Structural Failure Detection Using Neural Networks

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Abstract— **The structural failure detection system looks to recognize degradation in structures and/or machinery through the use of signal classification. This is possible in the recognition of the fact that the natural vibrational response of objects changes due to the change in the stiffness of the object. A neural network was be used to perform the necessary signal classification to detect structural abnormalities. The system consisted of an actuator to induce vibrations throughout the structure and sensors to record the vibrational response of the structure. The data collected from the sensors was recorded in order to train the neural network model. The trained neural network was able to distinguish between a reinforced structure and one without any internal supports.**

I. INTRODUCTION

The prevalence of structural failures and crack formations causes major difficulties in civil and aerospace engineering practices. For example, aircraft servicing and maintenance requires the use of methodologies that are time consuming and dependent on human interpretation. According to the National Research Council:

> The most critical issues inhibiting a successful maintenance program include inadequate inspection standards, lack of quantitative defect interpretation, and lack of definitive rejection criteria. In addition, inspections for large-scale parts, ... is extremely time-consuming and tedious. [1, p.67]

The objective of this project is to create a system that will detect structural failures prior to their occurrence. The system achieves this by monitoring the frequencies given off by the structure. These frequencies are then processed by a neural network in real time to produce predictions on the structural integrity of the object. This system can then be used as an alternative to the time-consuming, human dependent methodologies we employ today.

Previous products and inventions related to signal processing have not achieved significant or effective solutions to detecting structural failure in an autonomous manner. The paper written by Issam Abu-Mahfouz and Amit Banerjee seeks to find specific features to uses distinguish between intact and compromised structures using Fuzzy Relational Clustering [2]. Currently available products, such as the Fluke 3561 FC, measure vibrational responses and alert users based on frequencies selected by the user. These methods do not solve the task without the involvement of human judgment. Other solutions, such as the crack detection system using image processing techniques to detect cracks proposed in Na Wei's, XiangMo Zhao's, Xiao Yu Dou's, HongXun Song's, and Tao Wang paper [3], would not be practical in covering large areas in a structure. Our system will provide a prediction system that independently provides predictions with a neural network using a vibrational exciter that can vibrate large areas of a structure.

II. IMPLEMENTATION OF STRUCTURAL FAILURE DETECTION SYSTEM

The detection system can be divided into two major components: the hardware and software components. The electronic hardware will be responsible for inducing vibrations onto the structure and collecting vibrational data emitted from the structure. The software component will consist of: a control system to control the exciter and collect vibrational data, and the neural network to process the data and predict the state of the object. These components interact with each other in order to produce the detection system. Figure 1 illustrates the specific interactions between these components.

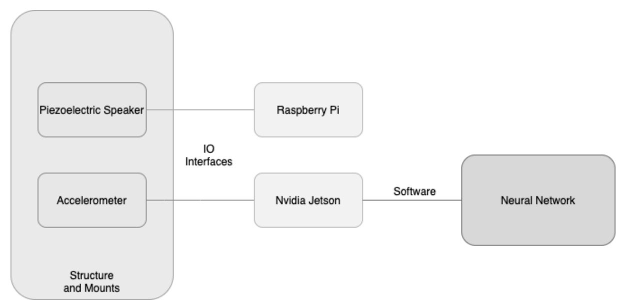


Fig. 1: System diagram containing major components of the structural failure detection system

A. Materials Used

The systme requires special electronics that can induce vibrations throughout an entire structure and measure the structure's vibrational response. It will also require a design for a structure to use the structural failure detection system on and mounts that will properly attach the sensors and speaker onto the structure. The specific electronics that are used in the system include:

- Arudino Uno
- 2 MP6050 Accelerometer and Gyroscope Sensor Modules
- Dayton Audio DAEX58FP Flat Pack 58mm 25W 8-Ohm Exciter (Speaker)
- Mean Well LRS-150-24 Switching Power Supply
- Diymore TPA3116DA DC 12V 24V 100W Mono Channel Digital Power Audio Amplifier Board
- Jumper Wires
- AUX Cable

- Laptop / Computer
- Electronic Device With AUX Port

The structure that was used consists of interconnected edges that create a dodecahedron. There are also 4 faces that are filled so that there is space to mount the sensors and the exciter,this also gives us space to mount the sensors and speaker in many possible locations. This structure also has an internal support beam to provide additional support. Figure 2 provides drawings of this structure.

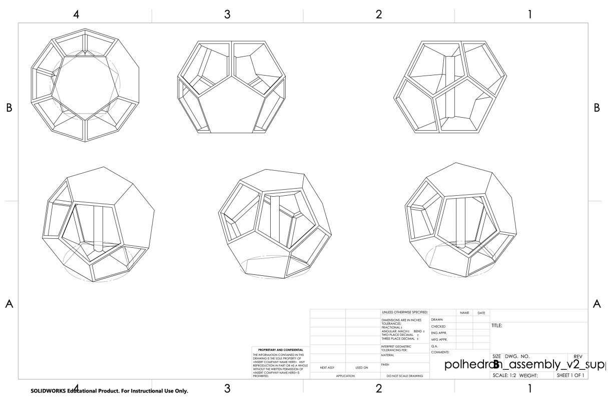


Fig. 2: Dodecahedron Structure With Internal Support Beam

An identical dodecahedron was also designed without a internal support beam. This would simulate a structure that is structurally weakened. This is illustrated in figure 3.

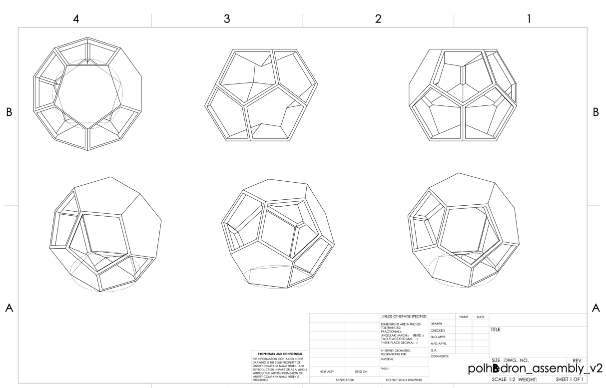


Fig. 3: Dodecahedron Structure Without Internal Support Beam

B. Hardware System

The hardware system primarily consists of the speaker, 2 sensor modules, and an Arudino. The exciter will create vibrations at a set frequency to emit throughout the structure. It will be controlled through an electronic device that will play an audio file with this set frequency through an aux cable. The amplifier and power supply will supply the speaker with power for it to run. The setup for the speaker components is shown in figure 4.

The sensor modules will be solely in charge of recording the vibrational response of the structure. They will do so by measuring displacement of the structure cause by the speaker. This data will be collected through the Arudino Uno and transmitted to the laptop/computer. The laptop/computer will feed this data into the neural network to predict whether the structure is structurally sound. The layout of this system is displayed in figure 5.

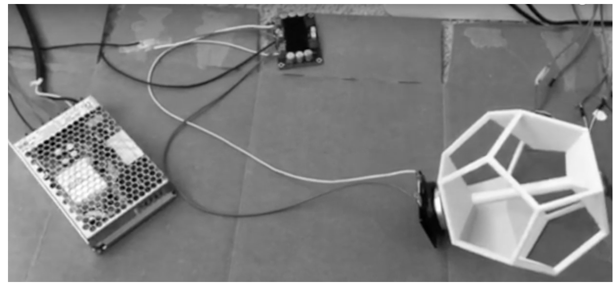


Fig. 4: Speaker Components of the Structural Weakness System

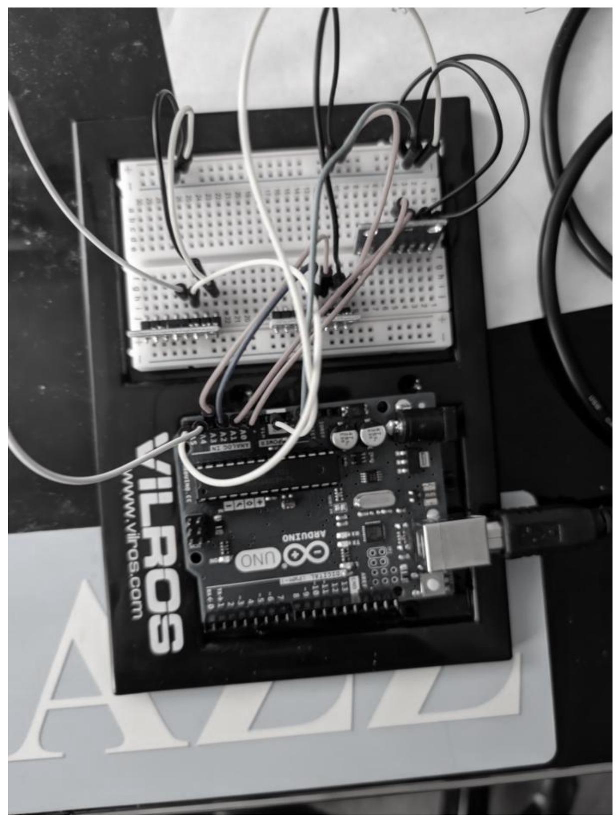


Fig. 5: Layout of Sensor Modules and Arudino Uno

C. Software System

The software system consists of the data collection from the structure through control of the speaker and sensors and the neural network itself. The data collection system is run through the Arduino and the 2 accelerometer and gyroscope modules. The microcontroller communicates with 2 modules through the I^2C communication protocol to receive accelerometer and gyroscope data. This data is then transmitted to the laptop using serial communication with a USB port.

The neural network is modeled after the model used in Hamidreza Sadreazami's, Miodrag Bolic's, and Sreeraman Rajan's paper [4]. It is a Long-Short-Term Memory (LSTM) recurrent neural network due to its good performance in regards to "capturing dependencies in time series data"[4]. The time-series vibrational data captured in the system is the best input for this particular neural network model, thus is used in the system to make predictions. The neural network is 4 layers deep with a 100 LSTM cell layer. This is fed into a dropout layer, that drops predicts from random LSTM cells to prevent the model to overfit to our training data. The last two layers will take these predicts and make a conclusion on whether the structure is structurally sound.

III. PROCEDURE AND METHODS

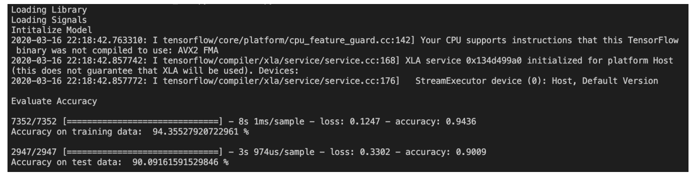
Time was spent reviewing the best techniques to perform the classification of different time signals. This allowed for a preliminary design of the neural network model that will be used for the structural failure detection system. Time was also spent determining a speaker/exciter strong enough to induce vibrations evenly throughout an entire structure. Research was conducted in determining the needed sensors that would be precise enough to record the minuscule changes to the structure. The preliminary designs for the structure and mounts for sensors and the speaker were make.

The electronics were wired together and tested. The code that drives the data collection component of the project was also implemented and tested with the sensor modules. The dodecahedron structures modified and 3-D printed, which allowed for the mounting and assembly of the electronics for data collection.

The vibrational data was collected from the structural detection system for a couple days. The system was ran with the speaker emitting a 100 HZ frequency. This allowed enough data to be collected for neural network training and assessment.

IV. RESULTS AND TESTING

The results of the project were very promising. Our team was able to successfully collect data from the structure and feed that data into a neural network to be analyzed. We were able to manually confirm that the sensors did output different data for each of the two structures we had created. The structures are two 3-D printed dodecahedron structures, one with a supporting column in the center and one without. These structures were successful in demonstrating different structural integrity properties. These structures coupled with our entire system of sensors and data monitoring systems made for a complete detection system. For the neural network, we were able to achieve upwards of 90% accuracy with our testing data and 94% with our training data. This was done with a data set of 7,200 sets of 128 time samples from our sensor data. The output of the neural network is shown in figure 6. Our team was satisfied with the results produced as we were able to show that our idea can be implemented in the real world and works as envisioned.



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Loading Library
Loading Signals
Intitalize Model
2020-03-16 22:18:42.763310: I tensorflow/core/platform/cpu_feature_guard.cc:142] Your CPU supports instructions that this TensorFlow
 binary was not compiled to use: AVX2 FMA
2020-03-16 22:18:42.857742: I tensorflow/compiler/xla/service/service.cc:168] XLA service 0x134d499a0 initialized for platform Host
(this does not guarantee that XLA will be used). Devices:
2020-03-16 22:18:42.857772: I tensorflow/compiler/xla/service/service.cc:176]   StreamExecutor device (0): Host, Default Version

Evaluate Accuracy

7352/7352 [==============================] - 8s 1ms/sample - loss: 0.1247 - accuracy: 0.9436
Accuracy on training data:  94.35527920722961 %

2947/2947 [==============================] - 3s 974us/sample - loss: 0.3302 - accuracy: 0.9009
Accuracy on test data:  90.09161591529846 %
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Fig. 6: Output of the Neural Network

V. CONCLUSION

The system was tested to see whether it could produce data that could be sent to the neural network and the whole set-up was configured to capture data. The learning process for the neural network was started and the network was trained to an accuracy of 94%. This result was attained with a small training data set, further training of the system would have improved this metric but this was sufficient for us to assert our claim that such a system could be effectively deployed.

REFERENCES

[1] National Research Council. 1996. New Materials for Next-Generation Commercial Transports. Washington, DC: The National Academies Press. https://doi.org/10.17226/5070.

[2] Abu-Mahfouz, I. and Banerjee, A. (2017). Crack Detection and Identification Using Vibration Signals and Fuzzy Clustering. Procedia Computer Science, 114, pp.266-274.

[3] Wei, N., Zhao, X., Dou, X., Song, H. and Wang, T. (2010). Beamlet Transform Based Pavement Image Crack Detection. 2010 International Conference on Intelligent Computation Technology and Automation.

[4] Sadreazami, H., Bolic, M. and Rajan, S. (2018). On the Use of Ultra Wideband Radar and Stacked LSTM-RNN for at Home Fall Detection. 2018 IEEE Life Sciences Conference (LSC).