Damage Detection of Structures using Artificial Intelligence

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Abstract

Damage Detection comes under the area of Structural Health Monitoring(SHM). We intend to find out information about cracks in metallic structures after the application of changing load. In our project we intend to find the following info about the cracks:

1. Presence
2. Location
3. Severity (Quantification)

We intend to collect the data from experimentation under laboratory conditions. We take a standard rod, create a notch and create a crack using the fatigue machine available in the lab. We then intend to collect as much data as possible regarding the correlation between data from the sensor and the known observation regarding the cracks. We intendthree to use optical fiber sensors for our purpose. With the help of Deep Neural Networks(DNNs) we create a function approximator which can give the above three information about the cracks just by using the data from the laser sensor. We would also like to publish the dataset in the public domain, to help in further research. Our project will help in applications in construction, bridge building, ship building, aviation industries, space technology,etc.

Introduction

According to Wikipedia,

> **Structural health monitoring** (**SHM**) refers to the process of implementing a damage detection and characterization strategy for engineering structures such as bridges and buildings.

Damage detection thus comes under the broad field of Structural Health Monitoring (SHM).

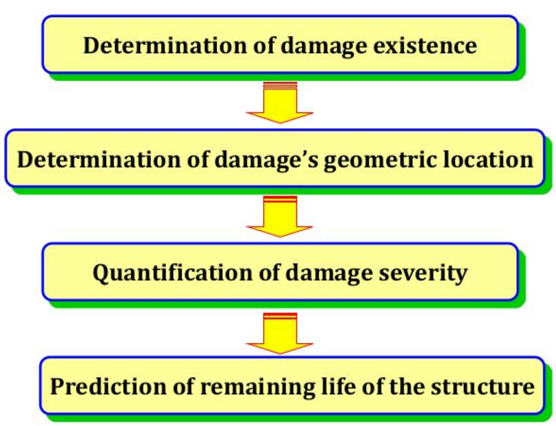

Figure 1: Steps of Structural Health Monitoring (SHM)

Types of detection under SHM:

1. Visual Inspection - fully experience based subjective evaluation.

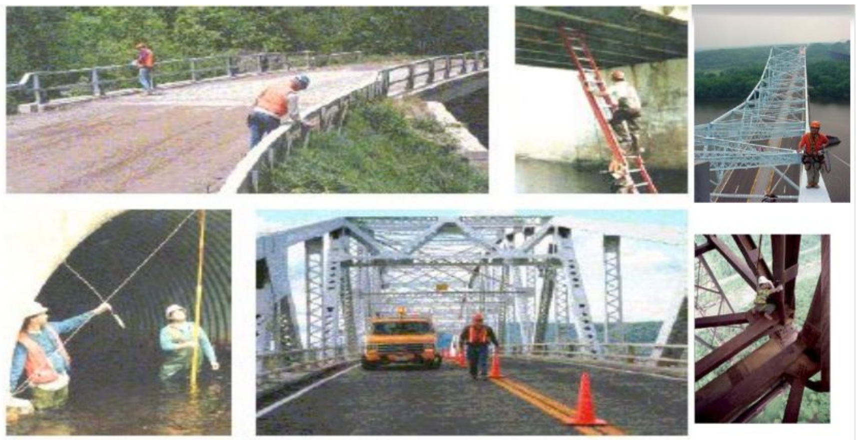

Figure 2: Structural Health monitoring by Visual Inspection

2. Non-destructive Testing (NDT) - use of various technologies done by individuals with a high degree of technical knowledge. Eg: Magnetic Particle Testing, Dye Penetration Testing, Radiography Test, Eddy Current Test, Ultrasonic Test, Acoustic Emission Test, Thermal Infrared Test.

Figure 3: Performing NDT test on Railway Tracks

Our project comes under Non-destructive Testing. Vibration based tests are popular under NDT, but with the emergence of new technologies leading to new sensors, the field is spreading fast. Developments in Optical Fiber technology have enabled its use in damage detection. Several papers exist which describe the use of Optical Fiber Sensors for Damage Detection in Composite Structures such as glass/epoxy slab. But most of this research is based on the expensive Fiber Bragg Grating sensor. Our research focuses on the use of less expensive simple Optical Fiber Sensors, on Metallic Structures and Concrete Structures both. Data collection is often plagued by noises by sources such as measurement, environment(temperature, humidity), unknown and non-stationary input,etc.. This is where Data based statistical modelling techniques come in. Statistical modelling techniques such as neural networks aid in hassle-free modelling of complicated relationships. So, we just have to collect data from all these varying situations and then “let the data speak for itself” by feeding it all into the neural network which will find the correct relationship accounting for these noises.

Pre-Experimental Preparation

Materials

Aluminium rods of various sizes are collected. Three optical fiber strips of one-third, two-third and full length are mounted on the top surface of the beams. A second series of experiments concerning concrete rods will also be done after the aluminium rods.

Creating Notch

Notch is required to create cracks. In accordance with the **European Code of Practice for Creep Crack Initiation and Growth Testing of Industrially Relevant Specimens**, we chose **Single Edge Notched Bend** model for creating notches in our specimens.

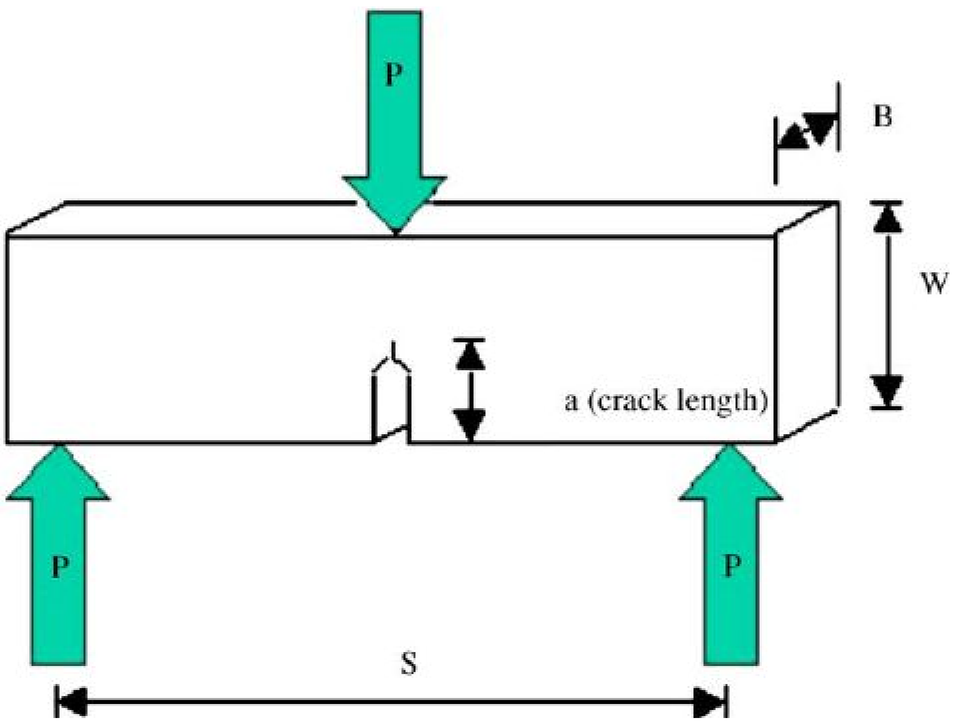

Figure 4: Sample Single Edged Notched Specimen

Full width Notches of different sizes are made at different locations in different specimens. Notch location and size are noted.

Crack Initiation and Growth

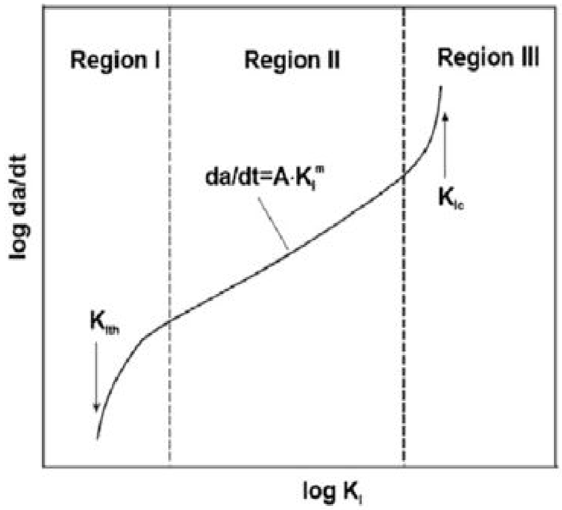

Figure 5: Creep Crack Growth Curve

Creep crack is initiated using the notch. It is grown using Axial Load Fatigue Testing Machine. Crack size and severity are noted using visual cues.

Experimental Setup

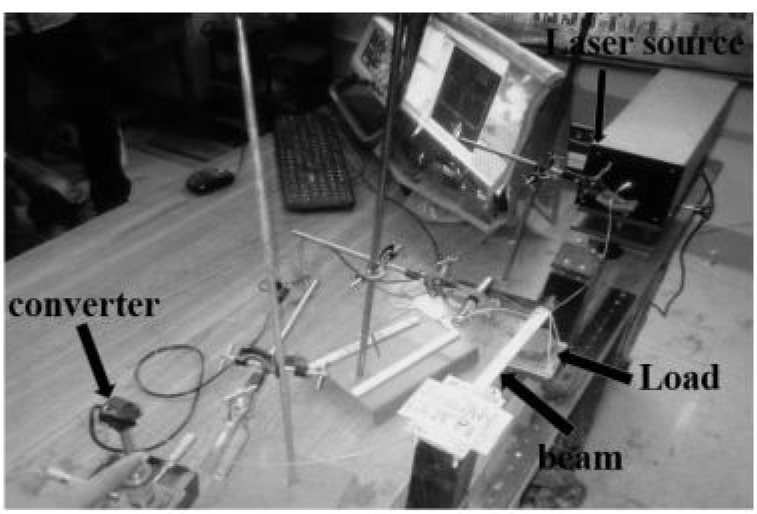

Figure 6: Experimental Setup

The beam is loaded like a cantilever beam with a free end and other end attached to the support. A load is put on the free end.

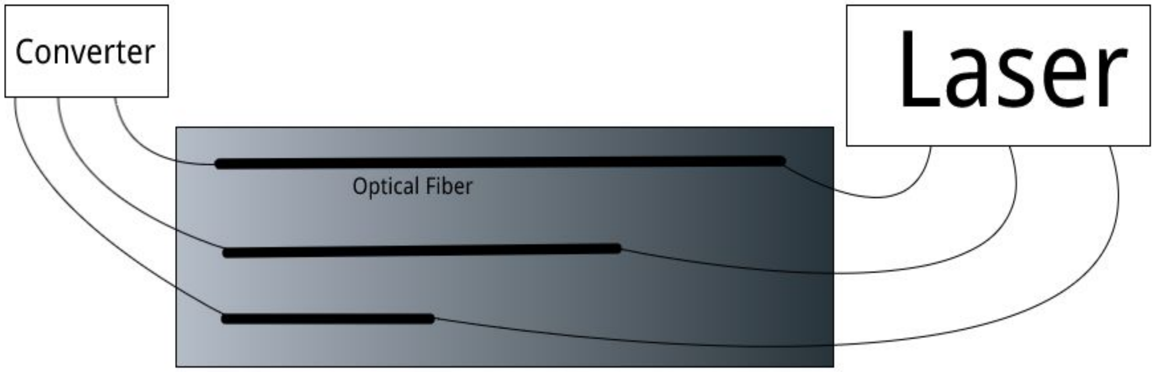

Figure 7: Electrical converter and Laser connected to the Optical Fiber Sensors on top of the specimen (notch not shown)

It is assumed that three fibers of different lengths will give us more information about the crack than that obtained from a single one.

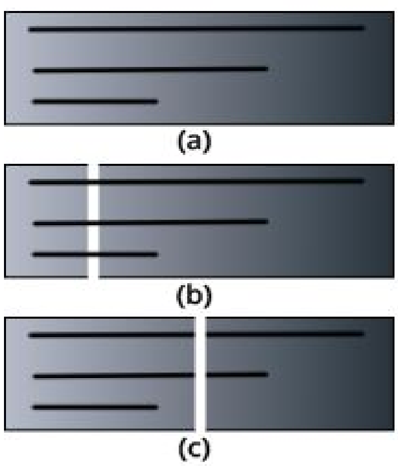

Figure 8: (a) specimen without notch, (b) specimen with notch in the left half, (c) specimen with notch in the middle

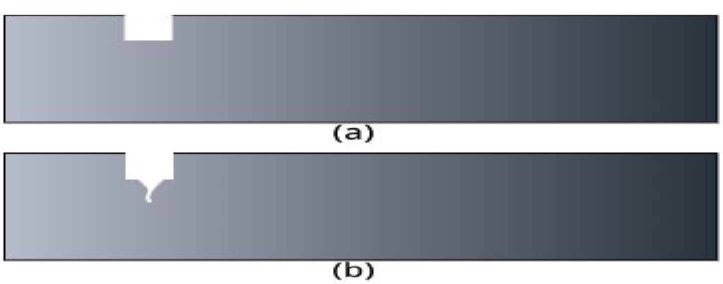

Figure 9: (a) specimen with notch but without crack, (b) specimen with notch and crack

Methodology

The experimental set-up as shown demonstrates feature extraction from output signal. A four layer feed forward neural network architecture is adopted. It has one input layer with a node each for each feature, two hidden layers and an output layer. Each node from the input layer is connected to a node from the hidden layer and every node from the hidden layer is connected to a node in the output layer. Some weight is usually associated with every connection. Input layer represents the raw information that is fed into the network. This part of the network never modifies its values.

Hidden Layer accepts data from the input layer. It uses input values and modifies them using some weight value according to requirement. This new value coming as output of the hidden layer is then sent to the output layer after modifying it by some weight using a relation between hidden and output layer. Output layer processes information received from the hidden layer and produces an output. This output is then processed by activation function. The outputs generated help in qualitatively identifying the location of the notch.

In practice this algorithm is currently employed as follows: after each input pattern is presented to the network, the consequent error vector across output units is determined and back-propagated through the network to update the weights. The next pattern is then presented and the process repeated. The back-propagation process will generally converge to a minimum that satisfies the criterion imposed by the user, usually that the sum of the squares of the error of the output signal will be less than a predetermined value. The hidden layer and output layer transfer functions are considered as sigmoidal functions.

The iterative process of updating of weights continues till the error of output of the output neurons achieves an acceptable limit. This completes the training of the neural network and the network is ready to take further input to predict relative location of the notch.

Data Collection

Varying loads are applied starting from zero, and the signals are recorded for each of them for 5 seconds. The signal amplitude is collected each 100 microseconds.

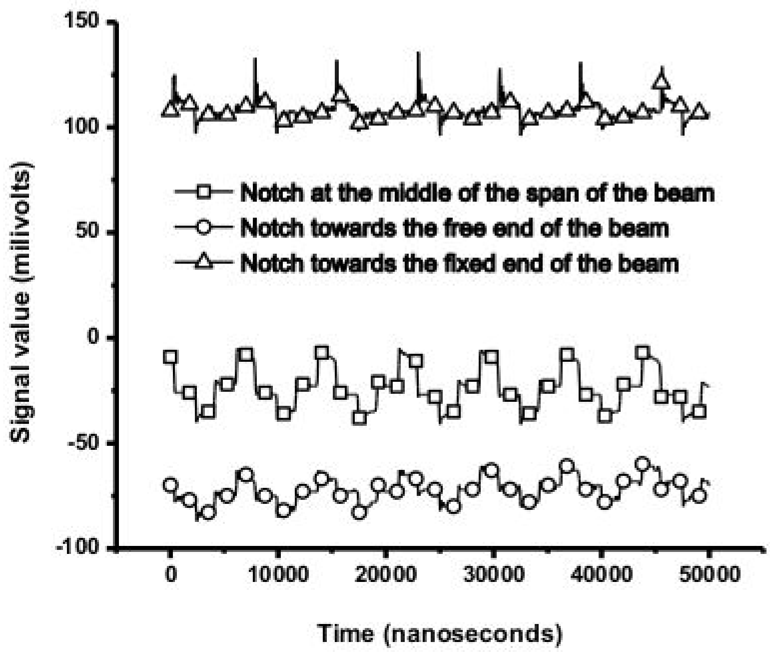

Figure 10: Output obtained from oscilloscope for qualitative differences in position

Data is obtained from this signal about its phase, amplitude and waveform. This will contain information about the crack that we need.

Function Approximator

Function approximation is a technique for estimating an unknown underlying function using historical or available observations from a particular domain.

Artificial neural networks can learn to approximate a function which is unknown, hence they are used as approximators.

Under supervised learning, inputs and outputs make up a dataset, and the algorithm learns how to efficiently map input cases to output cases. This mapping is governed by a mathematical function, which is called the mapping function, and it is this function that a supervised learning algorithm seeks to best approximate.

Neural networks are a fine example of a supervised learning algorithm and it seeks to approximate the function represented by the obtained data by calculating the error between the predicted outputs and the expected outputs and minimizing this error during the training process.

While it is known that a mapping function may exist, it is not clear what the function actually is. This actual but unknown function that maps inputs to outputs is called the target function. The goal of the learning process is to get as close to the target function as possible through approximation using available data.

Experiments are conducted to achieve observations from the domain of interest in order to generate cases of inputs and outputs. The more sample cases there are, the closer the obtained function is to the mapping function. Also, the less noise there are in the observations made, the more precise is the approximation made of the mapping function.

Since neural networks are universal approximators, they are used for function approximation in this case.

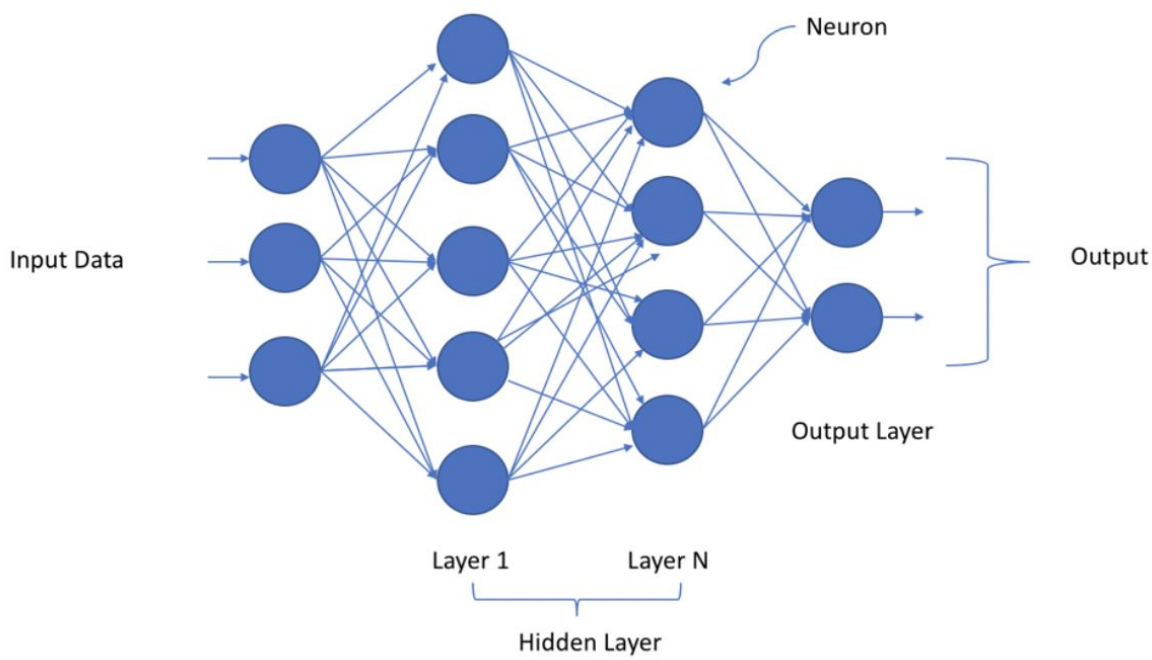

Figure 11: Sample Deep Neural Network

The neural network is composed of an input layer, two hidden layers and an output layer. Input layer has 150 neurons (50x3 for each of the optical fiber strands), hidden layer 1 has 128 neurons, hidden layer 2 has 128 neurons and output layer has 4 neurons. Each node in the input layer is connected to a node in a hidden layer and they are connected to a node in the output layer. Some weight is usually associated with every connection. Input layer represents information that is fed into the network. Hidden Layer accepts data from the input layer. It uses input values and modifies them using some weight value. The value produced by the hidden layer is then sent to the output layer after modifying it by some weight relating hidden and output layers.

Here is the main function of the Neural Network in python:

```
def model(X, Y, nn_architecture, learning_rate = 0.0075, num_iterations = 3000, print_cost=False):
    np.random.seed(1)
    # keep track of cost
    costs = []

    # Parameters initialization.
    parameters = initialize_parameters(nn_architecture)

    # Loop (gradient descent)
    for i in range(0, num_iterations):

        # Forward propagation: [LINEAR -> RELU]*(L-1) -> LINEAR -> SIGMOID.
        AL, forward_cache = L_model_forward(X, parameters, nn_architecture)

        # Compute cost.
        cost = compute_cost(AL, Y)

        # Backward propagation.
        grads = L_model_backward(AL, Y, parameters, forward_cache, nn_architecture)

        # Update parameters.
        parameters = update_parameters(parameters, grads, learning_rate)

        # Print the cost every 100 training example
        if print_cost and i % 100 == 0:
            print("Cost after iteration %i: %f" %(i, cost))

        costs.append(cost)

    # plot the cost
    plt.plot(np.squeeze(costs))
    plt.ylabel('cost')
    plt.xlabel('iterations (per tens)')
    plt.title("Learning rate =" + str(learning_rate))
    plt.show()

    return parameters
```

Figure 12: Python code of Neural Network

Propagation Algorithm Of Neural Network Architecture For SHM

Back-propagation is a core component of neural net training. In backpropagation, the weights of a neural net are fine-tuned based on the error rate obtained in the previous iteration. The correct tuning of weights enable reduction of error rates and makes the model more reliable by increasing its generalization.

Back-propagation essentially translates to backward propagation of errors. Back-propagation is a standard method of training artificial neural networks. This method assists in the calculation of the gradient of a loss function with respect to all the weights present in the network.

• The data obtained from observations is entered to train the model

• Weight matrix is initialised

• Input to the hidden layer are found

• Output from hidden layer are found

• If there are multiple hidden layers, the input and output steps are repeated for the appropriate number of times

• The input to the output layer is found

• The output from the output layer is found

• Error is calculated using the appropriately chosen method

• The error value is checked to decide if it is within acceptable bounds

• If the error is not within acceptable limits, then weights are updated and the control is transferred to the weight initialisation stage

• If the error is within acceptable limits, the process ends

• Appropriate inference is made from the obtained result

• The obtained data may be stored for future reference

Results

The output layer has 4 neurons corresponding to:

1. Detecting existence of damage. => 0 (no damage) or 1 (presence of damage)
2. Location of the crack. => Number between 0 and 1. (depicting the ratio of the location of crack to the total length of the specimen)
3. Depth of crack => Number between 0 and 1. (depicting ratio between depth of crack and total depth of specimen)
4. Average width of crack => Number between 0 and 1. (depicting ratio between average width of crack and total length of specimen)

Conclusions and Future Scope

We were unable to conduct experiments and collect data due to the lockdown. Our report shows how damage detection can be done using simple fiber optic sensors and neural network algorithms. Depending on the experimental experience we intend to expand the scope of this project and work on actual buildings, with the real time data processed and sent to a smartphone (data about the strain, reliability and life). This will include our project under the domain of **Smart Sensors for Structural Health Monitoring** and **IoT**, and will be able to publish our work in journals of this kind.

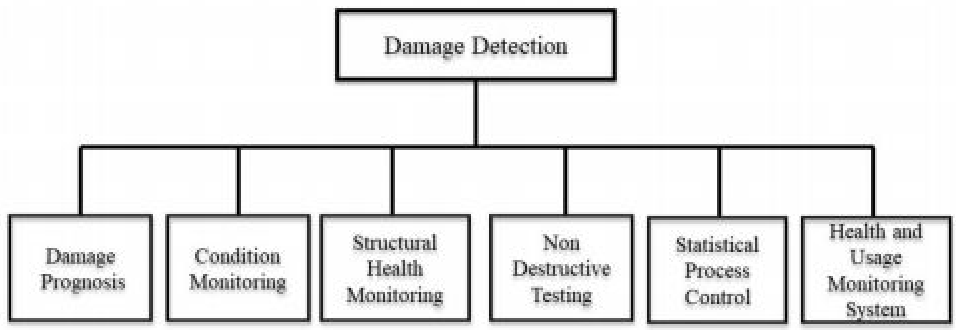

Figure 13: Damage detection disciplines

Smart Sensing Technologies

Advent of computationally efficient smartphones, inexpensive high-resolution cameras, drones, and robotic sensors has brought a new era of next-generation intelligent monitoring systems for civil infrastructure. Vibration-based condition assessment has garnered a prominent method of evaluating the health of large-scale infrastructure. The use of contact-based sensors for acquiring vibration data becomes uneconomical and tedious due to their instrumentation cost, centralized nature, and densification required to collect sufficient data for system identification of modern complex structures. A need to advance and develop alternative methods for efficient sensing systems results in next-generation measurement technology of structural health monitoring.

The abundance of handheld smartphones with easily programmable framework has helped in modifying relevant software to acquire vibration data using embedded sensors in the smartphone. The inexpensive cameras have been used to capture images and videos that are utilized to understand the structural behavior with the aid of advanced signal processing techniques. The inaccessible components of structures require noncontact sensors such as unmanned aerial vehicles (UAVs) or so-called drones and mobile sensors to acquire structural data.

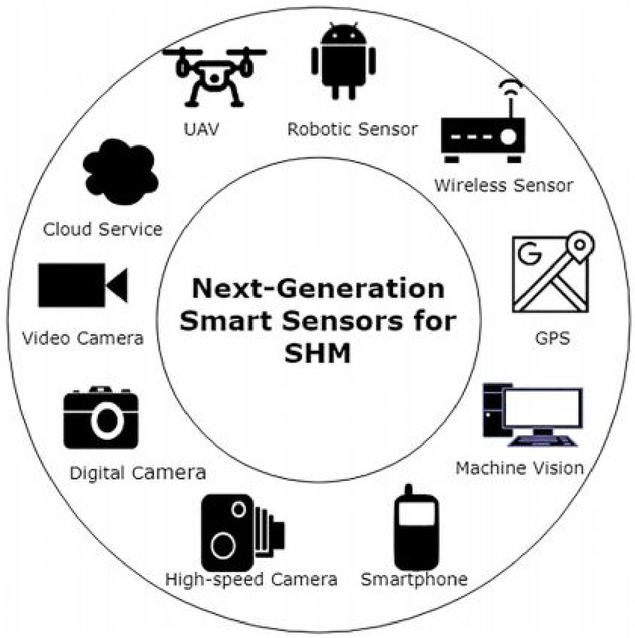

Figure 14: A schematic of various next-generation sensing technology used in the SHM

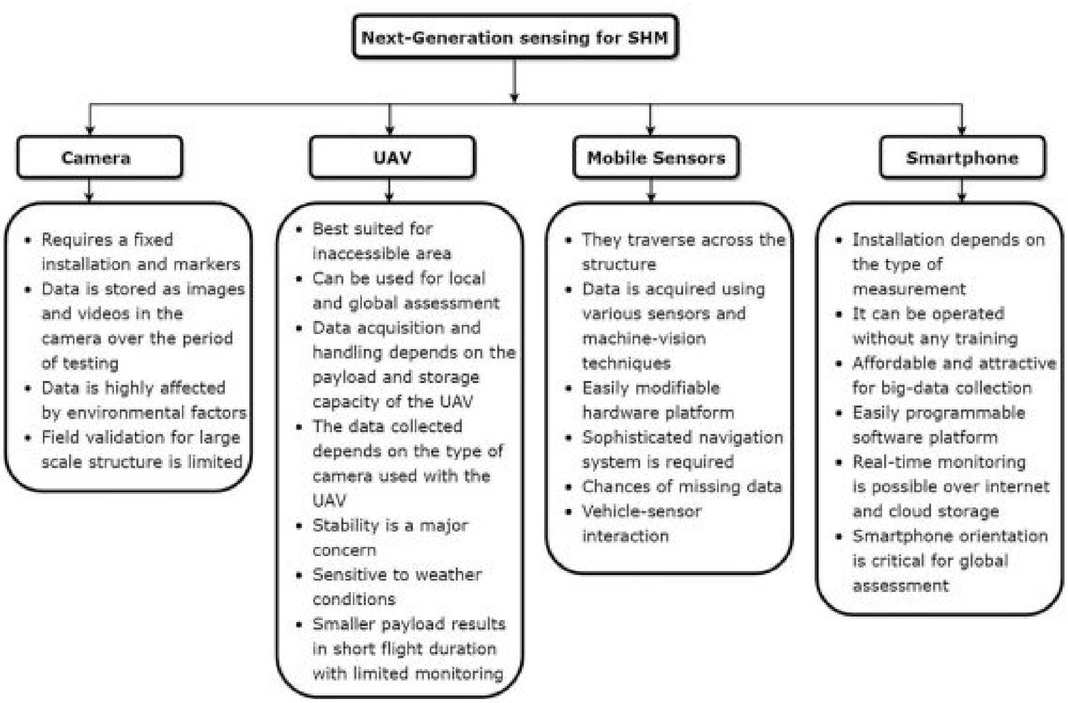

Figure 15: Key findings of various next-generation sensing technologies

Sensors

Incidents such as building and bridge collapse are on rise in many parts of the world without little apparent warning. Due to the increased number of incidents it has become of increasingly paramount importance to develop methods detecting the degradation or damage that result in these events. Thus, buildings and critical infrastructure could be monitored, much like a patient in a hospital, for signs of degradation or impending disability or collapse. The sensors are very important to know the state of the health of the structures and technologies are like human brains to analyze the abnormal situation.

Characteristics of Sensors for Monitoring Health of Structures:

1. Range
2. Sensitivity
3. Accuracy
4. Stability
5. Repeatability
6. Static and dynamic characteristics
7. Energy Harvesting
8. Compensation due to change of temperature and other environmental parameters

Wireless Sensor Nodes equipped with Inexpensive Strain Gauges	MEMS Inertial Sensors	Impedance Measurement System for Lead Zirconate Titanate (PZT) Ceramics	Optical Sensors	Fibre Optic Accelerometers
Accelerometers	Optical Accelerometer Unit based on Fiber Bragg Gratings,	Bragg grating-based Optical Fiber Sensors Integrated into Carbon Fiber Polymer Reinforcement (CFPR) Rod	Electrical Resistance Strain Gauges (ERSG)	Fiber-Optic Sensors (FOS)
Acoustic Sensing Cantilevers	Piezoelectric Sensors	Micro-Opto-Electro-Mechanical Systems (MOEMS) Acoustic Sensors		

Optical Fibre Sensors

Over the last two decades, optical fibre sensors have attracted substantial attention and shown to be capable of monitoring a wide range of physical measurands for SHM applications.

The availability of inexpensive, rugged, and large-core plastic-based optical fibres has resulted in growing interest amongst researchers in the use of conventional glass-based fibres as low-cost sensors in a variety of areas including chemical sensing, biomedicine, and the measurement of a range of physical parameters. The sensing principles used in plastic optical fibres are often similar to those developed in glass-based fibres, but the advantages associated with plastic fibres render them attractive as an alternative to conventional glass fibres, and their ability to detect and measure physical parameters such as strain, stress, load, temperature, displacement, and pressure makes them suitable for structural health monitoring (SHM) applications.

The advantages of optical fibre sensing in engineering structures are well known and these include their insensitivity to electromagnetic radiation (especially in the vicinity of power generators in construction sites), being spark-free, intrinsically safe, non-conductive and lightweight, and also their suitability for embedding into structures. To date, a number of key optical fibre sensors have been reported and their applications for damage detection in composite structures are given in review articles. Optical fibre-based sensors such as fibre Bragg gratings (FBG), intensiometric and polarimetric-type sensors and those based on interferometric principles (e.g., Fabry-Perot) have been shown to offer specific advantages in their niche area of applications.

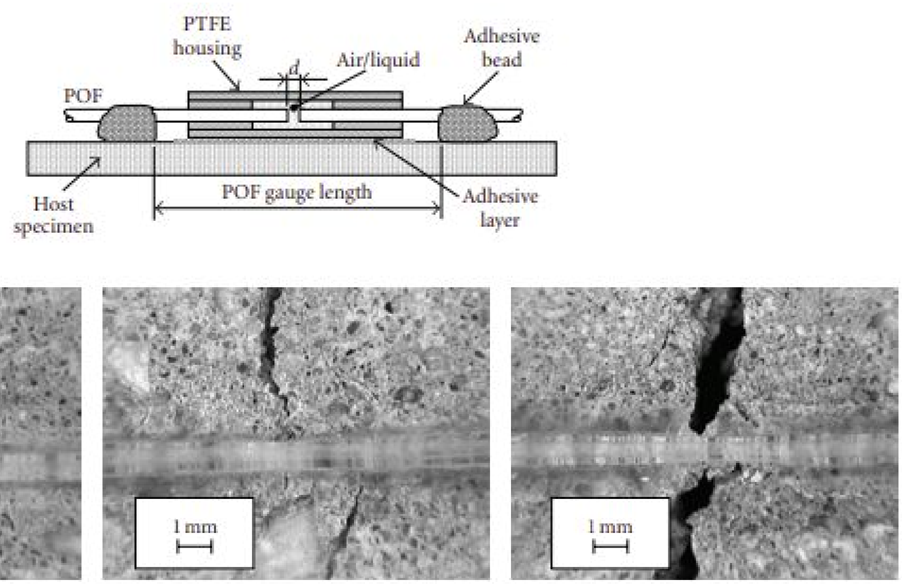

Figure 16: Schematic and Photomicrographs of Plastic Optic Fibre Graphs

Of the various types of optical fibre sensors, intensiometric sensors represents one of the earliest and perhaps the most direct and basic type of optical fibre sensor used for SHM purposes. Here, the sensing principle is straightforward and relies on monitoring the intensity level of the optical signal as it modulates in response to the measured quantity.

Although monitoring of the intensity level of optical signal has often been cited to be a drawback as a result of possible power fluctuation in the signal level and influence of external environment unrelated to the measured parameter (e.g., micro and macro bending along the fibre length), standard referencing techniques may be used to counter this problem. With the availability of stable and inexpensive light sources and low bend-sensitivity fibres, the intensity based approach offers excellent commercial prospect for large-scale applications from a cost-effectiveness point of view. In addition, the intensity-based technique is also suitable for frequency analysis in vibration measurements since precise and absolute measurement of the structural strain or displacement values are not required—given that the sensor has sufficient sensitivity to detect the oscillatory nature of the vibration signal.

Piezoelectric Sensors

Recently, there has been a growing interest in deploying smart materials as sensing components of structural health monitoring systems. In this arena, piezoelectric materials offer great promise for researchers to rapidly expand their many potential applications. These techniques range from piezoelectric electromechanical impedance and ultrasonic Lamb wave methods to a class of cutting-edge self-powered sensing systems.

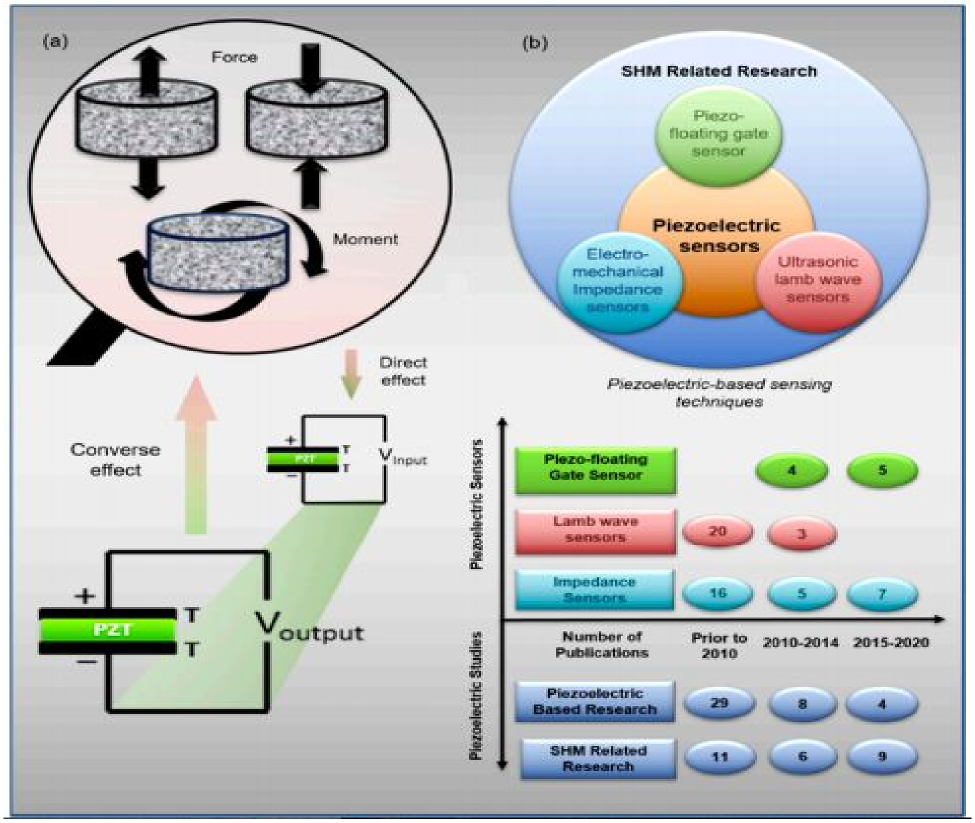

Figure 17: Piezoelectric Sensors Schematic

In general, piezoelectricity implies the production of an electrical charge from a piezoelectric material when stressed mechanically. A reverse mechanism is also true, as a mechanical strain/stress is produced when an electrical field/charge is applied. Figure 17 demonstrates the piezoelectric sensing process, utilizing the direct or inverse response of the piezoelectric effect to monitor structures. In this context, piezoelectric materials have been used in different sensing devices as actuators, sensors, or both.

Further discussion about the future trends of piezoelectric sensing implies that this sensing technology can play an important role in the SHM systems of next-generation smart and connected civil infrastructure platforms. More research is needed to harness the capabilities of piezoelectric sensing techniques for other large-scale infrastructure systems. This will mainly involve finding solutions for spatial monitoring with less sensing nodes and enhancing the energy harvesting efficiency for more advanced self-powering applications, particularly for embedded systems.

Machine Learning

Applications of Machine Learning (ML) algorithms in Structural Health Monitoring (SHM) have become of great interest in recent years owing to their superior ability to detect damage. ML can efficiently perform several analyses of clustering, regression and classification of damage in diverse structures, including bridges, buildings, dams, tunnels, wind turbines, etc. The diverse ML algorithms used in this domain have been classified into two major subfields: **vibration-based SHM** and **image-based SHM.** The efficacy of deploying ML algorithms in SHM has been discussed and detailed critical analysis of ML applications in SHM has been provided.

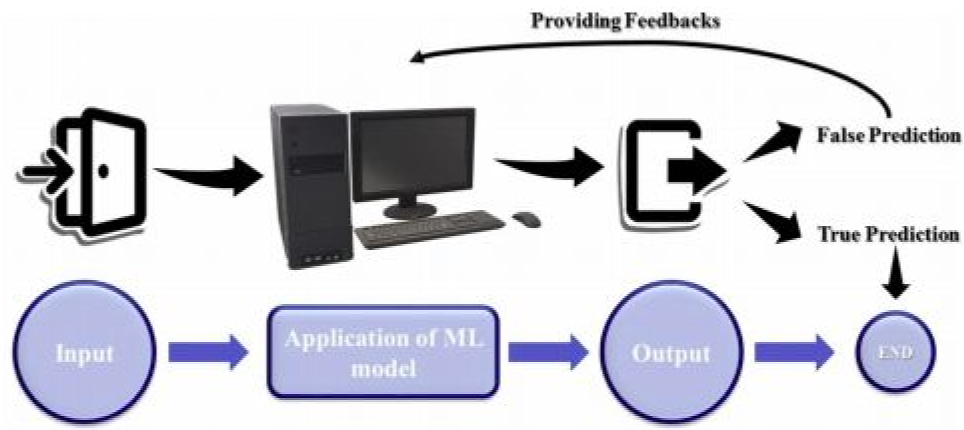

Figure 18: Machine Learning Life Cycle

Most algorithms that are available in the open literature are supervised learning algorithms that need to be labelled manually. There is a need to implement unsupervised learning for monitoring tasks using clustering to broaden the scope of applications of CNNs. Of the existing applications, about 95% have limited detection algorithms on the shallow scale of the distribution of cracks dealing with crack distribution, width, length, spalling, scaling and eforescence. More advanced studies go beyond that scope to determine whether the reinforcement is exposed, the steel rebars are corroded, etc. However, in order to make algorithms more robust and therefore more appealing to the industry, researchers need to relate these concepts not only to the diagnosis level, but also to the damage mechanisms within concrete. For instance, several chemical mechanisms can occur underneath the concrete surface, while the exterior surface may appear integral and free of cracks and damage. accordingly, further research is needed to cover the following aspects: Relating crack initiation to concrete mixture design, curing conditions, mechanical and environmental conditions of the structure, such as the chemistry of the pore solution, mechanical loading, seismicity of the area, temperature, humidity, etc. Some phenomena that are dependent on those conditions include carbonation of the concrete cover, corrosion of steel reinforcement, freeze–thaw damage, sulfate attack, shrinkage strains and cracking, etc.

Applications:

Bridge Health Monitoring (BHM)

BHM is the application of SHM and inspection techniques to bridge structures. Causes of degradation of bridge structures include materials aging , corrosion of metals and structural supports , mechanical overloading and other damage mechanisms . Bridge Health Monitoring (BHM) consists of collecting quantitative data from various sensors located within or on the surface of the structure. This Real-Time feedback creates a dataset monitoring system used to assess the condition of the bridge. Processing real-time complex big data has been a challenge in BHM.

Building Health Monitoring (BUHM)

Recently, experts have introduced ML algorithms to monitor the condition of high-rise buildings considering their proven effectiveness in other fields.

Dam Health Monitoring (DHM)

To illustrate the behavior of the concrete dams based on real time monitoring, several mathematical models have been proposed, including statistic, deterministic and hybrid models. Such models serve to assess the behavior of dams by analyzing real time data, considering hydrostatic pressure, environmental temperature and time effects to be the main variables. Due to uncertainties in using this kind of approach, several AI techniques have been implemented, making fusion between conventional models and heuristic algorithms, and leading to hybrid models. In recent years, ML has become a new accurate tool in DHM.

Wind Turbine Health Monitoring (WTHM)

Different problems faced by WTB during their lifecycle, and methods used to detect damage in WT, including acoustic emission event detection, thermal imaging, ultrasonic methods, model based approaches, fiber optics, laser doppler vibrometer, electrical resistance-based damage detection, strain memory alloy, X-radioscopy, eddy current and other methods have been reported. Accordingly, big data has accumulated. Data science is needed for classification and prediction of WT damage, hence the need for ML.

Another successful application of CNN is a baseline recognition task that determines the component type, checks the spelling condition, evaluates damage in percentage (no damage, minor damage, medium to severe damage, collapse) and predicts the mechanical source of damage.

Relating the cause of cracks to structural conditions, for example by detecting mechanical loads causing the cracks, application of fracture mechanics with possibility to predict the stress field around the crack and then assessing the remaining stresses that the structural element could resist in the short and long-term. This could be broadened by empowering the algorithm to propose solutions for the diagnosed problems based on available resources, such as the knowledge of experts, international codes, etc. Another evolving research item in this field is real time concrete crack detection, which needs more consideration and greater efforts to transfer images to video rendering that could efficiently detect cracks in a timely manner.

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