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Reliability based impact localization in composite panels using Bayesian updating and the Kalman filter

Llewellyn Morse *, Zahra Sharif Khodaei, M.H. Aliabadi

Department of Aeronautics, Imperial College London, South Kensington Campus, Roderic Hill Building, Exhibition Road, SW7 2AZ London, UK

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ABSTRACT

In this work, a reliability based impact detection strategy for a sensorized composite structure is proposed. Impacts are localized using Artificial Neural Networks (ANNs) with recorded guided waves due to impacts used as inputs. To account for variability in the recorded data under operational conditions, Bayesian updating and Kalman filter techniques are applied to improve the reliability of the detection algorithm. The possibility of having one or more faulty sensors is considered, and a decision fusion algorithm based on sub-networks of sensors is proposed to improve the application of the methodology to real structures. A strategy for reliably categorizing impacts into high energy impacts, which are probable to cause damage in the structure (true impacts), and low energy non-damaging impacts (false impacts), has also been proposed to reduce the false alarm rate. The proposed strategy involves employing classification ANNs with different features extracted from captured signals used as inputs. The proposed methodologies are validated by experimental results on a quasi-isotropic composite coupon impacted with a range of impact energies.

1. Introduction

The application of Structural Health Monitoring (SHM) techniques in the aviation industry has gained noticeable attention in the recent years due to the increased use of composites in aircraft for the many advantages they offer over traditional materials. However, impact damage in composites, in particular Barely Visible Impact Damage (BVID), can be a major concern if not detected in time. SHM is a promising technique that can result in impact [1–5] and consequently damage detection and characterization [6–11] by monitoring of the structure with permanently installed sensors. Based on the sensing technology, sensors can be used in passive or active configurations. However, for any SHM system to be adopted as a non-destructive damage inspection (NDI) technique it must comply with high reliability requirements under operational conditions. One way to improve the reliability of any decision-making algorithm is by adopting Bayesian updating or the Kalman filter. For a SHM system to be employed reliably in practice, it should be capable of distinguishing between different impact events which may result in damage or not (false alarm) as well as operating with a high level of reliability in cases when one or more sensors have become faulty during service.

Abbreviations: BU, Bayesian updating; KF, Kalman filter; ANN, Artificial Neural Network; CWT, Continuous Wavelet Transform; ToA, Time of Arrival.

* Corresponding author.

E-mail addresses: llewellyn.morse12@imperial.ac.uk (L. Morse), z.sharif-khodaei@imperial.ac.uk (Z. Sharif Khodaei), m.h.aliabadi@imperial.ac.uk (M.H. Aliabadi).

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Bayesian updating (BU) has been used in the field of SHM for both damage detection [12–15] and impact detection [16–18]. One notable example of the use of BU in passive sensing is Schumacher et al. [16], where a Time of Arrival (ToA) triangulation and BU approach was employed to determine the source of acoustic emissions (AEs) in a reinforced concrete block. A Markov chain Monte Carlo (MCMC) algorithm was used to provide posterior distributions for ToAs. Results showed that the BU approach resulted in more accurate location estimates than traditional deterministic algorithms and performed slightly better than the mean solution of the traditional algorithms, while at the same time providing quantitative estimates for error and uncertainties. Yan et al. [17] used a similar approach to estimate the source of AEs in a stiffened aluminium panel. To provide more accurate estimates for the AE source locations, the ToAs for each AE were found at three different frequencies using the continuous wavelet transform (CWT), and the resulting probability distributions obtained from a MCMC algorithm were fused together. Results showed that this fusion technique improved the accuracy of the AE source location estimates and reduced their uncertainty.

One notable example of the Kalman filter's (KF) use in passive sensing is Niri et al. [19] where the extended Kalman filter (EKF) was used to estimate AE source location and Lamb wave propagation velocity in an aluminium plate. The EKF is different from the KF in that it can be used for non-linear systems. The AE source coordinates and Lamb wave propagation velocity were unknown and were treated as independent random Gaussian variables. The ToAs for the Lamb wave signals were calculated using the CWT. It was shown that the coordinates of the AE sources could be detected to within 5% average percentage error after 10 iterations of the KF algorithm. Moon et al. [4] applied the KF to the problem of tracking the location of multiple AE sources in quick succession. A ToA triangulation method was used with ToA being determined using the CWT. Results showed that the AEs could be detected with good accuracy using the KF if they occur successively in a straight line. The KF becomes less accurate when the AEs deviate from this line. Most of the reported work concerning passive sensing [16–19] has focused on either BU or the KF in isolation, or in some cases, compared them with other methods. But a comprehensive comparison of the two methods has not been addressed.

ANNs have found increasing use in the field of impact localization over the past decade. One notable example of the use of ANNs for impact localization is De Stefano et al. [20] where ANNs were coupled with a Genetic Algorithm (GA) for the purpose of optimising the position of piezoceramic sensors on a composite plate. Voltage data obtained from low velocity impacts were used as the inputs to the ANNs. Once the ANNs were trained, the proposed method could determine the optimal combination of three sensors with the test dataset. To test the robustness of the method when applied to a real operating environment, white Gaussian noise was added to the voltage data of the test dataset. It was found that the optimal sensor combination in the presence of noise was not necessarily the same as that found without the presence of the noise, suggesting that the determination of the optimal sensor combination should consider the robustness of the combination to possible random variations in sensor data. De Stefano et al. [21] employed a similar strategy as in [20] for the optimisation of sensor locations for impact localization problems on a quasi-isotropic composite plate. A trilateration approach was undertaken, involving an ANN being trained for each individual sensor, instead of for a combination of sensors as in the traditional approach. The trained ANN for each sensor could provide an estimate of the distance between the sensor and the impact location. The impact location could then be estimated by using the distance from two other sensors with a least-squares approach. The trilateration approach was found to provide results 10 times faster than the traditional approach while also providing more accurate impact location estimates. Sharif-Khodaei et al. [22] built upon this work by investigating the capabilities of ANNs when applied to a more complicated structure subjected to a wide range of impact masses, velocities, and energies. Impacts were conducted on the inner and outer surfaces of a finite element (FE) model of a stiffened composite panel to simulate impact events such as runway debris or tool drop. To test the applicability of the ANN to real operational conditions, white Gaussian noise was added to the ToA data. It was found that the ANN could detect 90% of impacts within an approximate detection radius of 100 mm while only using 4 piezoceramic sensors, one in each corner of the panel, representing a small error relative to the dimensions of the panel. The work carried out by Sharif-Khodaei et al. [22] provides the foundation for the ANN-based impact localization methodology described in this paper.

A false alarm in the context of SHM is defined as an erroneous report of damage. In impact detection, false alarm can be defined as identifying an impact event as alarming when the level of the energy is low enough as not to cause any harm to the structure. If an impact of very low energy is identified as alarming it can cause significant monetary loss due to unnecessary maintenance and the grounding of the aircraft. It is therefore important that the false alarm rate, i.e. the percentage of non-damage-causing impacts (false impacts) that are mistakenly identified as damage-causing impacts (true impacts), is minimised. One notable example of minimising false alarm was presented by DeSimio et al. [23] where a classification system based on active sensing was used to determine which fasteners on a thermal protection system panel were loose. The work presented in this paper seeks to build on previous studies on false alarm carried out with active sensing systems and take the first step to applying the concept to passive sensing systems, with the aim of reliably differentiating between damaging and non-damaging impacts for a small range of impact conditions.

In a recent work Yan et al. [24], BU and the KF were employed to estimate impact location and reconstruct force time history using a purely numerical based approach. Numerical examples were performed on a composite plate, and it was found that the proposed method was effective for impact load identification. However, no work has been reported in which a classification strategy for passive sensing systems has been developed to identify false impacts or in which the possibility of one or more faulty sensors has been considered. In addition, the applicability and reliability of SHM techniques for impact detection under real operational conditions remains questionable.