MACHINE HEALTH DIAGNOSTICS USING ACOUSTIC IMAGING AND ALGORITHMS FOR MACHINE LEARNING

Alessia Aulitto[1], Ines Lopez Arteaga[2], Dragan Kostić[3], Faysal Boughorbel[3], Sergio De Rosa[1] and Giuseppe Petrone[1]

[1] Università degli Studi di Napoli "Federico II", Italy
E-mail: al.aulitto@studenti.unina.it, sergio.derosa @unina.it, giuseppe.petrone@unina.it

[2]Eindhoven University of Technology, The Netherlands
Email: I.Lopez@tue.nl

[3]ASM Pacific Technology
6641 TL Beuningen, The Netherlands
Email: dkostic@alsi.asmpt.com, fboughorbel@alsi.asmpt.com

ABSTRACT

Nowadays monitoring health conditions of machines is necessary to reduce costs and repairing time and to secure the quality of the products. Therefore, the potential of acoustic measurements in combination with machine learning techniques for non-invasive diagnostics of machine performance has been investigated. The idea is to establish relations between the acoustic images produced by a sound camera and the machine conditions and then create a strategy for processing the images using Convolutional Neural Networks. Several working conditions of the machine have been considered and experiments have been performed both under nominal and abnormal conditions of the machine, obtained by mimicking the presence of a disturbance. The use of the algorithms for image classification allows isolation of the faults in the machine behaviour by the definition of the primary sound sources. The procedure shows promising results with a short computational time, easy application and high accuracy.

1 INTRODUCTION

The semiconductor manufacturing is one of the most technology-evolving market sectors. In order to reach a competitive position in semiconductor industry the most important challenges that a fabrication plant must face are the reduction of costs and the increase of production. Predictive maintenance is one possible way to address these challenges. Many manufacturing stations are already equipped with sensors, such as accelerometers, and data coming from these sensors are often processed with Machine learning algorithms. However, a body-mounted sensor represents an extraneous mass and it affects the dynamics of the system. This problem leads to the necessity to find a measurement equipment for non-intrusive condition monitoring and a sound camera shows promising results in this sense. The idea is to establish relations between the acoustic images produced by the camera and the machine conditions using Machine Learning algorithm in order to predict the behaviour of the system by artificially simulating the presence of a disturbance.

2 PREPARATION

The experiments are performed on a wire-bonder machine produced by ASM Pacific Technologies [1]. The sound emitted by this machine during operations is recorded with the sound camera Sorama CAM64 [2] that comes with a Portal to analyse the produced acoustic images. The images will be used to feed a Convolutional Neural Network (CNN), built using Python and TensorFlow [3].

2.1 Wire-bonder and abnormal conditions

The wire-bonder machine has three orthogonal stages moving along three orthogonal axes and the motion of each stage is controlled by a closed loop. Detailed instruction on the wire-bonder are in [4]. Focusing on the feedback controller in the loop, increasing its gain means increasing the bandwidth so the dynamics of the system can be affected by abnormal vibrations at resonance frequencies. Working on the feed-forward controller instead it is possible to insert an artificial force which mimics the braked response with friction or to introduce a random force that simulates the vibrations coming from the environment. All these disturbances will introduce new frequencies of the oscillation that can be found by analysing the sound emitted from the machine.

2.2 Sound camera and acoustic images

Sorama CAM64 can record the sound coming from a sound source and it can produce different kinds of acoustic images. Further information about the camera can be found in [5]. In the intent of the project the spectrograms will be considered: they are frequency-vs- time chosen to identify which axis or combination of axes of the machine are performing operations by the analysis of the emitted sound.

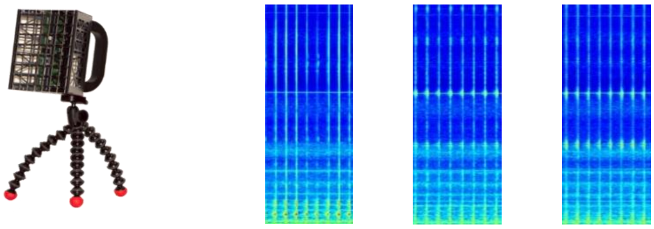

Figure 1: Sound camera and portions of spectrogram

In Figure 1 three portions of the spectrograms collected during the experiments are presented and by observation a user can recognize which stage is moving. The scope of the project is to teach to a computer to learn directly from the images collected.

2.3 Convolutional Neural Network

Machine learning techniques and Convolutional Neural Networks (CNN), exploit the capability of computers to receive data and to learn from them, by modifying the algorithms step-by-step. More information about the use of CNN can be found in [6]. Images coming from the Sorama Portal should be frameless, then cut in slices and then resized to be squared ones. Each image comes with a label that underlines which stage of the machine was acting when the image was collected. Furthermore, the images are split in two groups: a training set, used to insert in the network the recognition and classification phase and a test set, to test the capability of prediction. The workflow of the process is presented in Figure 2.

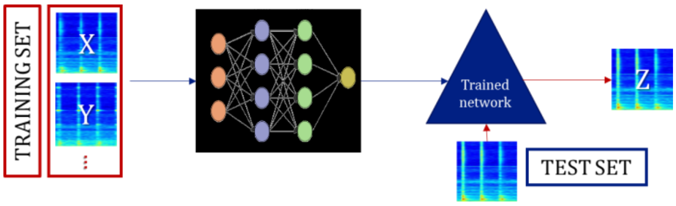

Figure 2: Map of the process using CNN

3 STATEMENT OF THE PROBLEM

Several working conditions of the machine are tested. First set of measurement is collected during the motion of the stages with a given trajectory and a fixed acceleration. To test the robustness of the procedure other three trajectories in normal conditions are tested and a smaller dataset is created. Then, new images are collected by artificially simulating the three types of abnormal behaviour mentioned in the paragraph 2.1.

3.1 Prediction in healthy conditions

The images in the first dataset are 2896, squared, with pixel value between 0 and 255 and then rescaled in the range 0,1. They are then converted in greyscale in order to reduce the computational cost and then organized in 8 classes, with 8 different labels. The accuracy is around 95%. Testing the images coming from different trajectories there is an expected reduction of the accuracy that oscillates around 85%, according to the reduction of the number of images in the dataset.
In Figure 3, an example of the classes in the network is presented.

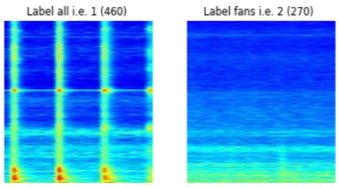

Figure 3: Example of the classes of the network in healthy conditions

3.2 Prediction in artificial unhealthy conditions

The first type of abnormal behaviour is simulated by increasing the gain of the feedback controller. Some frequencies will show a higher SPL and, in the spectrum, it will result in a higher peak at some resonant frequencies, as presented in Figure 4.

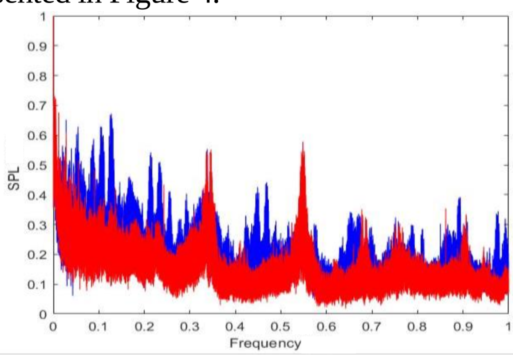

Figure 4: Spectra in presence of resonance frequencies (blue) and in normal conditions (red)

The values presented in the plot have been normalized due to confidential issues. Furthermore, to mimic the effect of the friction a force will be introduced: this force is given by a constant Coulomb friction component and a viscous one depending on the velocity. In this case new frequencies will show a tail behaviour. In the case of random vibration, it should be underlined that a horizontal line in the spectrogram is representative of a harmonic function. In the spectrogram three groups of horizontal lines will appear, due to the definition of the chosen disturbance. In addition to the first network, three networks will be built by using the images coming from these three experiments. The fourth network is representative of all the disturbance sources and it is composed by 28 classes, instead of the eight classes of the network for the healthy conditions. In Figure 5 the result of the complete network is presented.

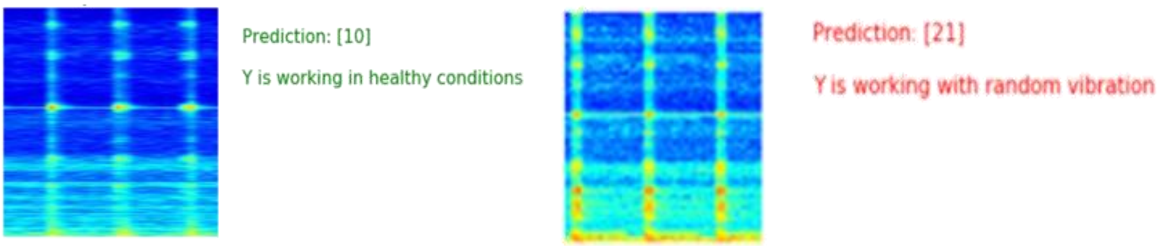

Figure 5: Results of the prediction phase

4 CONCLUSIONS AND FUTURE APPLICATIONS

The final network can recognize which stage or combination of sage is performing operations, if the wire bonder is working in healthy conditions or if one of the disturbance sources is changing the dynamics of the machine. In conclusion, the behaviour of the machine influences the frequencies of the emitted sound and using a sound camera is possible to detect the deviances from the normal conditions. The initial hypothesis about the use of spectrograms to get suitable information for neural network application is confirmed and, despite the reduced number of layers, the accuracy of the image classification procedure is high. In the end, the application of the sound camera shows promising results in condition monitoring without changing the dynamics of the machine. In the coming future, further application of the mentioned procedure will lead to a deeper knowledge of the problem: new kinds of disturbances will be tested also on several machines in the workstations. New images, such as the hologram can give information about the spatial distribution of the emitted sound in order to identify the locations of the primary sound sources during the motion of two stages. Furthermore, new types of Machine Learning techniques can perform the classification tasks directly on the recorded sound without using the acoustic images. So, the project opens the way to new possibility to investigate in the field of application of sound camera for non-intrusive condition monitoring and predictive maintenance.

5 REFERENCES

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