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HEALTH MONITORING AND DIAGNOSIS OF AERONAUTICAL SYSTEMS WITH NON GAUSSIAN MULTIVARIATE STATISTICAL PROCESS CONTROL

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ABSTRACT

This work focuses the application of fusion of vibrational condition indicators (CI) using multivariate non-Gaussian statistic distributions to characterize and discriminate fault conditions in a helicopter oil cooler system. Gaussian Mixed Models (GMM) is applied to describe a set of health and fault states using the Expectation Maximization Algorithm (EMA) with optimized parameters. Clustering of health and fault states are performed based on confidence intervals (p-values) of identified GMM probability density function and proper statistical distances calculated from the identified GMM states, including a generalization of the Mahalonobis Distance (MD) for GMM and the Kullback-Leibler (KL) divergence. The complete process of the system diagnostic is optimized: from selection of training data and CI's to fitting the GMM and the applicability of several fused Health Indicators (HI). Performances are compared by ROC curves and computational time.

Keywords: health and usage monitoring systems, Gaussian mixed models.

INTRODUCTION

Health and Usage Monitoring Systems (HUMS) are an important new development for improvement of safety and reduction of maintenance cost. A HUMS generally employs accelerometers, from which Condition Indicators (CI's) are calculated. A high value of such a CI may indicate a specific failure (Bechhoefer, 2007). Each critical component contains vibrational sensors, from which several CI's can be calculated to detect different types of failure (Bechhoefer, Duke and Mayhew, 2007). This detection is based on the premise that characteristics of data remain relatively unchanged, until structural damage alters the dynamic properties of the system and its measured responses. When the number of components and failure modes increases and each CI has his own alarm threshold, either the probability of false alarm is unacceptable or a lot of failures will be missed. Besides, system overview and dependency between CI's is lost. Therefore, it is generally chosen to combine multiple CI's of a given component into one overall Health Indicator (HI). The system is now described by a multivariate statistics, and on the assumption of normality, a multivariate Gaussian can be fitted. Anomalies can be tested using the χ^2-distributed Mahalanobis Distance (MD) or Hotelling's T^2 statistic (Gomes et al., 2011). If, however, normality cannot be assumed, a general solution is to approximate the distribution by a Gaussian Mixture Model (GMM) (Gomes, 2007). The complete processes is addressed by selecting the proper CI's, choosing the training and testing data, fitting the GMM distributions of the health and fault states, converting the fused data into an overall HI and finding the proper threshold to optimize the fault detection.

RESULTS AND DISCUSSION

The ROC curves for differently selected training data are shown in Figure 1, while the number of components, k, the AUC and the computational time for each curve are given in Table 1. The CI's used are the kurtosis and the amplitudes of the first three harmonics. The best fit is chosen by the Akaike Information Criterium (AIC) out of a k-range from 1 to 6 for the data fractions and from 6 to 12 for the database-trained GMM. The Probability Density Function (PDF) of each data point is used as HI. It can be seen that the performances are very good, since the Area Under the ROC Curves's (AUC) are high and the curves are very close to the upper left corner. This implies that the healthy data of the different helicopters overlap well and that using such a database for training services is allowed in this case.

Table 1 - Properties of the ROC curves for several sets of training data

Data	k	AUC	Time (s)
First 30%	3	0.9934	4.83
First 50%	3	0.9985	6.40
First 70%	3	0.9998	30.65
Database	10	1	41.77

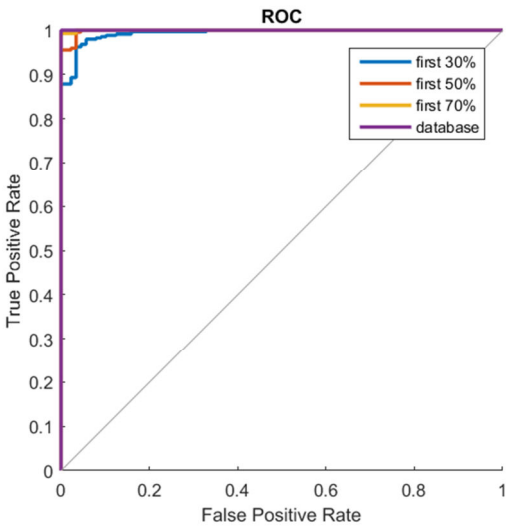

Fig. 1 - ROC curves for several sets of training data

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