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# A probabilistic multi-class classifier for structural health monitoring

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ABSTRACT

In this paper, a probabilistic multi-class pattern recognition algorithm is developed for damage monitoring of smart structures. As these structures can face damages of different severities located in various positions, multi-class classifiers are needed. We propose an original support vector machine (SVM) multi-class clustering algorithm that is based on a probabilistic decision tree (PDT) that produces a posteriori probabilities associated with damage existence, location and severity. The PDT is built by iteratively subdividing the surface and thus takes into account the structure geometry. The proposed algorithm is very appealing as it combines both the computational efficiency of tree architectures and the SVMs classification accuracy. Damage sensitive features are computed using an active approach based on the permanent emission of non-resonant Lamb waves into the structure and on the recognition of amplitude disturbed diffraction patterns. The effectiveness of this algorithm is illustrated experimentally on a composite plate instrumented with piezoelectric elements.



## 1. Introduction

Structural health monitoring (SHM) is an emerging technology designed to automate the inspection process undertaken to assess the health condition of structures. In a smart structure, SHM systems may automatically process data, state regarding structural conditions, and highlight any need for human intervention [1]. The output of any SHM process should provide information regarding the type, the location, and the severity of the damage. Thereby, the SHM process is classically decomposed into four sequential steps: detection, localization, quantification, and prognosis. SHM involves many disciplinary fields (material science, structural analysis, signal processing, data mining, fracture mechanics, fatigue life analysis, etc.) and has been the topic of extensive research efforts over the last thirty years. This technology is now progressing toward operational service and recent surveys have shown that even reluctant industry areas are now convinced that SHM is the key technology that will enable the transition from schedule-driven maintenance to condition-based maintenance [2]. Researchers are now exploring ways to adapt information technologies in order to reduce system monitoring costs while simultaneously broadening their functional capabilities. In this paper, we address the detection, localization and quantification steps of the SHM process.

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### 1.1. Damage-sensitive features generated using Amplitude Disturbed Diffraction Pattern

SHM system operational results can be classified into four different sequential levels: detection, localization, quantification, and prognosis [1]. Several different techniques that depend on the structure's material, on the technology used for acting and sensing, on the position, size, and nature of damage may be employed to perform SHM [3]. They could be sorted in two main categories: global or local.

Among others global SHM methods, we can highlight vibration based approaches [4,5]. These methods are categorized based on the type and nature of measured data. Significant examples include: model updating [6]; statistical time series and modal analysis [4]. In those approaches we seek to track changes in global structural parameters (mass, stiffness, flexibility, damping) and modal parameters (modal frequencies, associated damping values and mode shapes) by analyzing changes induced in the global dynamic behavior of a structure. Experimental identification of these dynamic properties indeed gives insight on the structural damage conditions, see [7–9] and references therein. Multivariate techniques have been also used in global vibration-based SHM: examples are the Principal Components Analysis (PCA) [10] and ICA [11]. In the case of nonlinear damage, specific vibration-based approaches have also been developed recently by the authors using cascade Hammerstein models [12]. An extensive overview of nonlinear global vibration-based SHM methods can be found in [13].

For local inspection, we can employ electro-mechanical impedance or displacement/strain as features indicating the presence of damage [3]. As these methods are local, their sensibility is strongly linked to the position of the sensors. In that category, we can also highlight acoustic emission or high frequency wave-based approaches that have the advantage to be sensitive to very small damages and offer the capability of propagation over a significant distance [14]. Evaluation of wave propagation on solids is one of the most successful techniques for damage monitoring [15]. One piezoelectric actuator emits periodic burst pulses exciting Lamb waves in the structure under inspection, and a set of sensors records signals, representing the respective structural responses. These signals are processed in order to extract damage related information such as location, size, orientation, type among others [14]. One of the outstanding advantages of using Lamb waves for SHM is that such waves can travel over relatively long distance and can be used to monitor various types of damages (as delamination, disbonds, fiber breaking, impact, etc.) [16].

To construct measurements that are sensitive to the damage, we use in this work an active SHM approach based upon a correlation technique that relies on wave diffraction patterns recognition. Damage-sensitive features are generated thanks to the Amplitude Disturbed Diffraction Pattern (ADDP) phenomenon observed using permanent emission of selected non-resonant Lamb waves in the structure. ADDP assesses the disturbances that damage brings to the acoustic wave propagation in the structure. These disturbances depend upon the damage severity and position as well as on the frequency of the exciting signal. With an appropriate calibration procedure, it is thus possible to detect, localize, and quantify the damage using ADDP. This process has already been successfully used as a multi-touch sensing approach to tactile sensing [17]. The formulation of this process as a damage location one has been presented in [18]. In this paper, the ADDP process will be used to generate the damage-sensitive features that will allow detecting, localizing, and quantifying the damage.

### 1.2. The need for a probabilistic multiclass classification tool in SHM

The extraction of damage-sensitive features from measurements is a process that is most powerful when it is followed by pattern recognition [19]. Indeed, in a statistical pattern recognition paradigm for SHM, it is usually rather difficult to obtain data from damaged structures because of cost and of practical constraints. However, when such data are available, a whole new range of algorithms can be used [19] and the problem of damage detection, localization, and quantification can be cast as one of the classifications [20,21].

As the structures under study can face damages of different severities located at various positions, multi-class classifiers are naturally needed. Furthermore, because of the lack of available data in the damaged state and of the environmental effects, the experimentally obtained damage-sensitive features may differ from those learned offline by the multi-class classifier. A multiclass classifier that provides probabilities associated with damage existence and with each damage location and severity instead of a binary decision is thus greatly desirable for SHM. With such a classifier, damage locations can for example be ranked from the most probable to the least one, thus providing helpful guidance for the inspection task. Indeed, the reliability assessment of SHM systems is the key issue in ensuring their successful implementation. For example in aerospace maintenance procedure minimizing structural teardown to access regions to be monitored is one of the claimed benefits in using SHM rather than classical nondestructive evaluation (NDE) systems. Moreover, given that the diagnosis (class assignment) will be made on the basis of measured data, it is important that the chosen pattern recognition algorithm is able to accommodate a degree of imprecision commensurate with expected levels of measurement error and noise. This requires that the damage detection, localization and quantification of SHM outputs' have to be assorted with a probability. This probability is then considered as a level of the trust in the SHM systems results.

In this work, where a statistical pattern recognition paradigm for SHM is considered, we propose to provide a metric helping the condition-based maintenance decisions for in-service structures. This is possible by capturing during the training phase a part of the effect of environmental variability. This will represent the probability of how likely are SHM system outputs. Moreover, to ease the practical implementation, by simply thresholding these a posteriori probabilities at each node, the soft-decision approach can be converted to the conventional hard-decision approach.