An Automated System for Surface Damage Detection Using Support Vector Machine

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Abstract:

The global objective of this paper was to build an automated prediction system for surface damage. Practically, the damage initiates from the free surface because of the high-stress concentration that presents in valleys of the surface profile. Hence, the surface condition is a major factor in the fatigue strength of the metal. In this paper, the surface condition has been measured using an optical confocal measurement system (Alicona). Arithmetical mean height and Surface Flatness have been selected as input data source for the machine learning model. The machine learning model was built using the Support Vector Machine method. The role of this model is to select the best surface parameters to detect surface damage. The results show that the Surface Flatness parameter provides better prediction for surface damage than the Arithmetical mean height parameter.

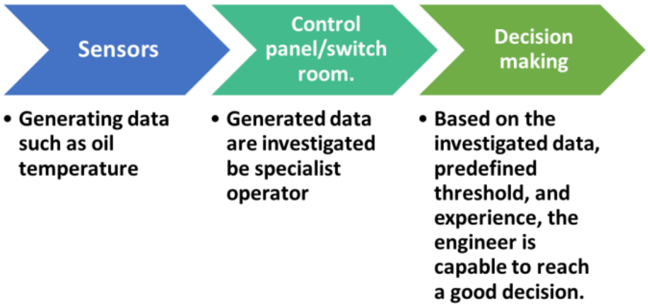
Keywords: Surface damage, Optical confocal, Arithmetical mean height, Surface Flatness, and Support Vector Machine.

1. Introduction

All mechanical structures contain defects at the Nano/microscale level, which are usually hidden and may have been produced during the manufacturing process. Identification of a fatigue failure at an initial stage is a challenging task and hence prediction of onset of the next stage is uncertain and may often be ambiguous. Practically, a structural component must be replaced or repaired once the damage size reaches a predefined threshold risk, often a mechanical structure could be put in service before the threshold risk limit. This concept is known as damage tolerance in the discipline of mechanical engineering, where dam- age tolerance of a structure can be assessed by health monitoring that defines the critical damage level of the structure under consideration. In other words, the damage size must to have a strict definition, where the structure is effectively non-operational [1,2,3].

In previous decades, due to the lack of information on micro-scale damage of a system, it was difficult to predict the degradation of system performance. However, after developing the strategies of a health monitoring system, the damage at different stages can be detected and accounted for, so that the structural performance can be improved and the probability of unexpected structural failure are significantly reduced [4]. In engineering applications, monitoring is a continuous process, where the actions are needed to assure structural integrity and system performance of the process. Generally, monitoring is a continuous activity, where maintenance events or alerts can be initiated based on monitored information. Thanks to the time-dimension of monitoring, which enables us to obtain information for current and previous state respectively or to maintain the nominal condition of the system. Thus, maintenance events or alerts can be initiated based on monitored information [5,6].

The information on health monitoring is generated by data acquisition from sensors embedded in the system. Alarms/warnings systems are built based on the significance of the measured data deviation from nominal measurements. Usually, monitoring decisions are based on predefined threshold values, signal analysis, statistics algorithms, and assessment of the monitoring system. Fig.1 shows sequences of a process that are often used in industries plants [7]. Since the end of the last century, researchers and engineers have developed a structure monitoring system in different engineering fields (e.g, civil, mechanical, aerospace, electrical, and communication). Health monitoring system facilities and supports making a decision by a Health Management (HA), where HM can be deiced to maintain these structures effectively and to extend their sustainability. HM refers to the methodology that is used to make good decisions or recommendations about operation, mission, and maintenance actions [8].



Fugure1: General view of the maintenance process in industries plants.

One of the significant objectives of the end-users and the maintenance team is to evaluate the integrity of the mechanical structures on a continuous real-time basis [9,10,11]. The current state of art attempts to achieve the following objectives:

1. Minimizing the downtime: downtime term refers to the amount of the time that the application is out of service (not operating) due to unexpected failure.
2. Avoiding catastrophic failure: SHM alerts the maintenance team when the structure has deteriorated beyond a critical damage level.
3. Improving the maintenance service: SHM improves the inspection schedule based on the condition-based maintenance, where the condition-based maintenance monitors the damage growth continuously and requests maintenance when the damage reaches critical safety limits.
4. Improving safety and reliability: SHM minimizes human involvement, hence human errors, downtime, and labor are reduced.
5. Reducing the maintenance cost: SHM has a significant economic impact, where the cost for maintenance duties (monitoring and repair) is negligible as compared to the cost for reconstruction of new structures. Furthermore, using SHM saves almost 40% on inspection time, and accordingly reducing inspection labor cost.

The waterfall model is one of the common strategies that are applied in SHM. This model consists of six stages as shown in Fig. 2.

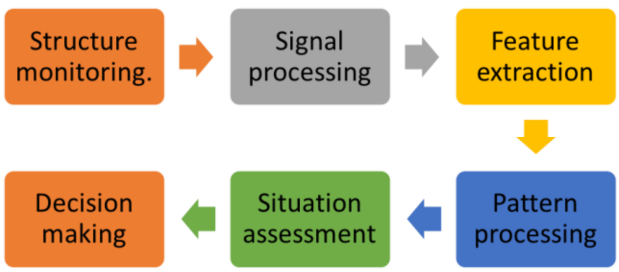


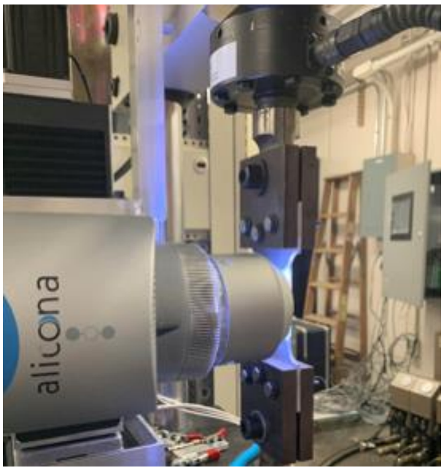
Figure 2: The waterfall model for health monitoring system.

This paper provides a novel methodology for the third, fourth, and fifth stages of the Waterfall model. In the stage of the feature extraction, two surface textures (Arithmetical mean height and Surface Flatness) have been extracted from all surface textures; while in the pattern processing, the surface textures have been split into two sets based on the status of the surface; such that the first set contains the undamaged surface features, while the second set contains the damaged surface features. In the situation assessment stage of the waterfall model, this paper builds an automated model using the Support Vector Machine method to classify the surface features either to the undamaged surface class or to the damaged surface class.

The paper is organized into five sections including the present section. The second section explains the experimental procedure on a test apparatus and the associated instrumentation. The third section describes the methodology adopted in this paper; this section presents an overview of the Support Vector Machine. The fourth section discusses the output of the SVM, and compare between the model performance of the Arithmetical mean height and Surface Flatness. The fifth section summarizes and concludes the paper with recommendations for future research.

2. Description of The Experimental Apparatus:

This section shows the experimental apparatus that has been used in this paper, as shown in Fig. 3. The experimental apparatus contains two systems; a computer-instrumented and computer-controlled fatigue testing machine, and a confocal microscope (Alicona). Alicona has been used to obtain the measurements of the surface textures for evaluation of the surface state. Ten typical experiments of 7075-T6 aluminum alloy have been conducted to obtain enough data for building a strategy for evaluating the status of the surface. Fig. 4 shows the 2D drawing of a notched test specimen (made of Al7075-T6 alloy). The dimensions of tested specimens are 3 mm. thickness, 50 mm width, and (1 mm * 3.5 mm) slot cut at the edge. The type of cyclic loading of these experiments is tension-tension load cycles at 60 Hz. The applied loads fluctuated between 11,000 N and 6,000 N.



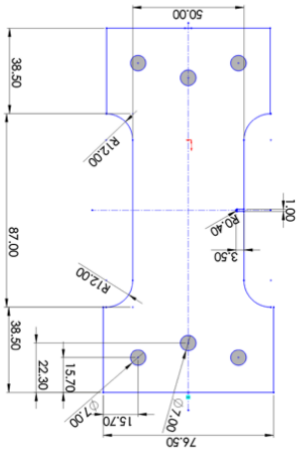


Figure 3: The experimental apparatus. Figure 4: Specimen geometry used for fatigue testing.

The optical metrology device (Infinite-Focus Alicona) has been used to measure two surface textures; the Arithmetical mean height and the Surface Flatness. In the optical system, the surface roughness is usually obtained by estimating the variations in the focus, where the small depth of the focus in an optical system is combined with vertical scanning. Fig. 5,6 illustrate the status of the notch surface of the tested specimen by generating a 3D surface topography for both non-damaged state and damaged state, respectively [12,13].

Figure 5: 3D surface of undamaged specimens.

Figure 6: 3D surface of damaged specimen.

Table 1 shows technical specifications of Infinite- Focus device features.

Table 1: Technical specifications of Alicona.

Technical feature	**Specifications**
Vertical resolution	can be as low as 10nm
Range of the vertical scan	*3.2 mm - 22mm*
Measured area	*0.4mm × 0.4mm*

3. Methodology of Damage Analysis:

Support vector machine:

A support vector machine (SVM) is one of the super- vised learning methods. SVM is often used for regression and classification problems. The principle of the SVM algorithm is to find a hyperplane that provides the best method to separate data points of one class from those of another class by defining the largest margin between the two classes. The largest margin indicates the largest width of the slab parallel to the hyperplane; such that no data points exist in this margin.

Digging deeper into the mathematical details, SVM uses kernel methods which is one of the machine learning algorithms. In this method, the features can be transformed by a kernel function where Kernel functions map the data to a different mapped feature space. The objective of this transformation is to find a higher dimensional space with the expectation that the classes are easier to separate. Let is consider that $x = (x_1, x_2, .., x_n)$ are training dataset, and they are classified into a binary class $y_i = \{+1, -1\}$. Based on this data, a Hyperplane is built using the following equation:

$$w^T x + b = 0 \qquad (1)$$

where, the normal vector to the Hyperplane is $w^T = \{w_1, w_2, ..., w_n\}$, & b is the bias. Once w^T & b are defined, the Hyperplane can be created and the dataset can be assigned to the correct classes. The best hyperplane is obtained when the largest object-free area is determined. [14,15].

Confusion matrix:
The confusion matrix of this paper is built for a binary classification which is a matrix of size (2 × 2). This matrix is contracted with predicted values on one axis and actual values on another axis. The confusion matrix typically provides four possible outputs, as shown in Fig. 7. The model performance accuracy is estimated from the confusion matrix based on the following equation [16].

Accuracy = (True Positive + True Negative)/(sum of all observations) (2)

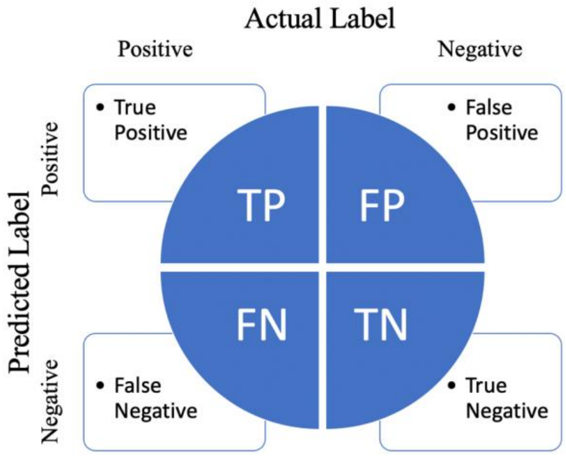


Figure 7: The structure of a confusion matrix.

4. Results and Discussion:

This section presents and discusses the experimental results for the determination of fatigue damage on the surface based on the performance of the SVM model. In this paper, the outputs of the SVM are present in the confusion matrix. The confusion matrix columns represent the target class (true class); while the con- fusion matrix rows represent the predicted class. The outputs that are correctly classified exist in the diagonal cells of the confusion matrix, while the outputs that are missed classified present in the off-diagonal cells of the confusion matrix. Figures show the classifier accuracy of the arithmetical mean height model and the surface flatness model.

Fig. 8 and 9 show the classifier accuracy of the arithmetical mean height model and the surface flatness model, respectively. The accuracy of the arithmetical mean height model is almost 67% & 87%. On the other hand, the accuracy of the surface flatness classifier is 87%. The accuracy of the sur- face flatness classifier for fatigue surface damage detection is significantly better than the accuracy of the arithmetical mean height classifier (by almost 30%). The main reason for having the best accuracy in the surface flatness model is that the measured data of the undamaged class is separable from the data of the damaged class. This separation in data is caused by the concept of the surface flatness method; where this surface texture measures the amount of variation up and down the y-axis over the entire surface, and definitely, these variations in the y-axis of the damaged surface differ from the undamaged surface.

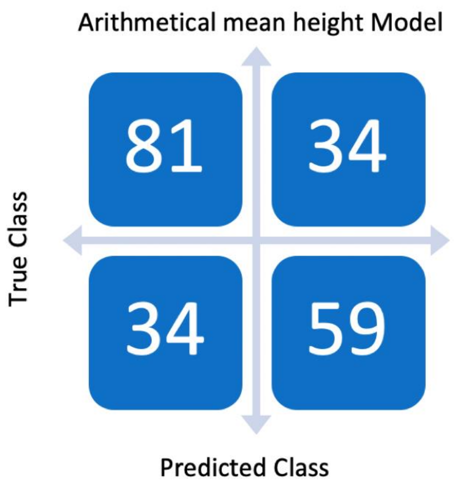


Figure 8: Confusion matrices of the Arithmetical Mean Height model: ~ 67% performance accuracy.

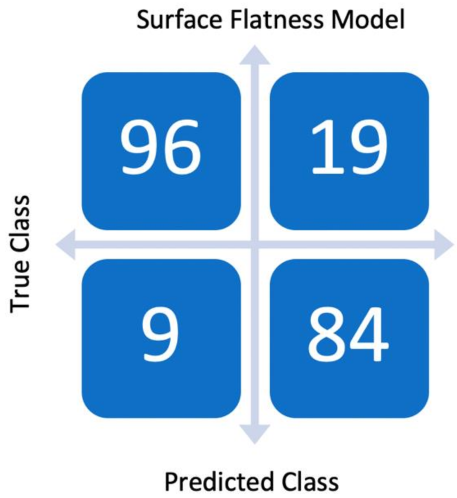
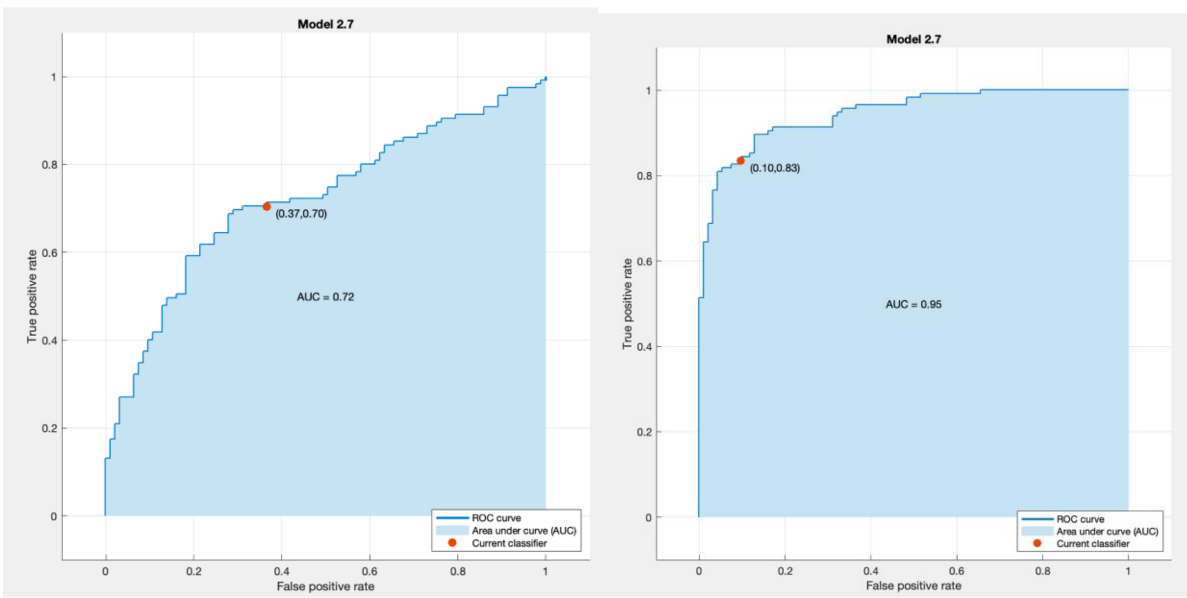


Figure 9: Confusion matrices of the Surface Flatness model: ∼ 87% performance accuracy.

The Receiver Operating Characteristics (ROC) and the area under the curve (AUC) are other methods that measure the model accuracy. Practically, the ROC shows the relationship between the false positive rate of detection (specificity) on the x-axis with the true positive rate of detection (sensitivity) on the y-axis across different cut-off thresholds. On the other hand, AUC is the area underneath the entire ROC curve, and it measures the overall performance of a binary classifier. The value of AUC has a range of (0.5–1.0), where the minimum value represents the worst performance of a classifier and the maximum value would correspond to a perfect classifier [17]. In this paper, the ROC and AUC methods are applied to verify the previous model accuracy of the confusion matrix. Fig. 10 (a) and (b) present ROC curves and AUD for the arithmetical mean height model and the surface flatness model, respectively. The optimal model (i.e., 100% sensitivity and 0% specificity) is obtained in the upper-left-hand corner. As seen in Fig. 10 (a) and (b), the ROC performance of the flatness surface model surpasses that of the arithmetical mean height model, because the ROC curve is closer to reaching the upper-left-hand corner than those of the arithmetical mean height model. Also, the AUC value of the arithmetical mean height model is 0.72, while it is 0.95 for the flatness surface model.



(a) ROC of the arithmetical mean height model. (b) ROC of the surface flatness model.

Figure 10: Receiver operating characteristics (ROC) for all experiments.

5. Conclusion

The presented work illustrates the effects of surface textures on prediction of the fatigue damage on the surface of polycrystalline alloys. An optical metrology device called Alicona has been used to measure two surface textures which are: arithmetical mean height and the surface flatness. The support vector machine method has been applied to build a model that could classify the undamaged and damaged sur- face. It is concluded that the surface flatness pro- vides the best classier with an accuracy of 87%, while the lowest classifier performance is arithmetical mean height, with (up to) 67% accuracy.

6. Acknowledgment

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