A Review of Impact Damage Detection in Structures using Strain Data

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ABSTRACT

This paper aims to provide a state-of-the-art review on impact damage detection techniques in structures using strain data. An overview of impact detection systems is provided. These include sensors, specimens, and impact sources used for developing and testing strategies. The review is focused on approaches that use impact strain data (passive approach) to determine simultaneously the location and/or energy of an impact at the time it occurs. These approaches can be classed into two main groups, one based on analytical models and the other based on data-driven models. The former uses a first-principle model obtained from physical laws, whereas the latter describes complex relationships between input and output data obtained by experiments or simulations. Although some weaknesses and strengths are cited, we did not attempt to compare these approaches, and we do not comment the quantitative results.

Keywords: Impact detection, data driven models, analytical models, strain analysis

1. INTRODUCTION

Impact damage detection in structures

One of the great challenges in mechanical, aerospace and aeronautical industries, among others, is attaining the ability to detect damage to structures in the incipient state. On the one hand, this will guarantee the integrity of structures, increasing their security. Additionally, maintenance and repair costs could be considerably reduced.

According to Brand and Boller [1] in the aeronautical industry, for instance, most structural inspections (61%) are performed visually. This inspection includes several levels of observation, from simple eye recognition to the use of microscopes and scanners. Visual inspection is effective for the detection of surface and near-surface damage. Besides visual inspection, other methods of Non-Destructive Testing (NDT) are used, most of which were developed at the beginning of the 1960s. In the 1970s, other techniques based on models and simulations were generated, the most established being inspections with ultrasonic waves and eddy currents. Ultrasonic inspections are based on analysis of wave phenomena, such as attenuation, reflection, dissipation, diffraction, harmonic generation and others. The eddy current technique detects changes in the electromagnetic impedance caused by defects in the material. In general, these techniques have a local scope, because they require prior knowledge of the kind of damage and its location; besides, the structure must be out of service, tests are performed manually, and the portion of the structure to be examined must be accessible [2][3].

Beyond these conventional techniques, in recent years, different techniques have been continuously developed under the concept of "Structural Health Monitoring" (SHM). Recently, Worden and Farrar have compiled a special issue on SHM, introducing the concept and presenting an overview of sensing systems, inverse methods, and time- and frequency-scale methods [4]. In their multidisciplinary book, Staszewski et al. [5], cover all the recent developments in smart sensor technology for health monitoring in aerospace structures, providing a valuable introduction to damage detection techniques.

The concept of "smart structure" has been extended simultaneously with SHM. These smart structures are associated with the integration of sensors and actuators, controllers and signal processors distributed in order to increase the functionality of the conventional structures.

Damage caused by an external impact is a major concern in the design of aerospace structures. For instance, low-velocity impact can cause delamination in composite materials. Impact can occur during manufacture, service or maintenance, and typical sources of impact are falling tools, collision with animals, runway stones, debris, and ballistic impacts.

In many cases, the identification of this damage, known as "Barely Visible Impact Damage" (BVID), by visual inspection methods is difficult. For structures susceptible to impacts, NDT routines must be performed over the entire surface because the location of the impact is unknown. This operation is time consuming, has an economic cost and requires the structure to be out of service. Therefore, systems that can detect the occurrence of impacts and estimate their location and energy are very helpful in structural maintenance [6].

Damage identification systems

In general, a complete structural damage identification system should consist of three major components, indicated by Beard et al. [7]. These are:
an actuator/sensor network,
a data acquisition system with all the integrated hardware, and
software to monitor the "health condition" of the structure in situ.

Currently, there exist several kinds of sensors that can measure strain waves and that could be used in structural damage monitoring. These include, among others, piezoelectrics, fibre optics and strain gauges. Sensors can be bonded to the surface of the structure or integrated within the structure. Data acquisition systems include all the essential hardware for transforming the signal from sensors into an interpretable set of data (filters, amplifiers, etc.) and for transporting this information from the sensors to the devices that interpret the signals (conditioning electronics, DAQ systems, computers, etc). The software for monitoring, detecting, locating and identifying damage should consider and include: (i) pre-processing data techniques for de-noising, smoothing, normalization, etc; (ii) feature extraction and feature selection methods for reducing the dimensionality of the problem; and (iii) a strategy for damage identification in the strict sense.

Damage which alter the stiffness, mass or energy-dissipation properties of a structure (e.g., corrosion, fatigue, cracking and delamination) should be analysed using an active system composed of actuators and sensors, with the structure exposed to known external energy inputs from the actuator (see Figure 1). In other words, damage identification is based on the phenomenon of strain wave propagation. An excitation signal is applied, and the dynamic response is examined. The damage will alter the measured dynamic response of the system.

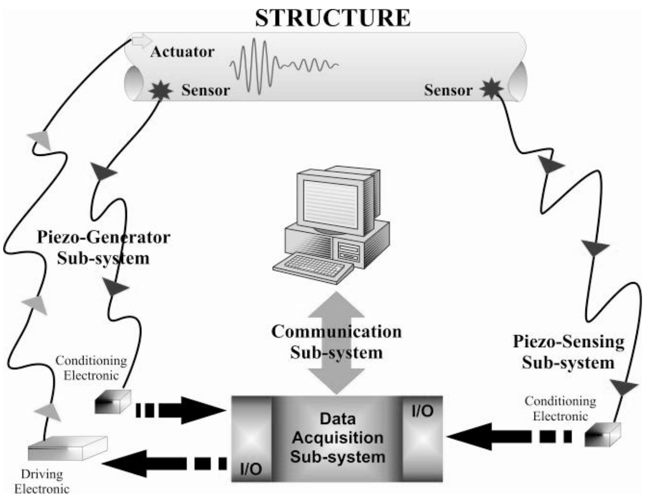

Figure 1. Active system for vibration-based damage identification (from Mujica et al. [8]).

The detection and localization of sudden and unpredictable damage (e.g., impacts loads) on a structure are possible because of the propagation and attenuation of surface stress waves that result from an impact. This damage should be analysed using a passive system, which consists only of sensors attached to a structure. The energy input to the structure is random, and its source is usually unknown (see Figure 2).

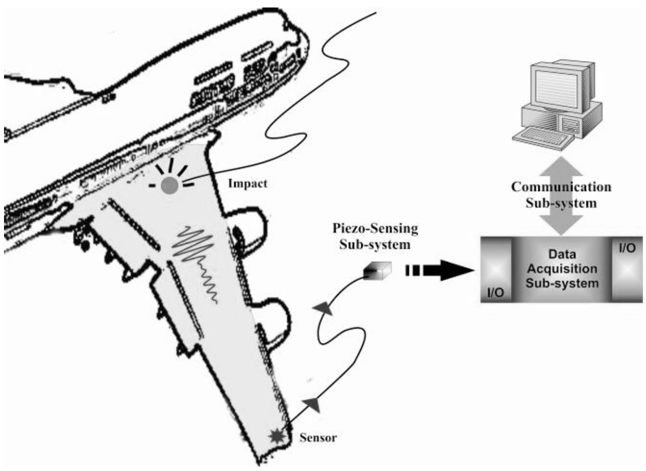

Figure 2. Passive system for vibration-based damage identification (from Mujica et al. [8]).

Some of the transducers used in SHM can be used as sensors and actuators, and therefore, depending of the configuration, some systems can be used as active/passive systems.

Principle of impact detection

When a structure is exposed to a mechanical impact on the surface, a transient strain pulse is introduced. The acoustic or strain wave is propagated into the structure along spherical wave fronts. The arrival of these waves at the surface where the impact was generated produces displacements, which are measured by the receiving transducers or sensors. There exist in the literature a considerable number of studies on acoustic waves generated by impact sources in metallic and composite materials (e.g., Gardiner and Pearson [9], Weems et al. [10], Takeda et al. [11], and Prosser et al. [12]).

Once the structural area is equipped with a set of sensors, at least two different evaluations should be performed: (i) impact detection, which should be performed simultaneously with the impact occurrence, and (ii) impact damage detection and identification (post-impact damage). The former is focused on the detection, location and, in some cases, determination of the impact force. This is possible only by using a passive system. The latter usually uses an active system to assess the structure after the impact. This assessment includes information such as whether damage was produced, and its location and severity.

Specimens used for testing impact damage detection strategies

At present, structures are mainly manufactured using composite and/or metallic materials. Most metallic elements have a high risk of damage by cracking, corrosion, bonding/debonding of joints, and impacts. Although the fuselage and wings of aircraft are externally inspected between flights, cracks below external layers or a broken inner rib may be undetected. Microscopic cracks could be generated under variable loading conditions or impacts. Regardless of the fact that these cracks are apparently insignificant, severe and unexpected loads can lead to significant plastic deformation of a component in service, as reported by Staszewski in [13].

Besides their high strength, low weight and design flexibility, composite materials are also resistant to fatigue, corrosion and impact damage. This is a great advantage for the industry, and numerous manufacturing companies are introducing increasing amounts of composites into their products. The biggest aeronautical producers, Airbus and Boeing, manufacture their latest aircraft (A380 and B787) using composites for almost 50% of the whole structure. [14]. In aerospace structures made of composites, impacts, delaminations and bonding/debonding of joints are the most common and relevant defects [13].

Virtual structural components (modelled by using finite elements) and small specimens have been used in laboratories to test algorithms and/or in systems for impact damage detection using strain data. At the beginning, metallic and composite plates were used; later, more complex structures, with embedded sensors, or structural components were studied.

Carbon fibre reinforced polymer (CFRP) plates with an embedded smart layer, such as the one shown in Figure 3, were used, among others, by Ross et al. in [15], Hu et al. in [16], and Haywood et al. in [17].

Two stiffened composite panels from a Boeing 777, manufactured with T800H/3900-2 graphite/epoxy, were used by Seydel and Chang in [18] and [19].

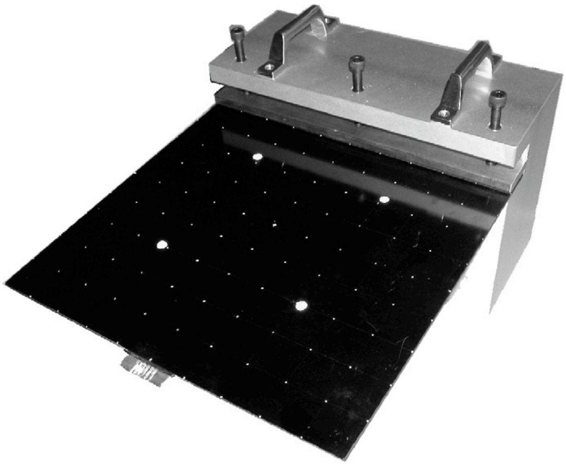

Figure 3. CFRP plated used by Hu et al. in [16].

A composite box structure representative of aircraft wing skin parts was used by Staszewski et al., in [20] and by Worden et al. in [21]. The structure is a composite plate riveted on the top flanges of four aluminium panels (Figure 4).

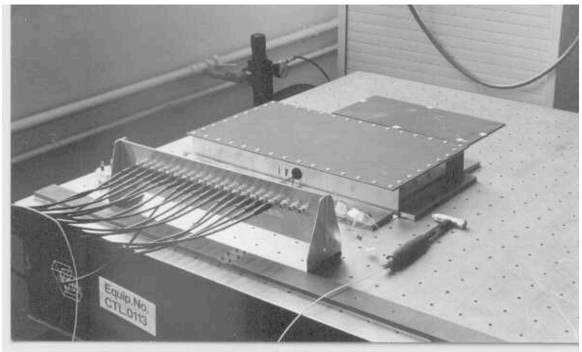

Figure 4. Composite box structure used by Staszewski and Worden et al. [20][21].

Park and Kim in [22] designed the virtual aircraft composite wing shown in Figure 5. (Note: The leading and trailing edge flaps were not included.) The wing has four ribs, 11 spars, and two skins that were assumed to be made of T300/5208 graphite/epoxy tape.

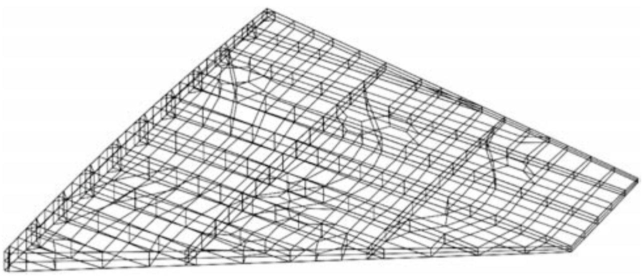

Figure 5. Wing finite element model (from Park and Kim in [22]).

Mujica, LeClerc, Mahzan and co-workers have used a scale version of part of a wing span with the corresponding leading and trailing edges in [23][24][25][26]. To impart strength to important areas of the panel, there are various ribs, spars and stringers running throughout the structure, and honeycomb cores are used at the leading and trailing edges, as shown in Figure 6. The trailing edge is composed of aluminium skins with an aluminium honeycomb core, the leading edge is made of composite skins with a lightweight honeycomb core, and the central section is made of thin composite material. Unfortunately, because the wing flap section was taken from a commercial aircraft, little is known about the specific materials and design parameters constituting the structure, such as the lay-up of the composite.

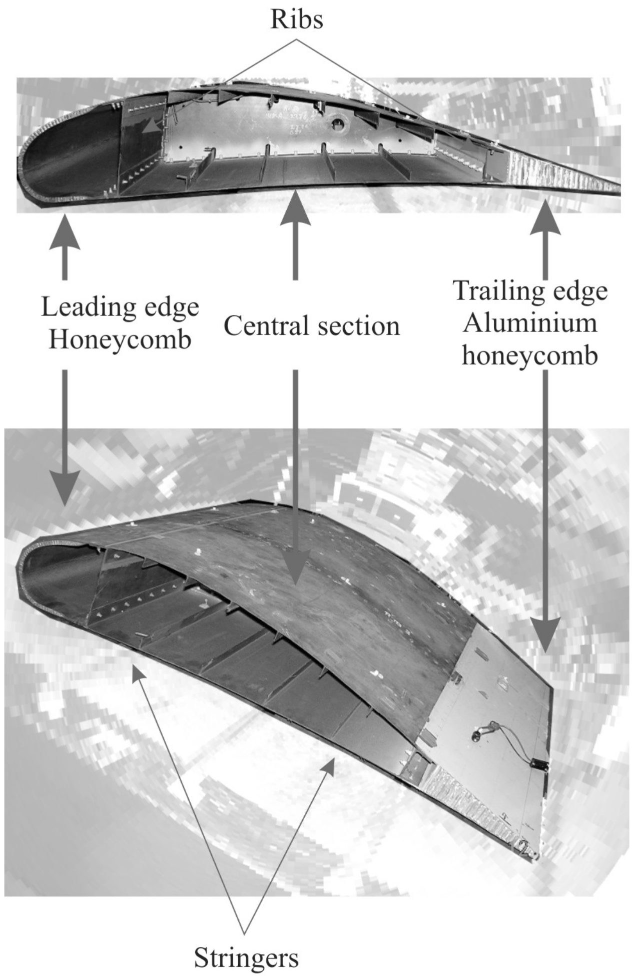

Figure 6. Wing flap section used by Mujica, LeClerc, Mahzan and co-workers in [23][24][25][26]..

To perform experiments in the lab, structures were impacted in two different ways, using either an instrumented hammer or an impact machine, as shown in Figure 7 and 8. The instrumented hammer is easier to handle than the impact machine, but the input energy is uncontrollable. The latter is useful if the exact energy and position of the impact must be recorded.

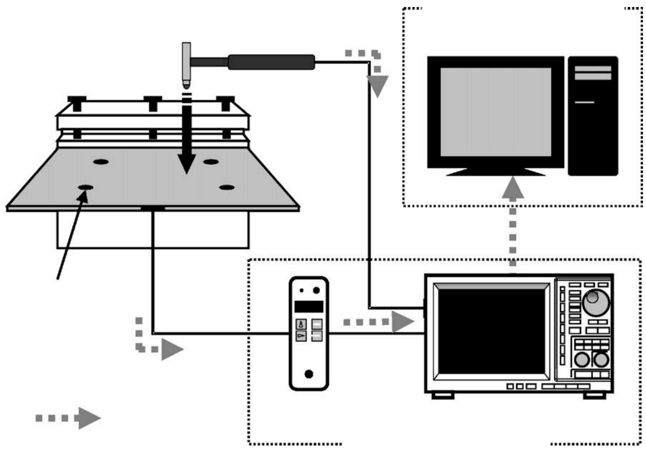

Figure 7. Experimental test using an impulse hammer (from Hu et al. [16]).

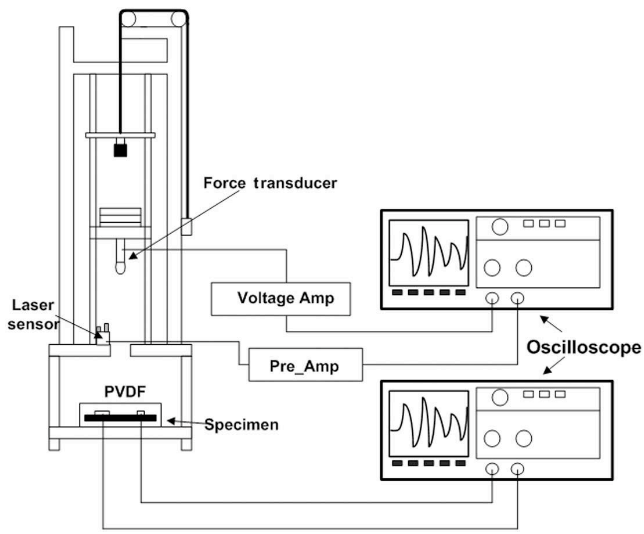

Figure 8. Experimental test using an impact machine (from Kim et al. [27]).

Overview

The objective of this paper is to report and review various approaches used for impact damage detection based on impact strain data (passive approach), including the different methods (e.g., triangulation procedures, machine learning, model-based approach) and sensors (e.g., piezo-ceramics, optical fibres) used. Although some weaknesses and strengths are cited, we did not attempt to compare these approaches and we do not comment the quantitative results.

Section 2 is dedicated to a review of the sensors for impact damage detection that are used most often. This category includes optical fibre and piezoelectric sensors. We also comment on a number of approaches used for optimizing sensor location.

The approaches developed until now for impact location and identification can be classified into two main groups, one based on an analytical model, the other on a data-driven model. The former, which will be presented in section 3, uses a first-principle model obtained from physical laws. Some of these approaches are based on equations of motion that characterize the dynamic response of the structure subject to a known impact. Measured sensor outputs were compared with the estimated responses from the model. If the two responses were not identical, some algorithm for identification and/or optimization was used for adjusting the parameters of the model to the new response. The new parameters characterize the impact location and force (when applicable). Other model-based approaches, which are used only for impact location but not for impact identification (i.e., the forces, kind of foreign object, damage produced by the impact, etc.), were clearly established. Triangulation procedures use the arrival times of stress waves produced by the impact at sensors with known locations.

The other main group of approaches to impact damage identification is based on the data-driven models that are presented in section 4. These models are capable of describing complex relationships between input and output data, and need a considerable amount of time-domain data. These methods are applied when a specific equation is not applicable.

An additional technique, which has not been included in the model-based approaches because it does not use first-principles laws but does not need a considerable amount of data, is presented in Section 5. This approach uses a system-transfer function to obtain a mathematical relation that predicts the structural behaviour.

2. IMPACT SENSORS

The effectiveness of the sensors depends on the quality of materials and connections, and the number of sensors (a single sensor may not contribute much additional mass to the structure, but several hundred such sensors may significantly change the structural response), among other things. Therefore, many researchers, such as Doyle et al. [28], have focused on advanced materials for signal acquisition (strain, stress, vibration, etc.), Worden and Burrows [29] on optimal locations of sensors, Martin et al. [30] and Kirikeraa et al. [31][32] on network sensors, Hong et al. [33] on signal multiplexing, and Sumners and Champaigne [34], Bastianni et al. [35], Mitchell et al. [36], and Champaigne and Sumners [37] on signal transmission via wireless.

Fibre optic and piezoelectric sensors are the most widely used for measuring strain waves produced by impacts in structures. However, there also exists another kind of sensors, known as Micro-Electro-Mechanical Systems (MEMS) [38]. On the other hand, Nakamura et al. in [39] report on a system able to detect impact in composite materials using a Fibre Bragg Grating-Piezoelectric Transducer (FBG/PZT) hybrid system. Most of these cases use a network of sensors embedded within, or bonded, to the component.

Optical fibre sensors

An optical fibre (US: fiber) is a glass or plastic fibre designed to guide light along its length. They are widely used in communication and enable transmission over longer distances and at higher data rates than other forms of communications. Optical fibres are also used to form sensors in a variety of applications; e.g., to measure strain, vibration, temperature, pressure, curvature, and concentration, among many others. Optical fibres present advantages including their light weight, resistance to corrosion and fatigue, insensitivity to the electromagnetic environment, high response bandwidth and geometrical flexibility. Udd [40] presents an overview of the use of optical fibres as sensors and their characteristics. Schindler et al. in [41] locate impacts in composite panels by using embedded fibre optic sensors.

Fibre Bragg Grating sensors (FBG) are a kind of distributed Bragg reflectors constructed in a short segment of optical fibre that reflects particular wavelengths of light and transmits all others. This is achieved by adding a periodic variation to the refractive index of the fibre core, which generates a wavelength-specific dielectric mirror. The concept of a single-element FBG sensor is illustrated in Figure 9.

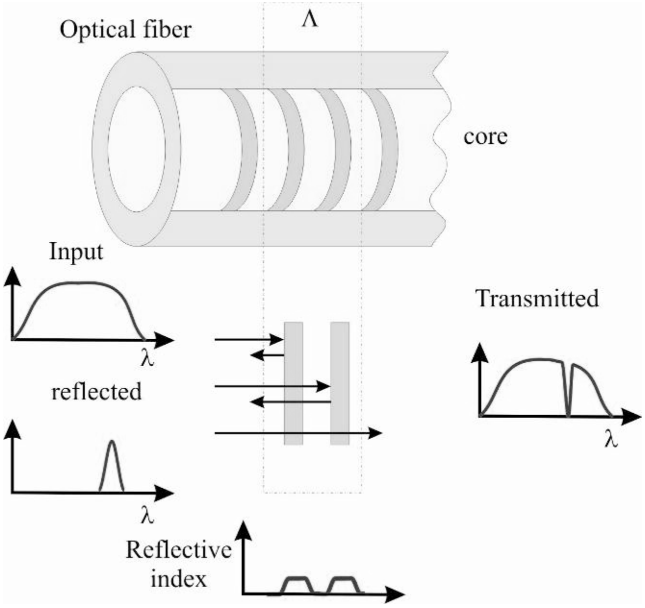

Figure 9. A fibre Bragg grating structure and sensing concept (from Kersey and Morey [42]).

Rao [43], knew by intuition in 1997 that FBGs would become the most promising candidates for fibre optic smart structures, in view of their multiplexing capability and intrinsic property, i.e., the fact that the measure is encoded directly in terms of wavelength, which is an absolute parameter and is not affected by disturbances to the light path.

Chang and Sirkis, in [44], presented a methodology for finding an appropriate optical fibre sensor and associated demodulation techniques to measure impact events. Several types of fibre optic sensors have been developed; for instance, the one described by Doyle et al. in [28] for the detection of acoustic emission in composite laminates, or the ones presented by Fuhr [45] and Tennyson et al. [46] for impact detection in large space structures.

Both multimode optical fibres and FBG sensors were used for detecting impact load and damage in several applications, including a composite pressure tank [47]. Gunther et al. [48] present an impact detection and location system based on triangulation that uses four fibre optic extrinsic Fizeau interferometric sensors embedded in a graphite/epoxy composite laminate. An extrinsic Fabry–Perot interferometer-based sensing system was employed by Greene et al. in [49] to determine impact locations on an aluminium sample and composite plate.

Piezoelectric sensors

Piezoelectric sensors are the most widely used sensors for damage detection based on strain data. Piezoelectricity is the ability of some materials to generate an electric potential in response to applied mechanical stress. This may take the form of separation of the electric charge across the crystal lattice. These materials usually also exhibit the converse effect; i.e., generation of mechanical stress and/or strain when an electric field is applied. Both effects can be seen in Figure 10.

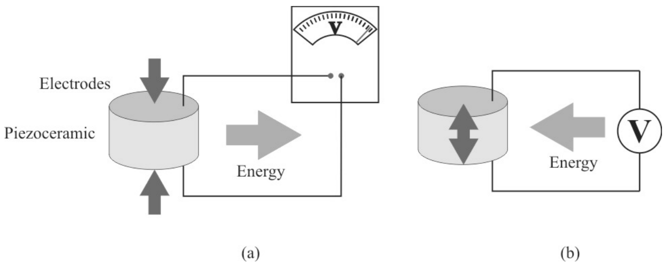

Figure 10. Piezoelectric effect: (a) direct and (b) inverse.

In the early 1990s, Lead Zirconate Titanite (PZT) piezo-ceramic sensors and Polyvinylidene Difluoride (PVDF) piezo-polymer sensors were evaluated by Weems et al. [10] for their suitability for impact detection in composite panels. Both sensors were mounted on the surface, and the PVDF sensors were also embedded in the core of the sandwich. Tests demonstrated that PZT could measure the dynamic strains caused by impacts. Later, Kim et al. [27] and Bar et al. [50] (to cite just a few of many papers in the literature) used PZT and PVDF sensors in composite laminates for impact damage detection.

The extensive progress in developing sensing devices has made adaptation and integration of sensors into structures more feasible. A polymer-based piezoelectric paint material has been developed and used for sensors by Egusa and Iwasawa in [51] and Zhang [52]. Piezoelectric paint is typically composed of tiny piezoelectric particles mixed within a polymer matrix. The fact that it can conform to curved surfaces and adhere well to the host structure is of great advantage.

The SMART layer, developed by Acellent Technologies [53], is a thin dielectric film containing a network of integrated piezoelectric transducers. It has a temperature tolerance of over 200 °C, which allows it to be embedded into, and co-cured with, a wide variety of composite materials and structures. These layers can be manufactured in several sizes and shapes, as shown in Figure 11. Ross in [15], Hu et al. in [16], and Haywood et al. in [17], among others, presented several applications of these layers for impact detection.

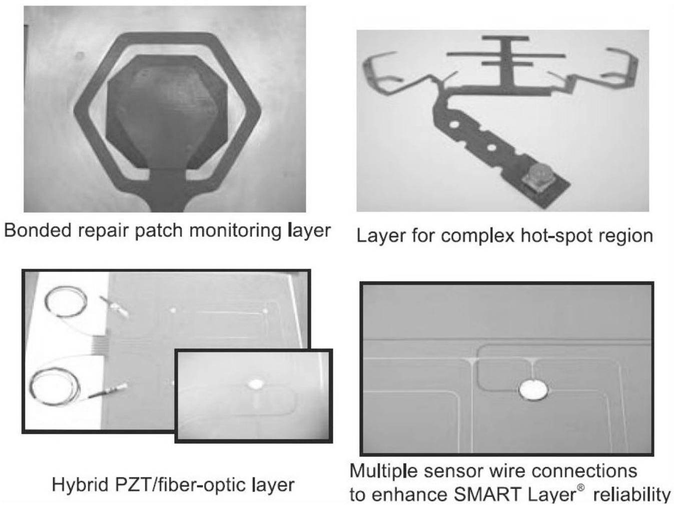

Figure 11. Smart Layer™ sensors. Courtesy of Acellent Technologies Ltd. [53].

Optimal distribution of sensors

One of the fundamental issues for the design of damage detection systems is to determine the optimum number of sensors for a particular application, together with their best possible location. The larger the number of sensors, the more the information that is obtained, but the cost is also higher, and while the sensors themselves are inexpensive, the overhead costs in terms of data acquisition systems and signal processing are not.

Several techniques have been developed for optimizing the location of sensors. A first review, presented by Worden and Burrows in [29], includes minimization of the covariance of the estimated parameters, Guyan model reduction, effective independence, kinetic energy, simulated annealing, etc.

Because the genetic algorithm (GA) is an excellent optimization tool, it has been used by Worden and co-workers in [29] and [54] for determining optimum sensor placement. Modifications in operations of reproduction, crossover and mutation for each GA were included by Staszewski in [55] and [56]. Afterwards, the fail-safe fitness of the mother gene was modified in [20], and results of the previous ones were improved. In these works, the search for the optimum is performed as follows. A gene is a vector of integers, each specifying the position of each sensor. An initial population is generated randomly. For each sensor distribution (gene), a neural network diagnostic is trained and the percentage error in predicting the impact is evaluated. According to the error and fitness, a new gene is generated looking for the best solution (minimal error with maximum frequency).

3. ANALYTICAL-MODEL-BASED STRATEGIES

First-principle or analytical models are derived using physical laws based on first principles. They are useful for damage assessment because they describe how the structure or components respond continuously to an external excitation. One criterion of analytical-model-based techniques for determining the location and energy of impacts is to minimize the difference between the modelled and actual responses. Handled in this way, the impact damage detection problem based on the analytical model has two major characteristics: (i) it is an inverse problem—force, impact energy and location should be found for a given system response—and (ii) it is a non-linear problem. Another criterion based on physical laws for estimating the location but not the force of impacts is based on the arrival times at each sensor of the strain wave produced by the impact. From these times, a triangulation procedure is performed to determine distances between the impact location and each sensor.

Methods based on equations of motion

The equations of motion of a rectangular, orthotropic, symmetrically laminated, elastic and shear-deformable plate are basically given as:

$$[M]\{\ddot{u}\} + [K]\{u\} = \{P^*\}, \qquad (1)$$

where $[M]$, $[K]$, $\{u\}$ and $\{P^*\}$ are the mass matrix, the stiffness matrix, the nodal displacement vector and the time-varying force. Assuming a concentrated impact loading, the lateral load per unit area $p(x, y, t)$ can be written as:

$$p(x, y, t) = F(t)\delta(x - x_c)\delta(y - y_c), \qquad (2)$$

where δ is the Dirac-delta function, and (x_c, y_c) is the contact point. The motion of the impacting object is described by:

$$m\ddot{\omega} = -F(t), \qquad (3)$$

where m and $\ddot{\omega}$ are the mass and acceleration of the object.

The system reported by Seydel and Chang in [18] and [19] consists of a structure model and a response comparator, as described in Figure 12. The model characterizes the dynamic response of the structure subject to known impact forces and locations. The comparator compares the measured sensor outputs with the estimated measurements from the model and updates the location and force history of the impact.

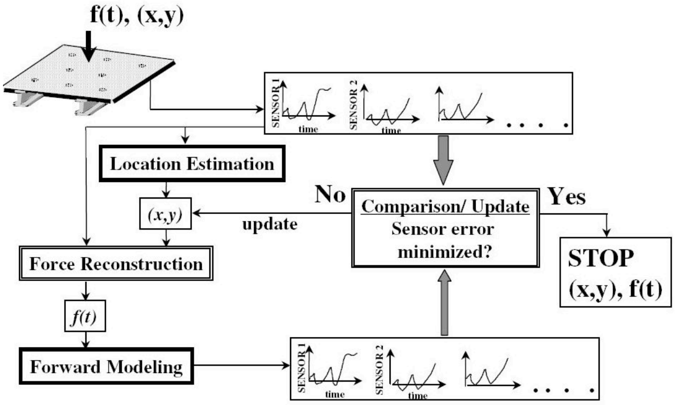

Figure 12. Overview of the model-based impact identification scheme (from [18] and [19]).

The major components of the system are as follows.

Forward modelling: based on equations (1–3).
Force reconstruction—using the inverse of the model used in forward modelling.
Comparison/update—comparison of modelled and experimental data to find the impact location.
Location estimation—based on triangulation procedures.

The inverse problem for force reconstruction has been solved, among others, (i) by Doyle and Martin in [57] and [58], using the spectral element method to generate a Green's function and calculating the impact force by some method of de-convolution in the frequency domain; (ii) by Wu et al. in [59] and [60] by finding the Green's functions for several possible impact locations, then finding a solution among those candidate locations using the least square optimization in time-domain optimization; (iii) by Christoforou in [61], using a least square optimization technique to minimize the model simulations with experimental measurements; and (iv) using the smoother filter on a beam by Choi and Chang in [6], on a plate by Tracy and Chang in [62] and [63], and on a plate with stiffeners by Seydel and Chang in [18] and [19]. An excellent review of inverse analysis for impact models was presented by Inoue et al. in [64].

On the other hand, the principle of time-reversed wave propagation was used to identify impact in plates by Adachi in [65]. If $u(t)$ is the solution of the governing equations in the structure, then $u(-t)$ is also a solution for the same equations. In this way, the method consists of two processes, as shown in Figure 13. The time history recorded by sensors is reversed and used as input to a model for locating the origin of this response.

Simulations based on the Finite Element Model (FEM) and the modal superposition method are widely used for determining the dynamic response produced by impacts on the structure. Several strategies are used to minimize the differences between these simulations and experimental data; for instance: the quadratic programming method by Hu et al. in [16], singular value decomposition by Shi in [66], the strain error method by Fukunaga and Hu in [67] and Park and Kim in [22] (minimizing the normalized error between true and calculated strain in a given element), the least square method by Matsumoto in [68], and the genetic algorithms by Doyle in [69].

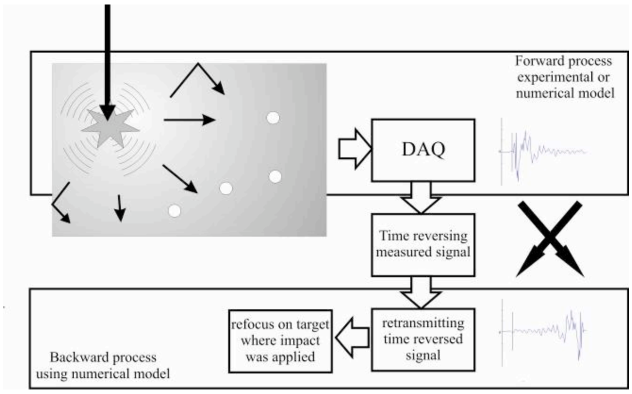

Figure 13. Block diagram of impact detection based on time-reversal processing (from Adachi and Sakai [65]).

Triangulation procedures

Impact detection can be also presented as an inverse problem that uses the arrival time of the stress waves to the sensors and their coordinates to locate the impact location. According to Salehian [70], three sensors are enough for determining impact location for isotropic materials. The location of the impact can be found by the following set of non-linear equations:

$$l_i = \sqrt{(x - x_p)^2 + (y - y_p)^2}\,, \tag{4}$$

$$t_i = \frac{l_i}{C_g}\,, \tag{5}$$

where x_p and y_p are the coordinates of the impact location, l_i is the distance between the impact location and sensor i, C_g is the wave propagation speed, and t_i is the arrival time of the stress wave at sensor i. Arrival times are related to the dominant frequency contents of the signal.

For composite (anisotropic) materials, this approach is not possible; because of variations in the frequency components of strain waves within different directions and different speeds, more than one C_g is unknown. According to Figure 14, values of l_i are also related to wave propagation speeds C_{gi}, angles θ_i and arrival times t_i.

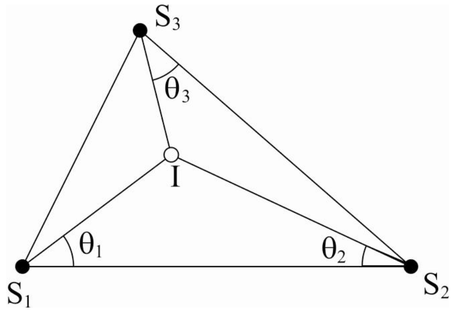

Figure 14. Sensor triangulation set-up used by Salehian in [70] and Meo et al. in [71].

After some mathematical manipulations, by solving equations (6), (7) and (8), the angles θ_1 and θ_2 can be calculated:

$$\frac{1}{cot(\theta_1) + cot(\theta_2)} \left(\frac{1}{sin(\theta_1)C_{g1}} - \frac{1}{sin(\theta_2)C_{g2}} \right) - \frac{t_{12}}{S_1S_2} = 0\,, \tag{6}$$

$$\frac{1}{cot(\theta_3) + cot(\hat{S}_2 - \theta_2)} \left(\frac{1}{sin(\hat{S}_2 - \theta_2)C_{g2}} - \frac{1}{sin(\theta_3)C_{g3}} \right) - \frac{t_{23}}{S_2S_3} = 0\,, \tag{7}$$

$$cot(\theta_3) = \frac{S_2S_3 sin(\theta_2)(cot(\theta_1) - cot(\theta_2))}{S_1S_2 sin(\hat{S}_2 - \theta_2)} - cot(\hat{S}_2 - \theta_2)\,, \tag{8}$$

where t_{ij} is the difference between arrival times at sensors i and j and S_iS_j is the distance between sensors i and j.

Coverley, Staszewski and co-workers in [72] and [17] presented a method that proposed combining classical triangulation with the genetic algorithm. Three different impact locations are assumed (A_1, A_2 and A_3), creating different wave propagation paths S_iA_i with appropriate angle variables θ_i as described in Figure 15.

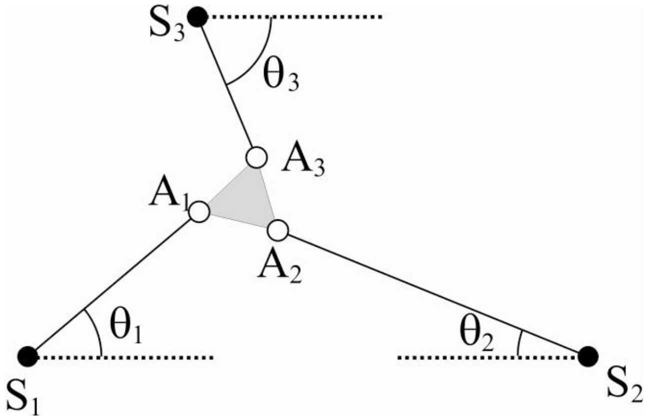

Figure 15. Sensor triangulation set-up used in [72] and [17].

A set of angle variables is randomly selected, and for each angle θ_i, the distance S_iA_i is calculated by:

$$S_iA_i = C_{gi}t_i\,. \qquad (9)$$

In this way, three different impact locations are calculated. Genetic algorithms are used to minimize the distances A_1A_2, A_2A_3 and A_1A_3, changing the angles in each iteration.

Another triangulation procedure was developed by Kundu et al. in [73] and [74]. From equations (4) and (5), with different mathematical manipulations, an error function is found as described below.

$$\begin{aligned} E(x_p, y_p) \;=\; & \big(t_{23}C_{g3}(C_{g2}l_1 - C_{g1}l_2) - t_{12}C_{g1}(C_{g3}l_2 - C_{g2}l_3)\big)^2 \\ & + \big(t_{31}C_{g1}(C_{g3}l_2 - C_{g2}l_3) - t_{23}C_{g2}(C_{g1}l_3 - C_{g3}l_1)\big)^2 \\ & + \big(t_{12}C_{g2}(C_{g1}l_3 - C_{g3}l_1) - t_{31}C_{g3}(C_{g2}l_1 - C_{g1}l_2)\big)^2 \end{aligned} \qquad (10)$$

By applying any optimization algorithm to minimize the error, the distances l_i, and therefore the location of the impact, can be found.

A triangulation procedure using an elliptical approach was presented by Paget in [75]. An example of an elliptical wave front is described in Figure 16.

The coordinate y of the impact is determined by a quadratic polynomial equation as follows:

$$ay^4 + by^3 + cy^2 + dy + e = 0, \qquad (11)$$

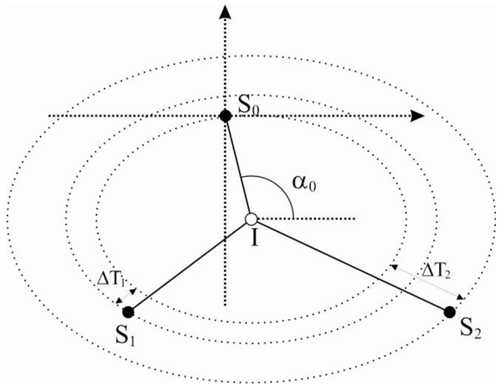

Figure 16. Sensor triangulation set-up used by Paget in [75].

where,

$$\begin{aligned} a &= \delta^2 - 16\kappa\phi^4 \\ b &= 2\delta\varepsilon + 16\kappa\phi^4(y_1 + y_2) \\ c &= 2\delta\xi + \varepsilon^2 - 16y_1y_2\kappa\phi^4 + 4\kappa\phi^2(\tau_1 + \tau_2) \\ d &= 2\varepsilon\xi - 4\kappa\phi^2(\tau_1 \cdot y_2 + \tau_2 \cdot y_1) \\ e &= \xi^2 - \kappa\tau_1 \cdot \tau_2 \end{aligned} \qquad (12)$$

In equation (12), all parameters are defined by the following sets of equations:

$$\begin{pmatrix} \delta \\ \varepsilon \\ \xi \end{pmatrix} = \begin{pmatrix} \chi^2 \\ 2\rho\chi \\ \rho^2 \end{pmatrix} - (2\phi \cdot v(0^o))^2$$

$$\left(\tau_2 \cdot \Delta T_2^2 \begin{pmatrix} -1 \\ y_2 \\ \tau_2/4\phi^2 \end{pmatrix} \tau_2 \cdot \Delta T_1^2 \begin{pmatrix} -1 \\ y_1 \\ \tau_1/4\phi^2 \end{pmatrix} \right) \begin{pmatrix} \alpha_1^2 \\ \alpha_2^2 \end{pmatrix}, \qquad (13)$$

where

$$\begin{aligned} \alpha_i &= (\Delta T_i \cdot v(0^o))^2 - x_i^2 \\ \phi &= v(0^o)/v(90^o) \\ \tau_i &= \alpha_1 - (\phi \cdot y_i)^2 \\ \kappa &= 4\tau_1 \cdot \tau_2(\alpha_1 \cdot \alpha_2 \cdot \Delta T_1 \cdot \Delta T_2 \cdot v(0^o)^2) \\ \text{for } i &= 1{,}2 \end{aligned} \qquad (14)$$

and

$$\begin{pmatrix} \rho \\ \chi \end{pmatrix} = \begin{pmatrix} x_2 \cdot \tau_2 & -x_1 \cdot \tau_1 \\ x_2 \cdot y_2 & -x_1 \cdot y_1 \end{pmatrix} \cdot \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix}. \qquad (15)$$

The coordinate x of the impact is calculated using the real solution from equation (11) and the following equation, for $i = 1,2$:

$$x = \frac{x_i(\tau_i + 2y_i\phi^2 y) \pm \Delta T_i \cdot v(0^o)\sqrt{\tau_i(4\phi^2(y_i - y)y)}}{2\alpha_i} . \quad (16)$$

In all procedures described above, the wave propagation velocities and arrival times must be evaluated. Beard and Chang in [76] show that the speed is a function of the angle of wave propagation. Therefore, the graph of the group speed C_g versus angle θ for different frequencies can be experimentally determined using time–frequency graphs as wavelet transforms [71].

On the other hand, the exact time of arrival of the signal may not be known directly from the signal either, because of signal distortion due to dispersion or because of the instrument noise level. Ross in [15] proposed the wavelet transform as a very accurate de-noising technique. Otherwise, these arrival times can be estimated by the signal arrival times for which the envelope function reaches its maximum.

Several examples of envelope functions can be found in the literature; for instance, Coverley and Staszewski in [72] use the Hilbert Transform, and Salehian in [70], Meo et al. in [71], Jeong and Jang in [77], and Gaul and Hurlebaus [78] use wavelet transforms. Some of these approaches can be extended to more than three sensors to improve the results.

4. DATA-DRIVEN-MODEL-BASED STRATEGIES

In contrast to the model-based approaches where a priori knowledge (either quantitative or qualitative) about the structure is needed, in data-driven or process-history-based methods, only the availability of a large amount of time-domain data is needed. These methods usually may be applied when a specific equation or algorithm is not applicable but adequate knowledge or data exist to derive a knowledge-based solution. Basically, these methods are based on advanced signal processing that includes feature extraction and selection, and a strategy for damage identification in the strict sense. There are different ways in which these data can be transformed and presented as a priori knowledge to assess damage on structures. Neural networks are the most important and widely used classifiers. Case-Based Reasoning (CBR) is a novel technique within an Artificial Intelligence (AI) background that has been used recently for damage identification and impact detection in structures. Otherwise, other techniques within the AI concept have been applied for impact detection. For instance, Shan and King present a fuzzy c-means clustering algorithm for feature selection, and an adaptive neuro fuzzy inference system (ANFIS) for impact location and magnitude estimation [79][80].

Artificial Neural Network

Because of the well-documented capabilities of Artificial Neural Networks (ANNs) as pattern recognizers, classifiers and function fitters, they have been a good option for addressing the problem of damage assessment in structures. Hahn et al. in [81], Sirkis et al. in [82], Schindler et al. in [41], Kudva et al. in [83], and Gunther et al. in [48] have initiated a number of studies based on advanced signal processing using ANNs for impact damage detection.

Worden and Staszewski in [21] and Staszewski et al. in [20] used two ANNs as regressors to predict the impact location and energy separately in composite materials. A typical multilayer perceptron was trained with experimental data using the back-propagation learning rule. The input to the ANN was determined by several time- and frequency-domain features: the time and magnitude of peaks (one or two per sensor). The output of the first ANN is just one neuron, which estimates the energy. For the second ANN, two neurons were used in the output layer (the x-location and y-location). A trial-and-error approach was adopted, and numerous structures were assessed in order to determine the optimum configuration. This approach was tested by Haywood et al. [17] in Smart Layer and by LeClerc et al. [23] in a large aircraft structure.

Liu et al. in [84] trained a single perceptron with back-propagation learning using arrival times from experimental data to locate the impact. A feed-forward ANN trained with experimental data and using a back-propagation algorithm was used by Akhavan et al. in [85] to estimate the impact contact force. Afterwards, Dua et al. in [86]reported an extension of the previous approach to detect and classify the impacts using finite element analysis (FEA) to simulate impact-induced strain profiles resulting from impacts. The whole time register of the strain signal was used in the input of the ANN; each sample then needs one neuron in the input layer. The classification was coded using grey code, so each neuron in the output layer represented one bit.

The Levenberg–Marquardt (LM) algorithm and the generalization method were applied by Sung et al. in [87]. The LM algorithm for non-linear least squares is incorporated into the back-propagation learning to increase the speed. Moreover, the generalization method reduces the detection error of the untrained data.

The real and imaginary parts of the Fast Fourier Transform (FFT) of strains from four sensors were used by Jones et al. in [88] to provide input to two feed-forward back-propagation ANNs in order to determine the location and magnitude of transverse impact events on isotropic plates. A feed-forward multilayer perceptron was used by Martin and Jata in [89] to find the impact location from relative arrival times in a layer of transversely isotropic material; in particular, in thermal protection systems of aerospace vehicles. Another feed-forward multilayer perceptron was used by Ross in [15] as a classifier of segments where impacts occurred in a Smart Layer.

Case-Based Reasoning

A novel impact location approach based on data from either simulations or experiments was presented by Mujica et al. [25]. They applied the principle of CBR to reach the goal. The original CBR methodology proposes a cycle of the four Rs. The CBR cycle basically consists of *retaining* the principal impact features (cases) for further *reuse*. The aim is to *reuse* these cases for solving new problems by analogy. An impact is located by *retrieving* similar features of impacts from the past and *reusing* its location in the new situation. *Reusing* implies a procedure of adapting the *retrieved* solution, which is then completed with the *revision* [90]. In practice, it is difficult to distinguish between the *reuse* and *revision* stages, and it may be best to think of these as a single *adaptation* stage [91].

In order to organize the information in memory, to reduce the dimensionality and to improve the previous results, Mujica et al. [24] use different techniques, such as Self-Organizing Maps (SOM), Principal Component Analysis (PCA), Projection to Latent Structures (PLS), Curvilinear Distance Analysis (CDA) and some extensions of them. The CBR cycle proposed is shown in Figure 17.

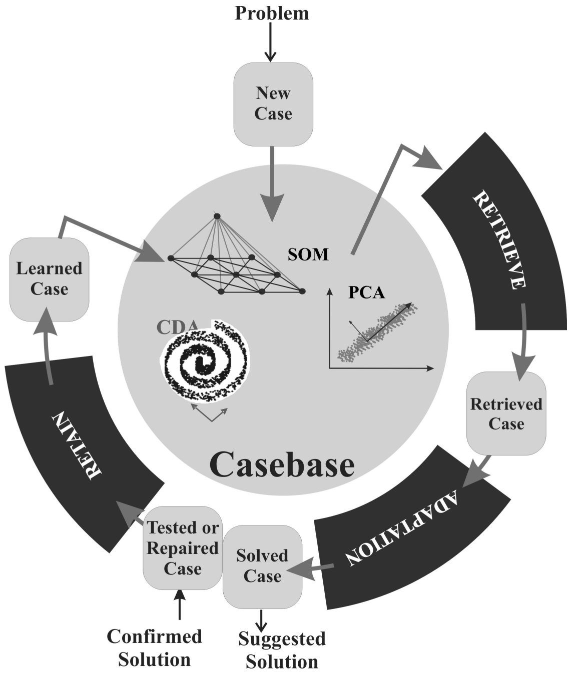

Figure 17. CBR cycle (from Mujica et al. [24]).

5. USING A TRANSFER FUNCTION

Park and Chang present in [92] a work that is not included in the analytical-model-based group but uses a system transfer function to obtain a mathematical relation that predicts the behaviour of outputs using input and output data gathered from experimental tests. The dynamic response of the structure subjected to an impact is considered to be linearly dependent on the impact force in some special cases. Therefore, the response *y(k)* at a point of the structure is related to the impact force *u(k)* by a state space equation, as follows:

$$\begin{aligned} x(k+1) &= Ax(k)+Bu(k) \\ y(k) &= Cx(k) \end{aligned} , \qquad (17)$$

where

$$A = \begin{pmatrix} a_1 & a_2 & \dots & a_{n-1} & a_n \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{pmatrix}. \quad (18)$$

$$B = \begin{pmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \quad C = \begin{pmatrix} b_1 & b_1 & \dots & b_1 \end{pmatrix}$$

For flexible structures, the parameters a_i and b_j are identified using the ARX (auto-regressive with eXogeneu inputs) model.

6. CONCLUSIONS

This review described briefly several approaches for impact damage detection in structures that use strain data. An overview of the impact detection systems was provided. Papers that have reported advances in sensors for detecting impacts were cited. Strategies were classified into two types, data-driven-model based and analytical-model based. The former is good for locating the impact but is not efficient enough to assess the force or energy. Besides, a considerable amount of data must be collected, which implies a tedious procedure to impact the entire surface of the structure. As regards the approaches based on analytical models, although they can estimate the local strain for a given impact force using an accurate physical model, the inverse solution cannot be calculated easily. Iterative methods have been proposed, but they are slow and difficult to use for complicated structures.

Many more papers can be found in the literature, but the authors have made an attempt to cite those that have contributed with novel concepts, variations or hybridization of previous approaches to improve their efficiency and application to structures more complex or more representative of real components.

7. ACKNOWLEDGEMENT

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