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Fast classification of engineering surfaces without surface parameters

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Abstract

A fast, new classification system for engineering surfaces has been developed and used to detect the incidence of wear. The novel feature of this system is that the classification can be performed without the need for any surface parameters. In addition, only normal working conditions data (the target class) are required to train a classifier. In this system, first, a surface to be classified is represented by a set of dissimilarity measures (e.g. differences in surface height) calculated between the unclassified surface and already pre-classified surfaces belonging to the target class. The representation set of measures is then used to assign a surface into the target class or reject as an outlier. Outliers are anomalies or faulty conditions that can be ill-defined, undersampled data or even unknown data. However, several problems still remain to be solved before the approach can be used as a fully functioning pattern recognition system for the applications in machine condition monitoring. This includes difficulties associated with selecting a right size of the representation set and building an accurate one-class classifier. These problems have been addressed in this study and analysis results for unworn and worn surfaces have been also presented. It was found that (i) skewness, correlation, principle component analysis dimensionality and boundary descriptor are well suited for selecting the representation set and (ii) a combiner of the Parzen and support vector data description (SVDD) classifiers with the median rule gives better classification results than single classifiers (i.e. Gaussian density, mixture of Gaussian densities, Parzen density and SVDD classifiers).

Keywords: Fractal dissimilarity measure; One-class classification; Failure detection; Worn surfaces

1. Introduction

The major task of condition monitoring a plant, e.g. gas turbine, diesel engine, artificial implant and knee joint, is to detect faults at an early stage. Early fault detection is typically achieved by analyzing outputs obtained from a set of sensors or laboratory equipments (e.g. acclerometers, oil analyzers, ferrographs) [1,2], microscopic images of wear particles and worn surfaces [3,4]. If the data obtained deviate significantly from its normal operating range, this might indicate a fault (such as a crack in gas turbine or wear damage on counterfacing surfaces) and a fault alarm should be made; alerting the operator of the machinery.

Various classification systems have been developed that are able to learn normal operating conditions and faults from training data [3]. Once the learning process is accomplished the classification systems are used to assign an unclassified data (e.g. unseen before wear particle, surface image, vibration signal or oil sample data) into a specific class. A class is defined as a group of surfaces, particles or other output data selected according to the criteria such wear mechanism, severity of wear, surface texture, operating conditions, etc. A basis of the classification systems is a database divided into a class representing normal conditions and classes representing faults, e.g. classes of unworn, slightly, moderately and severely worn surfaces. In this classification approach, a progression of wear, a severity of damage, different working conditions can be identified and monitored. However, this requires building a large database for all classes which is often time-consuming and expensive. Even though a large database is available, classes might not be well defined because of the following reasons:

- overlapping data: defects of different severity can occur at the same time,

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- difficulties and high costs associated with the data collection of some specific types of faulty machine conditions, and
- difficulties in identifying all possible defects.

One possible solution to this problem is a two-class approach. In this approach, data obtained from all faulty conditions are first grouped into one augmented class. Gathered data is then assigned two classes, i.e. either a faulty condition class or a class representing normal working conditions. A major problem is that the augmented class might not be well defined since

- some faulty conditions might be difficult and expensive to measure, and
- it might be cumbersome to identify all possible defects.

Recent research showed that a one-class approach (a 'novelty' detection) could yield the desirable results [5–9]. In this approach, a database contains only data obtained from normal working conditions, called a target class, and all other possible data are considered as anomalies or outliers. Outliers can be ill-defined and severely undersampled data or even unknown data, while the target class is well-defined and sampled. The classification problem is to assign an unclassified object into the target class or reject it as outlier. Since there is only one class the reference database is easier to construct, the ambiguities associated with defining faulty condition classes are eliminated and the whole classification process is both cheaper and more time efficient. The limitation is that the progression of a wear damage cannot be monitored and the severity of defects cannot be assessed. Since our main interest in this study is focused on an early fault detection this one-class approach appears to be an attractive choice.

Several problems, however, remain to be solved for the one-class approach. One of the main problems is that a core set of surface parameters that allows a clear discrimination between the target class and outliers cannot be easily found. One reason is that the parameters are often not unique for a specific surface and contain redundant information. Another reason is that their values may change significantly with scale, orientation angle and position at which the data was acquired. In addition, the number of these parameters can be large, giving rise to lengthy computational time. The second problem is which classifier or combination of classifiers should be used to achieve a high classification rate. A perfect one-class classifier or combiner will classify all target surfaces into the target class and reject all the others as outliers. This is difficult to achieve since the classifier must find a trade-off between decreasing the error I (the fraction of the target class that is rejected) and increasing the error II (the fraction of outliers that is accepted) as the volume of decision boundary increases (Fig. 1).

In this paper, the first problem is addressed using a recently developed approach, based on a specially devel-

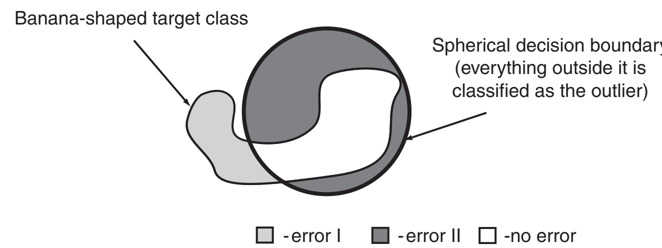

Fig. 1. Errors in one-class classification. A spherically shaped decision boundary is constructed using the banana-shaped target class data. It is assumed that outliers are uniformly distributed inside and outside the decision boundary. A one-class classifier is constructed by minimizing the gray areas representing the errors I and II. Note that if the error I is decreased by using a larger decision boundary the error II will increase automatically.

oped fractal dissimilarity measure [10,11]. In this approach there is no need for surface parameters, instead a representation set of dissimilarity measures (e.g. distances in surface heights) is calculated between an unclassified surface and pre-classified surfaces. A compactness hypothesis is behind this approach. This hypothesis states that surfaces that are sufficiently close to each other in terms of distance (e.g. surface heights) are similar in reality and belong to the same class. One problem, however, arises with these dissimilarity measures; it is unknown what size the representation set should have to achieve an accurate data presentation [12]. Four sampling criteria (i.e. skewness, principle component analysis (PCA) dimensionality, correlation and boundary descriptor) will be used to find a right size of this set [13]. To address the second problem, the performance of several one-class classifiers (i.e. Gaussian density, mixture of Gaussian densities, Parzen density and support vector data description (SVDD) classifiers [14]) and their combinations will be compared on an image database of unworn and worn steel surfaces. The most efficient and accurate classifier and combination of classifiers will be selected for the detection of worn surfaces. The one-class classifiers were computer implemented using the dd_tools 1.1.2. Matlab toolbox [15].

2. One-class classification problem

Assume that $\boldsymbol{Z}_i$ represents the surface data acquired by a measuring instrument (e.g. SEM stereoscopy, interferometric microscope) in the form of a 2D matrix. Entries of this matrix are outputs of a 2D discrete image function $z = f(x, y)$. This function assigns a surface height (encoded into a brightness value) $z \in L_z$ ($L_z = \{1, 2, ..., N_z\}$) to a point (encoded into a pixel) located on surface at $(x, y) \in L_x \times L_y$ coordinates ($L_x = \{1, 2, ..., N_x\}$ and $L_y = \{1, 2, ..., N_y\}$). N_z is the number of gray scale levels, N_x and N_y are the number of pixels in the x and y directions, respectively.

The classification problem is to assign the unclassified surface $\boldsymbol{Z}$ into a target class representing normal working conditions or to reject it as outlier. As an example, the