients, the SVM classifier was fed from different numbers of inputs. Table 3 shows the performance of the classifier versus different numbers of coefficients.

<table>
<thead>
<tr>
<th></th>
<th>50 coefficients</th>
<th>100 coefficients</th>
<th>200 coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not carburized</td>
<td>82,73%</td>
<td>92,82%</td>
<td>89,11%</td>
</tr>
<tr>
<td>Low carburization</td>
<td>77,73%</td>
<td>91,93%</td>
<td>92,92%</td>
</tr>
<tr>
<td>High carburization</td>
<td>90,73%</td>
<td>94,80%</td>
<td>93,41%</td>
</tr>
</tbody>
</table>

From this analysis, it’s possible to conclude that while using 100 coefficients the greater efficiency was achieved. The highest efficiency was obtained for separating tube 3 from others. The EP achieved was 94,80% using 100 coefficients. The confusion matrix obtained for this case is shown in Table 4.

<table>
<thead>
<tr>
<th></th>
<th>Output Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real class</td>
<td>High carburization</td>
</tr>
<tr>
<td>High carburization</td>
<td>93,07%</td>
</tr>
<tr>
<td>Other classes</td>
<td>9,67%</td>
</tr>
</tbody>
</table>
3.3 Multiclass Classifier

This classifier aims to separate all the classes simultaneously. Just like in the binary case, 70% of the dataset were considered for training stage and 30% for testing stage.

Employing the same approach, 100 coefficients were used in the FFT and the Kernel function was the quadratic as well. The confusion matrix related to this classifier is shown in Table 5. The EP obtained for 100 coefficients of FFT was 86.5%.

<table>
<thead>
<tr>
<th>Detected Class</th>
<th>Real class</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Not carburized</td>
<td>Low carburization</td>
<td>High carburization</td>
</tr>
<tr>
<td>Tube 1</td>
<td>83.33%</td>
<td>5.00%</td>
<td>10.83%</td>
<td></td>
</tr>
<tr>
<td>Tube 2</td>
<td>11.33%</td>
<td>91.67%</td>
<td>4.51%</td>
<td></td>
</tr>
<tr>
<td>Tube 3</td>
<td>7.00%</td>
<td>3.33%</td>
<td>84.66%</td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Multiclass confusion matrix.

4. Conclusions

The support vector machines differ from other classifiers in its generalization capacity. In this work, the SVM classifier successfully identified the classes of interest in both binary and multiclass cases. Establishing a comparison between the binary case and the multiclass case, it was evident the compliance of the results, once they got similar EPs, showing about 95% for binary and 87% for multiclass. In the future works, the system can be improved using Fuzzy techniques implementation in the SVMs and also considering to perform feature selection using principal component analysis.

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References