Health Monitoring of Milling Tools under Distinct Operating Conditions by a Deep Convolutional Neural Network model

1st Priscile Fogou Suawa
Chair of Computer Engineering,
Brandenburg Technical University
Cottbus–Senftenberg, Germany
Priscile.SuawaFogou@b-tu.de

2nd Michael Hübner
Chair of Computer Engineering,
Brandenburg Technical University
Cottbus–Senftenberg, Germany
Michael.Huebner@b-tu.de

***Abstract*—One of the most popular manufacturing techniques is milling. It can be used to make a variety of geometric components, such as flat grooves, surfaces, etc. The condition of the milling tool has a major impact on the quality of milling processes. Hence the importance of follow-up. When working on monitoring solutions, it is crucial to take into account different operating variables, such as rotational speed, especially in real world experiences. This work addresses the topic of predictive maintenance by exploiting the fusion of sensor data and the artificial intelligence-based analysis of signals measured by sensors. With a set of data such as vibration and sound reflection from the sensors, we focus on finding solutions for the task of detecting the health condition of machines. A Deep Convolutional Neural Network (DCNN) model is provided with fusion at the sensor data level to detect five consecutive health states of a milling tool; From a healthier state to a state of degradation. In addition, a demonstrator is built with Simulink to simulate and visualize the detection process. To examine the capacity of our model, the signal data was processed individually and subsequently merged. Experiments were carried out on three sets of data recorded during a real milling process. Results using the proposed DCNN architecture with raw data have reached an accuracy of more than 94% for all data sets.**

***Index Terms*—Accelerometer, Deep Convolutional Neural Networks, Health state detection, Machine Monitoring, Microphone, Milling, Predictive Maintenance, Sensor Fusion**

I. Introduction

Smart Manufacturing, Industry 4.0, Internet of Things (IoT) are the terms used to describe the evolution of the industrial sector. This trend of intelligent industry transforms the mode of operation of factories and workplaces, making them safer, more efficient, more adaptable, and more environmentally friendly [1]. Monitoring is a key aspect of the intelligent industry because it leads to robust maintenance systems and optimal planning of the operation of production systems [2]. It is a non-trivial task to monitor cutting tools because every manufacturing process is a system of non-linear time variation. Additionally, signals collected by many sensors during cutting are affected by machining conditions, making it difficult to monitor wear trends. However, it is an important task, as it reduces downtime in machining processes, decreases maintenance times and costs while increasing productivity.

The key step in the monitoring process is the decision-making step [3]. This article focuses on it and presents a model for detecting the health of milling tools under various operating conditions. Many data-driven techniques are available to implement the decision support solution, including classic machine learning and deep learning methods, see [4]–[6]. The proposed model is based on a Deep Convolutional Neural Network algorithm with sensor fusion. Experimental data used in this paper are data from the milling process on a real machine. Three separate data sets, each containing vibrations and sound signals, were recorded under various operating conditions and used for training the models.

The performances of the models obtained by the fusion of the two types of data used reached 97.1%, 94.4%, and 97.8% of accuracy in detecting the health states of the milling machine. A simulation model was built to visualize changes in machine health states, like traffic lights. That facilitates the interpretation of each state according to a predefined color.

The remainder of the article presents in Section II the description of the system studied. Section III describes the experimental details, including the proposed detection model and the different datasets, and Section IV concludes the document with points for future work.

II. Health Monitoring System Description

In this work, the main objective is to build a model to assess the state of the milling tools. When the tool allows precision machining and production of high-quality products, it is healthy. In our experiment, five numbers of health states have been recorded during the tool life. Tool life is the time during which the cutting edge, under the influence of machining processes, is able to work. From healthier to degradation, each state is differentiated by a set of characteristics as follows:

- '++' rolled chips, shiny metallic, no formation of degrees, milling pattern visible, smooth edge ;
- '+' blue chips, slightly rolled;

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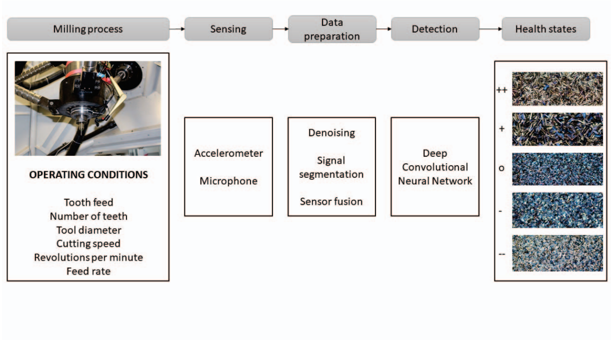

Fig. 1. Workflow of the system

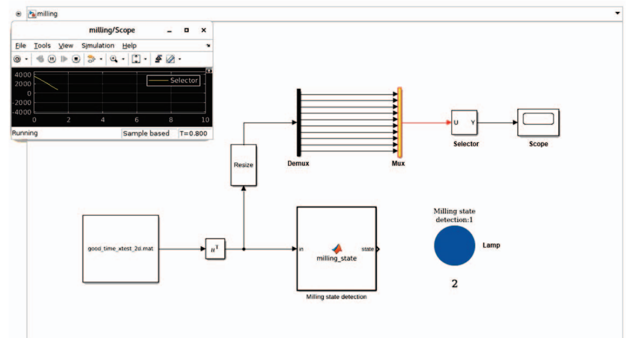

Fig. 2. Simulation model

- 'o' Scratches on the surface, slight formation of degrees;
- '-' light blue, slightly bent chips;
- '–' smooth chips, glossy white, strong degree of formation, polished surface, wavy edge.

Figure 1, show the main workflow of the system. Milling tool data was observed and recorded under multiple operating conditions to mimic a general evaluation of the tool, e.g., feed rate (*fr*), cutting speed (*cs*), number of teeth (*nt*), etc. First, vibrations and sound signals are recorded under three different sets of operating conditions. Then the raw signals are prepared to remove noise, normalize and merge the signals. After the preprocessing step, the DCNN model is trained as described in section III, using the output data from the previous step. The model is then ready and tested with new signals to detect the condition of the machine.

More precisely, let S_i, i=1,...,3 be the three sets of operating conditions, S_i= $\{fr_i, cs_i, nt_i, ...\}$. For each set of operating conditions, a model was trained with data recorded under the set concerned. Another interesting point with this evaluation of the tool under various conditions was to see which set of parameters allows the tool to stay healthy for long life.

III. Experiment details

In [11] a review of methods (deep learning and other AI methods) of monitoring the condition of machining tools based on data size reveals that when the amount of training data is excessive, the predictive capacity of traditional machine learning is not evolving satisfactorily. However, as the amount of training data increases, multilayer neural networks and deep learning methods exhibit superior performance for both learning and prediction. This motivated the choice of the model used for the work presented in this paper.

A. Monitoring DCNN-based Model

The proposed DCNN consists of a one-dimension input layer, followed by a quadruplet of Convolutional, batch normalization, Relu, and Pooling layers, repeated four times. All the convolutional layers have a kernel size of 1x100 with stride value 1, while all max-pooling layers have a kernel size of 1x2 with stride value 2. In hidden layers, ReLu is used as an activation function. Softmax is used as an activation function in the output layer since it detects five distinct categories. This DCNN was built from scratch with the training options, mini-batch Size: 200, Max epochs: 50, Optimizer: Adam, Learning Rate: 0.001, and its architecture is reported in Table I.

TABLE I
Deep Convolutional Neural Network Settings

Layer	Types	Settings
0	Input	Input height: 1 Input width: 3200
1 2 3 4	Convolution Normalization Relu Pooling	Filter height: 1 Filter width: 100 Number of filters:20 Stride: 1
5 6 7 8	Convolution Normalization Relu Pooling	Filter height: 1 Filter width: 100 Number of filters:30 Stride: 1
9 10 11 12	Convolution Normalization Relu Pooling	Filter height: 1 Filter width: 100 Number of filters:40 Stride: 1
13 14 15 16	Convolution Normalization Relu Pooling	Filter height: 1 Filter width: 100 Number of filters:50 Stride: 1
17 18 19	Fully-connected Softmax Classification	5 outputs

B. Dataset and Pre-processing

As mentioned earlier, the dataset used in this work contains real signals from the experiment on a milling machine. An accelerometer and a microphone have been fixed on the milling machine. They are also connected to a Red Pitaya board which is used as a sensor node to record signals from each sensor. The Redpitaya-Board is a small PC and uses a Xilinx Zynq 7010

TABLE II
Operating conditions defined for a milling experiment on a steel work piece material

Operating conditions	Dataset 1	Dataset 2	Dataset 3
Feed rate (mm/min)	252	360	432
Rotational speed (rpm)	5600	8000	9600
Cutter name	k4f1	k4f2	k4f3

System-on-Chip [8]. This System-on-Chip combines a dual-core ARM Cortex-A9, which runs a Linux distribution, and an FPGA, used for rapid data acquisition and AI acceleration. The board is deployed to acquire the amplified signals via an analog-to-digital-converter (ADC). Currently, the board is used to collect the data and forward the acquired data via Ethernet to a host PC. Three different sets of data have been recorded, based on three varying operating conditions, the feed rate, the rotational speed, and the cutter; see Table II. There are also operating conditions with constant values used in all cases; the ”diameter of the cutter”: 8 mm, the ”step over”: 45%, and the ”depth feed”: 2.5 mm.

Each dataset includes two sensors signals, vibration from the accelerometer and sound from the microphone. A denoising step was performed over each set of data using an empirical Bayesian method. This method employs a threshold rule based on the assumption that measurements are subject to separate prior distributions as determined by a probabilistic model [9]. As an output of the previous step, samples signals per sensor with a length of 32762 points were available for the next steps. Since signal length is of interest, a signal segmentation step was applied, generating signal chunks of length 1600 points. Finally, sensor data fusion was applied to combine vibrations and sound signals. Details on the fusion method can be found in [7].

As a result of the preprocessing step, a total of at least 3495 signal samples with a length of 3200 points were used on each dataset with 70% for training and the remainder for testing.

C. Implementation

As mentioned earlier, the goal of the experiment conducted in this paper is to monitor a milling machine by detecting its states from the healthy state until the degradation. The implementation scenario has been conducted in two phases with Matlab and Simulink frameworks. The first phase has two steps, the training, and the testing steps. Three models were trained with data from each dataset mentioned in Table II based on the DCNN algorithm presented in Section III. The evaluation is performed on the basis of the following performance indicators: the precision, which gives the percentages of all the samples predicted to belong to each class that is correctly and incorrectly classified; the recall, which gives the percentages of all the samples belonging to each class that is correctly and incorrectly classified and the accuracy [10].

The second phase consists in simulating the detection of the health states. Each class is represented by a unique color to visualize the different states of the machine through a lamp. As shown in figure 2, some blocks were used to build the model. The first block is the input of the Simulink model and is called ”From File Block”, it is used to load signal data into the detection model. The data are loaded from a Matlab file. In our experiment, the file ”good-time-xtest-2d.mat”, which contains a matrix of tests samples was loaded. The second block u^T is used to transpose the input samples vector to fit the requirement of the detection model. The next block ”Milling state detection” contains the monitoring model. It takes as input the sample signal and returns the state of the machine. This block is connected to a lamp that changes its color according to the state detected. The other side of the simulation model is used to plot and observe the signal variations. Since the signals are of a high length, it was necessary to resize the signal vector, then use the ”Demux” and ”Mux” blocks to segment the signals and select a portion with the ”selector” to display easily in the ”scope”. When the simulation is running, each sample signal is evaluated, and one can observe at the same time the state of the machine over the lamp and visualize signals variations.

TABLE III
PRECISION AND RECALL VALUES OF MODELS IN THE DETECTION OF EACH HEALTH CONDITION (CLS:CLASSES, D1-D3:DATA SETS)

		Precision (%)			**Recall (%)**		
	Cls	*Vibration*	*Sound*	*Fusion*	*Vibration*	*Sound*	*Fusion*
	++	98.3	96.4	**98.9**	99	**99.8**	99
	+	89.2	94.1	**95.3**	93.1	88.8	**95.7**
	o	76.1	90.7	**95**	88.1	92.9	**95.2**
	-	91	98.2	**99.1**	71.7	97.7	**98.3**
D1	**–**	96.7	98	**98.9**	**100**	**100**	98.9
	++	98.4	99	**99.8**	99.6	97.9	**99.9**
	+	92.4	90.1	**93.6**	79.2	92.1	**97.2**
	o	82.3	**85.6**	83.1	86.9	84.4	**93.1**
	-	85	88.3	**97.1**	87.7	**88.6**	83.2
D2	**–**	98.5	97.8	**99.4**	99.1	92.2	**94.4**
	++	**100**	99.5	99.9	**100**	99.8	**100**
	+	99.4	99.2	**99.6**	**100**	97.7	99.3
	o	89.1	94.5	**97.6**	**96.6**	94.8	95.3
	-	**92.3**	84.5	87.7	**90.1**	85.6	89.7
D3	**–**	**96.7**	95.5	96.5	91.4	96	**97.8**

D. Results and Discussion

This section presents the results obtained with the proposed DCNN architecture, which was used to train models using three different datasets, to monitor the state of a milling machine. The data in each set are measurements from an actual milling experience. They are different from each other by being recorded under various operating conditions as shown in Table II. On the one hand, models have been trained with data from each sensor individually to evaluate the capacity of the proposed DCNN architecture to detect health states, based on a single sensor. On the other hand, models have been trained with fused sensors data, to confirm the impact of the sensor fusion.

To assess all the models, multi-class confusion matrices were computed. The results obtained from the confusion matrices of all the experiments on the test data concerning precision and recall are summarized in Table III. The multi-classifier models achieved the best accuracy using the fused sensor data with 97.1%, 94.4 %, and 97.8 % respectively for the first, second, and third data set.

As mentioned above, the model proposed in this article was evaluated on three different data sets. From one data set to another, the operating conditions have increased. For example, the rotational speed of the last set of data is larger than that of the first. Analysis of the results reveals the following for each data set:

- Data set 1: Overall, the model detects each class well. For example, out of 93 examples of the ”-” class, 92 were correctly classified as belonging to said class; The results on this data set show that the proposed model manages to differentiate the health states studied for the milling machine because only a few examples were not assigned to their original classes.

- Data set 2: Here too, the model detects machine states well in most cases. With the exception of the ”-” class for which 200 examples were classified as belonging to the previous ”o” class. With this, it can be understood that the combination of the parameters used for the construction of this data set, could not easily contribute to the detection of the entry of the machine into a state of degradation because the indicators of the beginning of degradation are sometimes confused with indicators of previous health status.
- Data set 3: The results with this dataset also confirm the ability of the model to differentiate each machine health state, as most of the examples were given their original class.

Analysis of the results obtained shows that the operating conditions of a milling machine, which are characterized by variables such as the speed of rotation, have an impact on the quality of the signals recorded by the various sensors. This can make it difficult to automatically track the machine. Hence the interest in evaluating the machine under different operating conditions in order to distill the parameters which will not only make it possible to produce quality materials but also to facilitate the monitoring of the machine. These results also show the impact of the sensor fusion, which in our scenario, improves the performance of the models by around 2%. Note that the maximum gain the DCNN could get was 4% because the baseline result was already very high (96%). It is obvious that sensor data fusion is useful, even when it leads to only small improvements in some cases. The impact of the fusion can even vary during the operation of the machine. It means that a small impact in the average of the preciseness to detect the health state can lead in the specific case to a remarkable benefit.

IV. Conclusion and Future Work

In this article, a DCNN model based on the fusion of sensors is proposed as a monitoring system, to detect five health states of a milling machine. The set of health states contains healthy and degraded states. Knowing the degree of influence that the operating conditions can have in the field of milling tools, three sets of data recorded under different operating conditions were considered to evaluate the proposed model. These datasets include two types of signals, sounds, and vibrations which are used individually on the one hand and later merged to train different models. The objectives of this work include the proposal of a model, which can be used with raw signal data and achieve an acceptable level of performance in detecting the state of a milling tool. Another goal was to determine the set of operating conditions required to record the appropriate data to create a powerful milling tool condition monitoring system.

The experimental results revealed that the classifying DCNN model performed well in terms of precision, recall, and accuracy. It reached the highest accuracy of 97.1%, 94.4%, and 97.8% respectively for the first, the second, and the third data set with fused signals data over 88.4%, 91.2% and 96.5% with vibration signals and finally 94.9%, 92.2% and 96.5 with sound signals. Thus, it is possible to reach good performances using data from a single sensor with a robust algorithm like the proposed DCNN. However, the results confirm the impact of data fusion, which improved models performance by approximately 2%. Note that small increases in accuracy can be of great value when a large machine can be prevented from being damaged.

Finally, the experiments conducted in this work helped to select the best set of operating conditions that correctly differentiate the health states of the milling machine in our scenario. It is the one used for the third data set. The future work of this study is to use the selected set of operating conditions, to record several lifetime or run-to-failure sequences signals to build a suitable dataset that will be used to predict the remaining useful lifetime of the milling machine. Then suggest a hardware-based monitoring system applicable in real-time which will bring computation closed to the machine. Such a system can result in a shorter response time in the prediction process and in the avoidance of machine downtime since the degradation could be predicted earlier.

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