A Complete Internet of Things (IoT) Platform for Structural Health Monitoring (SHM)

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***Abstract*— Structural Health Monitoring (SHM) is becoming a crucial research topic to improve the human safety and to reduce maintenance costs. However, most of the existing SHM systems face challenges performing at real-time due to environmental effects and different operational hazards. Furthermore, the remote and constant monitoring amenities are not established yet, properly. To overcome this, Internet of Things (IoT) can be used, which would provide flexibility to monitor structures (building, bridge) from anywhere. In this paper, a complete IoT SHM platform is proposed. The platform consists of a Raspberry Pi, an analog to digital converter (ADC) MCP3008, and a Wi-Fi module for wireless communication. Piezoelectric (PZT) sensors were used to collect the data from the structure. The MCP3008 is used as an interface between the PZT sensors and the Raspberry Pi. The raspberry pi performs the necessary calculations to determine the SHM status using a proposed mathematical model to determine the damage's location and size if any. The All the data is pushed to the Internet filter using ThingWorx platform. The proposed platform is evaluated and tested successfully.**

Keywords— ADC; Butterworth Filter; Internet of Things (IoT); Pitch-Catch; Pulse-Echo; PZT; SHM;

I. INTRODUCTION

SHM is a nondestructive evaluation technique to monitor the integrity of civil structures such as bridges, aircraft, etc. Since the gradual deterioration of structures can happen for different reasons, such as continuous exposure to the inclement weather, overloading, etc., SHM is a vital tool to be implemented in old buildings, bridges, etc., to ensure the safety of human beings. Although researchers from different discipline took different approaches for SHM, most of the works in this field were done using civil and mechanical engineers' approach. Their works involved mostly to analyze natural frequencies of structures to make decisions. However, in this paper, the chosen approach was to develop a technique to analyze signals (electrical) and implement the proposed technique on an embedded platform.

Generally, to perform SHM, firstly, data needs to be collected using sensors. Different types of sensors such as ultrasonic [1], piezoelectric [2], [3], [4], [5], etc. can be used for SHM to generate signals traveling through solid configurations. Later, data collected from the sensors needs to be analyzed by applying different signal processing techniques, because a minor variation within the system triggered by different factors such as noises, temperature changes, environmental effects, might cause significant changes in the response from the sensors, concealing the potential signal changes due to structural defects [6]. Various signal processing techniques have been used to improve the SHM performance such as Wavelet denoising, Fast Fourier Transform (FFT), Wavelet transform, Cross-Correlation (CC), Principal Component Analysis (PCA), etc. Wavelet analysis can be used to remove noise from the signal [7] and detect damage in the structure [6]. Fast Fourier transform [8], [9] and wavelet transform [3] are usually used to get the frequency spectrum of sensors' output signal, and these spectrums also can help to design appropriate filters to remove noises. On the other hand, CC is the degree of similarity between two signals. For SHM applications, the signals to be compared are the base signal and the real-time signal. Another useful signal processing technique used in SHM is PCA, which uses orthogonal transformation to establish the linear relationship between input and output. The linear input-output relationship developed for a targetted structure can be exploited for an SHM process.

The use of guided waves, such as lamb wave, which can travel through a structure, has been becoming common among researchers [2], [3], [4], [5]. If there is a damage in the structure, the lamb waves would be reflected or scattered by the damage. To determine the damage, the difference signal is acquired and compared with a base signal. For structural damage localization, the key process is to acquire the time of flight and the amplitude of the response to the signal. The time of flight of these guided waves is linear and is directly dependent on the properties of the material, such as its modulus of elasticity and modulus of rigidity.

In this paper, a complete IoT SHM platform is proposed. A simple Butterworth filter is used to remove the noise. A proposed mathematical model is used to determine the damage's location and size if any. The ThingWorx platform was used to store real-time SHM information.

II. RELATED WORKS

Liang et al. addressed the sensor failure problem in a large-scale sensor network and proposed a self-diagnostic and self-reconfiguration reasoning method for SHM, which was verified by performing experiments in a real-world monitoring platform with an aluminum plate and actuator/sensor bonding [11]. On the other hand, Park et al. addressed the challenges of using an older baseline signal for SHM. A technique of using instantaneous baseline signals was proposed to compare with the real-time signal for making the SHM decision. For signal analysis Wavelet transform and CC techniques were used [12].

In [2], [3], [4], [5], piezoelectric (PZT) wafer for SHM was used with different signal processing techniques. However, there were some issues with getting the size of the damage. Zhang et

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al. used PCA to remove environmental effects from the signal. For dealing with the SHM data IoT was used. However, their proposed technique did not include finding the damage locations or severity of the damage [13]. Huo et al. proposed a system by using the combination of Cross Correlation Function Amplitude (CCFA) and Support Vector Machine (SVM) to determine the status of the structure [14]. IASC-ASCE benchmark's data was used to perform numerical verification of the system, and this verification was done by using MATLAB. Moreover, a vibration experiment of the truss structure was performed for experimental verification.

Hera et al. analyzed the data provided by American Society of Civil Engineers task group for a four-story building on their proposed SHM technique. This technique involved the use of Wavelet analysis and detected damage by the spikes in the Wavelet details. Spatial distribution patterns of the spikes were used to determine the location of the affected area [15]. In [1], damage detection based on Gabor Wavelet transform was explored. In [16], uncertainty was addressed the by using Bayesian Probabilistic theory for a model-based SHM, where structural models were identified from the modal data. The performance of this algorithm at real-time was unknown, as their proposed system was not tested on real hardware. Moreover, this approach is not good for a large scale damage [16]. In [17], the uncertainty of the system was also considered by Jiang et al. The retrieved modal parameters from structural vibration response were the inputs of a Fuzzy Neural Network (FNN) system, and the outputs from three different FNN setups were used as input of a data fusion center. By exploiting the fusion, the uncertainty of the modal data was minimized.

This paper focuses on the accessibility of the SHM information remotely. Since IoT, the global network of smart objects, has been becoming a great research interest of modern time, an IoT platform was exploited to provide remote availability of the data.

III. The Proposed Mathematical Model

In this model, two sensors (PZT) were used, which were able to generate, as well as receive signals. The generated signal by the PZT1 traveled through the structure, and PZT2 receives the signal (pitch-catch) as shown in Fig.1. When the signal gets reflected at the edges, it travels back to PZT1 (pulse-echo) [18]. The wave velocity of the signal, generated by PZT1, and the signal travel back to the PZT1, needs to be determined, W_s needs to be determined

$$\frac{L}{(T_h/2)} = W_s \tag{1}$$

L *is* the distance between two PZT sensors, and T_h is the peak to peak time difference. By utilizing W_s damage location, L found using the eq. (2).

$$L = \frac{T_h}{2} W_s \tag{2}$$

After calculating the position, the next step would be determining the damage width. First, the proportion of the damage position to the total length, S_1, could be determined by:

$$\frac{Lc}{Lh} = S_1 \tag{3}$$

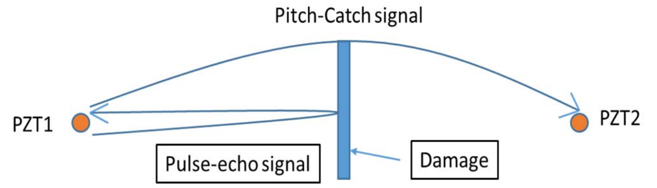


Fig. 1. Proposed Concept

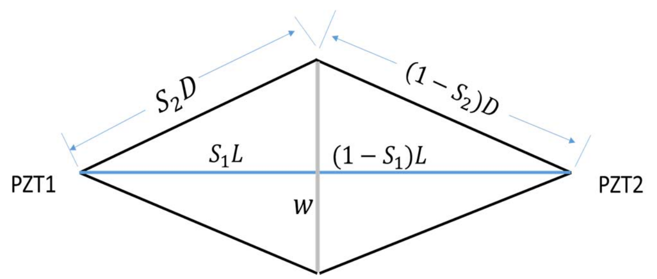


Fig. 2. Mathematical model diagram

Due to a damage being present, the wave takes longer to travel from exciter to sensor, which implies the wave travels a further distance. This distance, H, can be determined by:

$$T_t\, W_s = D \tag{4}$$

Where, T_t is the total time the wave takes to travel from exciter to the sensor with the presence of the damage. From these equations, a triangle can be made as seen in Fig. 2. L_c is the base and P_2H is the hypotenuse of this triangle. S_1 and $S$are very close in value and only equal if S_1 is ½. Whereas S_2 can be determined using the following equation:

$$\frac{(D^2 - L^2 + 2L\, S_1)}{2D^2} = S_2 \tag{5}$$

$$2\sqrt{(S_2D)^2 - L_c^2} = w \tag{6}$$

These equations are used if the damage has the same width above and below the axis.

IV. Butterworth Filter

To remove the noise, the filter used in this paper was Butterworth, which has a better compromise between attenuation and phase response compared to Chebyshev, Elliptical filters, as there would not be any ripple in the passband, as well as in the stopband. If a Butterworth filter is of n^{th} order, the transfer function coefficients would be of $n + 1$ length for a low or a high pass filter. On the other hand, the size would be $2n + 1$ for band pass and band stop filter [15]. Butterworth filter used in this paper was of 6^{th} order low-pass. If c and d are transfer function $H(z)$ coefficients, transfer function, $H(z)$ is expressed by equation (7). This transfer function determines which components of the signal to pass [19], [20].

$$H(Z) = \frac{B(Z)}{A(Z)} = \frac{c(1)+c(2)z^{-1}+\cdots c(n+1)z^{-n}}{d(1)+d(2)z^{-1}+\cdots d(n+1)z^{-n}} \tag{7}$$

V. PROPOSED SHM SYSTEM

A combination of Pitch-catch and pulse-echo techniques is proposed to monitor structure's health. This combination would also allow us to determine the damage location and size. Pitch-catch technique uses two PZT sensors; one as a transmitter or actuator (PZT1) and the other as a receiver (PZT2). PZT1 generated signal takes more time to reach PZT2 compare to the case where is no damage. This principle is used to establish a mathematical model to get the damage size.

On the other hand, the pulse-echo technique uses one PZT sensor as a transmitter, as well as a receiver. The received signal's delay is used to determine the damage location. Pulse-echo is a damage identification technique where short- duration waves are transmitted into the region to be studied, and reflected signals (echo) resulting from scattering and reflection are detected and displayed.

Fig. 3. shows the block diagram of the overall proposed system. In this algorithm, for both pulse-echo and pitch-catch techniques, thresholds of the received signals' delays need to be determined. For pulse echo technique, whenever the delay *dt1* is below the determined threshold implies that there is a damage in the structure. On the other hand, if there is any damage to the structure, the delay of receiving the signal for the pitch-catch technique would be higher than the determined delay, *dt2*.

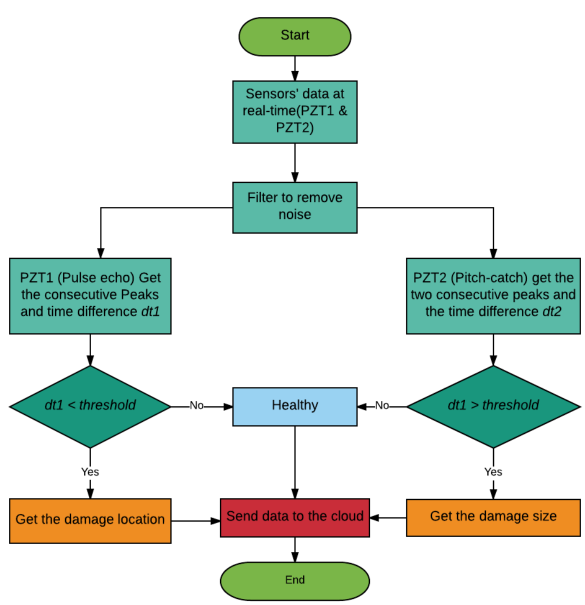


Fig. 3. Proposed system's flow chart

Fig. 4. shows the hardware architecture proposed in this work. The MCP3008 is connected to the Raspberry Pi using a Serial Peripheral Interface (SPI) bus, which can provide a synchronous serial communication. The interfacing between the Raspberry Pi and the MCP3008 can be seen in Fig. 5.

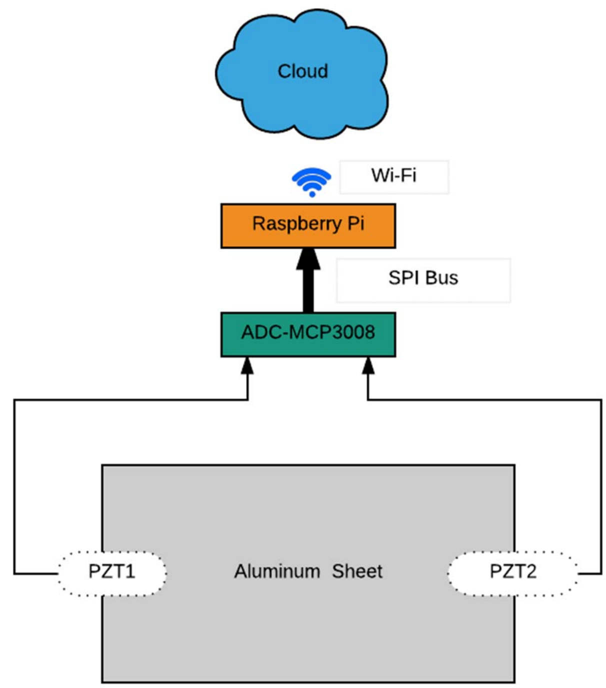


Fig. 4. Block diagram of the proposed Hardware architecture

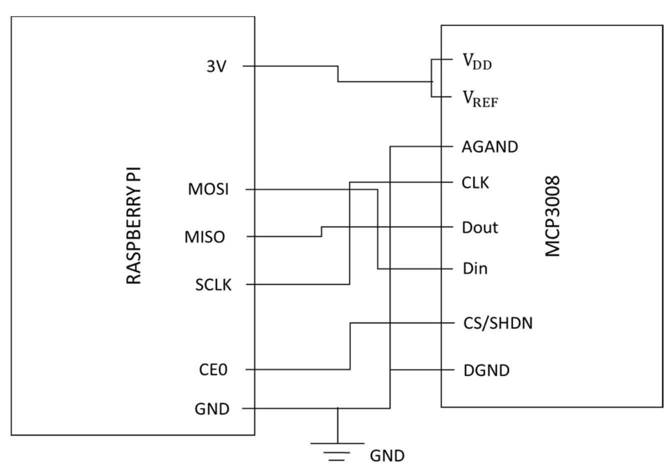


Fig. 5. Raspberry Pi and MCP3008 interface for SPI.

Function generators were used to mimic the signals generated for the aluminum sheets by the PZT actuator/sensor. The function generators were continuously generating signals. Later, these signals were feed as input to an MCP3008 analog to digital converter (ADC), and the outputs of this ADC were read using a Raspberry Pi. Data was saved to a .txt file and was immediately opened for processing. First, a digital buffer was run by the system to filter out the noise, using a Butterworth filter, and clean signals were obtained. Later, the filtered signals were run through a peak detection algorithm to find the peaks and their corresponding times. These peak times were exploited to determine the existence of a damage, and if any damage was detected, the mathematical model was used to get the location and size of the damage. Finally, these two values of size and location will be uploaded to the internet for remote monitoring.

VI. Result

To verify the proposed architecture, as well as the algorithm, experimental set-ups were done for the pitch-catch technique by generating signals using function generators. Noises to these signals were added using other function generators. For the pulse-echo technique, the same setup would be needed.

A. No damage in the structure

The threshold of the delay (between the base signal and real-time signal) depends on different factors such as the material of the structure, the distance between the actuator and the sensor, used PZT sensors' quality etc. The threshold assumed here was *1* ms. Channel 1 signal was considered as the base signal, whereas the signal of channel 2 was considered as a real-time signal. Fig. 6. shows that channel 1 and channel 2 signal almost overlapped and thus showing in the cloud (Fig. 7) that there was no damage to the structure.

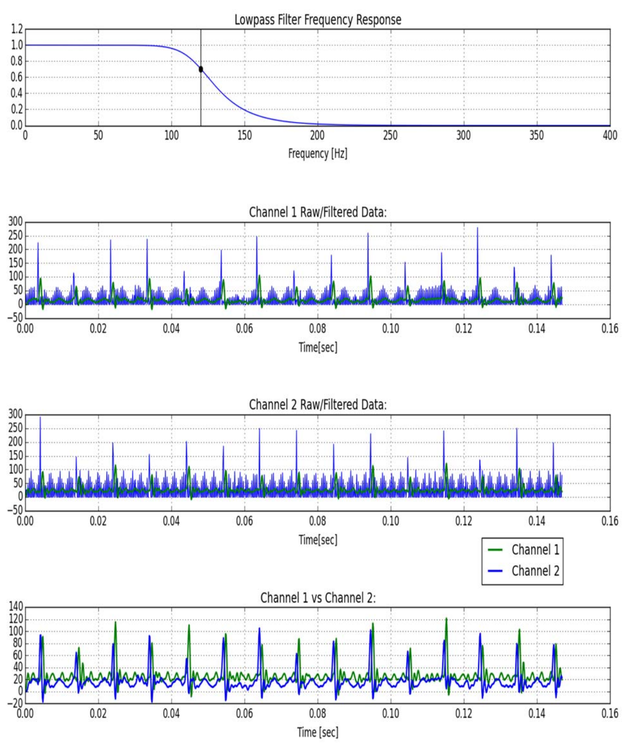
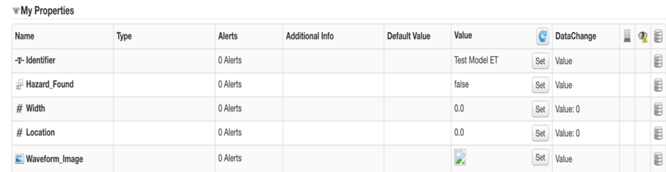


Fig. 6. Waveforms of the base and the real-time signal



My Properties

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Hazard_Found		0 Alerts			false	Value
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# Location		0 Alerts			0.0	Value: 0
Waveform_Image		0 Alerts				Value

Fig. 7. A snapshot of the ThingWorx's webpage.

B. With damage

The testing was done to verify that, when the delay between the base signal and the real-time signal was above the threshold, the system can detect the anomaly (damage), and calculate the damage size. (It was assumed that by using the mathematical model, the damage location was already known, which was 407.7 mm from the actuator towards the sensor). From Fig. 8 it can be seen that the delay between the signal from channel 1 and channel 2 was above the threshold, and showing in the ThingWorx's page (Fig. 9), "*Hazard Found: true*". Moreover, the calculated damage's location and size can be seen on this webpage, which is shown in Fig. 8.

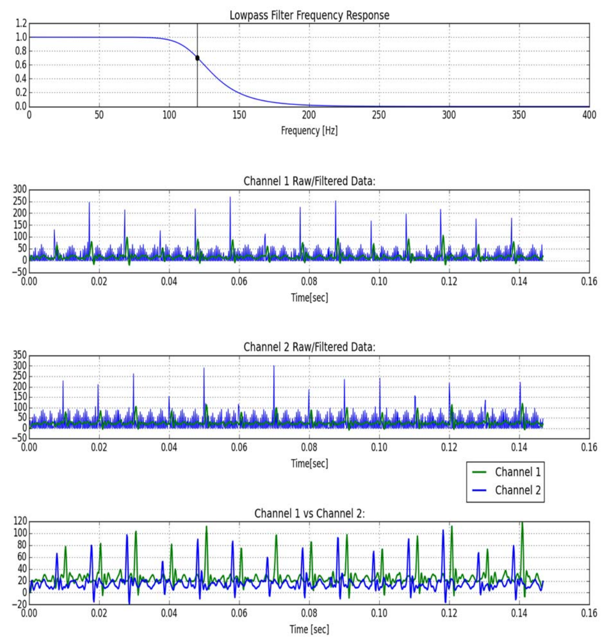

Figure 8: Waveforms of the base and real time signal

My Properties

Edit	Name	Type	Alerts	Additional Info	Default Value	Value	DataChange
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	Hazard_Found		0 Alerts			true	Value
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	# Location		0 Alerts			407.7	Value: 0
	Waveform_Image		0 Alerts				Value

Fig. 9. A snapshot of ThingWorx's webpage.

VII. CONCLUSION

Since IoT is gradually changing the way we used to interact with different devices, as well as applications, the blessings of IoT are appreciated by researchers from different disciplines. In this work, an SHM hardware platform with IoT was proposed. The hardware architecture consisted of a raspberry pi, an ADC, and a Wi-Fi module. A simple signal processing technique with less mathematical calculation was implemented in this architecture, which used a Butterworth filter (to remove noises) and a mathematical model (to get damage location/size). Later, the SHM information was pushed to the Internet for remote access.

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