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2019

Gopalakrishnan, P. K., Kar, B., Bose, S. K., Roy, M., & Basu, A. (2019). Live demonstration : autoencoder-based predictive maintenance for IoT. Proceedings of the 2019 IEEE International Symposium on Circuits and Systems (ISCAS). doi:10.1109/iscas.2019.8702230

<https://hdl.handle.net/10356/138250>

<https://doi.org/10.1109/ISCAS.2019.8702230>

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Live Demonstration: Autoencoder-based Predictive Maintenance for IoT

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Abstract—This live demo aims to show the performance of a two-layer neural network applied to predictive maintenance. The first layer encodes features based on prior knowledge, while the second layer is trained online to detect anomalies. The system is implemented on an FPGA, acquiring real-time data from sensors attached to a motor. Faults can be triggered artificially in real-time to demonstrate anomaly detection.

I. INTRODUCTION

In Industry 4.0, Predictive Maintenance (PM) is one of the most important applications of Internet of Things (IoT). Predictive Maintenance can be employed to reduce the down time of machines, to improve overall reliability of systems and to reduce operating costs. Machine learning can be used to predict the failure of a machine before the actual event occurs. Main challenges in PM are: (a) lack of enough data from failing machines to train binary classifiers, and (b) paucity of power and bandwidth to transmit sensor data to a cloud-based platform throughout the lifetime of the machine. Edge computing approaches can reduce the required data transmission, while necessitating implementations with very low energy consumption. In this work, we demonstrate an edge-computing based anomaly detection scheme that can be trained only using healthy machine data. To reduce the training time, we use an Auto Associative Extreme Learning Machine classifier (AAELM) [1, 2].

II. THE DEMO SETUP

Fig. 1 shows the demo setup. This setup is based on a small DC motor mounted on a platform. The motor is connected to an unbalanced load. The platform of the motor is fixed to a table using C clamps as shown in the figure. When the motor rotates, vibrations occur due to the unbalanced nature of the load. The amount of vibration can be controlled by adjusting the tightness of the C clamps.

Fig. 1. Demo setup

A sensor board (SensorTile IoT module from STMicroelectronics Ltd [3]) is used to pick up vibration from the motor platform. The module has three accelerometers and three gyroscopes. The outputs from these sensors are applied to a neural network classifier implemented on an FPGA using an HDL-based design methodology [1].

Fig.2 shows the internal block diagram of the proposed system design implemented in the FPGA from Xilinx Inc., which also houses an ARM core-based processor called Zynq®. A C program runs on this processor fetches the sensor data, in order to extract a number of useful features from them. This is done by an FPGA implementation of Stack Auto Encoder (SAE) core [2]. These extracted features are then fed to the AAELM core for both training and subsequent inference for anomaly detection in the sensor data.

Fig. 2. FPGA block diagram

The demo process is as follows: the motor is first set to run with a low level of vibration. The classifier is then used to learn the vibration pattern using the inputs from the sensor board, with a provision to accept additional inputs from other sources such as voltage, current and temperature sensors. All these inputs combined act as the input features for the classifier. After the completion of the learning process, the classifier switches to inference mode. In this mode, if the pattern of vibrations deviates significantly from the learned pattern, the classifier will produce an error output. This error can be indicated by an LED on the FPGA board or displayed on a PC connected to the board. During the demo, failures in the form of increased vibrations will be artificially induced to demonstrate anomaly detection. This mimics the real-life scenario where initially, the machine will be in a healthy state and later if malfunctions occur, they can be detected from the resulting vibration signature.

ACKNOWLEDGMENT

This work was conducted within the Delta-NTU Corporate Lab for Cyber-Physical Systems with funding support from Delta Electronics Inc. and the National Research Foundation (NRF) Singapore under the Corp Lab@University Scheme.

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