Deep learning in assessment of drill condition on the basis of images of drilled holes

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ABSTRACT

This paper presents novel approach to drill condition assessment using deep learning. The assessment regarding level of the drill wear is done on the basis of the drilled hole images. Two states of the drill are taken into account: the sharp enough to continue production and worn out. The decision is taken on the basis of the shape of hole and also the level of hole shredding. In this way the drill condition is associated with the problem of image analysis and classification. Novel approach to this classification task in the form of deep learning has been applied in solving this problem. The important advantage of this method is great simplification of the recognition procedure, since any handy craft prepared features are not needed and the focus may be concentrated on the most interesting aspects of data mining and machine learning. The obtained results belong to the best in comparison to other approaches to the problem solution.

Keywords: deep learning, convolution networks, drills condition, Tool Condition Monitoring

1. INTRODUCTION

Drill wear is an important problem in furniture manufacturing industries, which not only has the impact on a surface roughness of the hole but also influences the drill life. The issue is when the decision regarding replacement of a drill to avoid losses of material during industrial drilling should be made. The drill wear process depends on many factors, such as the applied speed rotation, drill diameter, value of torque, chip thickness, structure of material, thrust force, etc. To avoid considerations of so many parameters to which a lot of measurement sensors are required, we can focus only on the hole images, on the basis of which the drilling process can be controlled. It is known as the tool condition monitoring (TCM). The goal in TCM is to achieve the improved and cost effective product quality [1,2,3]. It means that tool (in this case drill) has to be used in its optimal capability before is replaced. The classical approach to TCM process is based on the scheme presented in Fig. 1. It starts from selection of the sensors responsible for on-line registration of different signals in the production. On the basis of these signals the most important diagnostic features are extracted, which are used as the input attributes to the automatic classifier, responsible for recognition of the drill state.

Figure 1. Regular approach to TCM process.

In the published papers different type sensors have been used. The papers [1,2,3] have examined the influence of sensors measuring the acoustic and vibration signals, power, torque and force. However, the accuracy of class recognition did not achieve the satisfactory value (below 90%). Many other sensors are also applied in TCM. To the most important belong: sound level sensor, flame detector, lubrication oil detector, edge position sensor, speed sensor, thermal deformation sensor, coolant temperature sensor, accelerometer, temperature sensor, torque sensor, acoustic emission sensor, surface roughness sensor, chip monitoring sensor, smoke sensor, image sensor and gas sensor.

The use of so many sensors increases the cost of drill monitoring and also complexity of TCM process. To reduce this complexity and cost of equipment we propose to diagnose the drill condition using only the image sensor. The idea is to take picture of the hole and apply the analysis of this image. On the basis of results of this analysis the condition of the drill is estimated. We show, that reliable diagnosis of the drill condition is possible on the basis of the images of the holes. This analysis will apply a deep learning approach using convolutional neural networks.

To compare our simplified approach to the classical multisensory method we take into account also the application of five sensors measuring the signals of feed force, cutting torque, noise, vibration and acoustic emission. Currently, the well-known algorithmic approaches to drill condition monitoring using many sensors are based on [1,2,3]:

- time domain description of the registered signals, including such statistical measures as average, peak, RMS, variance, crest factor, kurtosis, etc.
- frequency domain description of the signals, including the diagnostic features based on Discrete Fourier Transform (DFT) and Power Spectral Density (PSD).
- time-frequency analysis of signals, including the features based on Time-Frequency Representation (TFR), Short Time Fourier Transform (STFT) or wavelet analysis.

The experimental part of the research was performed on the basis of a standard laminated chipboard drilling process performed in the laboratory of Warsaw University of Life Sciences. The results of this analysis will be presented in the form of the average accuracy of two states of drill condition: the sharp and worn out.

2. DATA ACQUISITION

Database has been collected in in the laboratory of the Faculty of Wood Technology, Warsaw University of Life Sciences using standard Buselatto JET 100 CNC vertical machining Centre. The image of this machine is depicted in Fig. 2.

Figure 2. CNC machine used to collects the experimental data.

The material used in drilling process was a standard laminated chipboard, of the side view presented in Fig. 3a. The dimension of material was 150x35x18mm. Fig. 3b shows the images of five holes, made by the sharp drill (the first 3 holes on the left) and worn out drill (the next two on the right).

a)

b)

Figure 3. Standard laminated chipboard used in experiments (a) and view on examples of five drilled holes (b).

Only one type of drill was applied in data acquisition. It was the product of “FABA” - Poland, 12mm diameter, equipped with a tungsten carbide tips (Fig. 4).

Figure 4. Two-edged drill (FABA WP-01) with cutting edge HW of the diameter 12mm.

The images of the holes have been acquired in many drilling processes using the sharp and blunt drills. We have collected 450 images of drilled holes made by the new drills and drills of gradually worsening quality. In every case two images have been taken: one from the upper side (so called input hole) and the second from the bottom side of a drilled hole (the output hole). Totally, 900 images representing both classes of drill: the sharp and worn out have taken part in experiments. The typical results of using the sharp and blunt drills are depicted on Fig. 5.

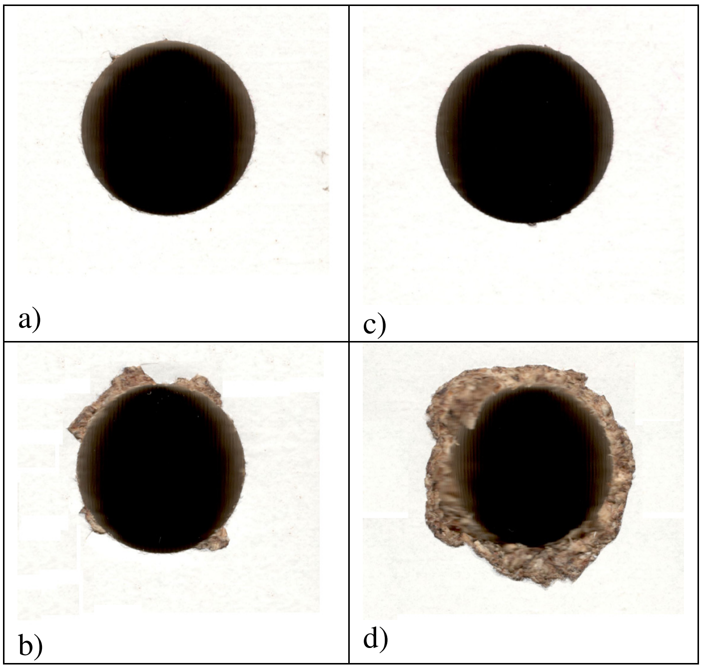

Figure 5. The images of a) input hole drilled by sharp drill, b) input hole drilled by worn out drill, c) output hole drilled by sharp drill, d) output hole drilled by worn out drill.

The exemplary cases presented in Fig. 5 show the evident differences between the images resulting from using the enough sharp and worn out drills. The damages of standard laminated chipboard, such as irregular, non-smooth edges of the hole are visible. Such distortions mean the bad quality of product and production losses in furniture industry.

The database for numerical experiments has been prepared using 5 new drills. In the first phase all of them have been used in laminated chipboard drilling process resulting in good quality holes. In the next phases the drills were gradually blunted eight times in a controlled way under the microscope Mitutoyo TM-505, exacerbating the degree of drill blunting, and the production process was continued using these blunted drills. After each blunting ten holes were drilled using each drill. This process resulted in total number of 5 (drills) x 10 (holes) x 9 (blunting process) x 2 (input and output holes) = 900 holes.

Each hole in a laminated chipboard was scanned and cropped. In this way, 900 images were obtained, each corresponding to the appropriate degree of blunting (9 succeeding degrees (classes) of drill blunting). According to expert decision the first 3 classes represented the acceptable results of product and the next 6 (from 4 to 9) the unacceptable. In this way the data have been split into two classes under recognition: class 1 representing the drills of acceptable condition from production point of view and class 2 – the worn out state of drill (too blunted to be used in production process). The data base used in experiments consists of:

1) Class 1 (sharp enough drill) - 300 images
    a. Upper side:150 images
    b. Bottom side: 150 images
2) Class 2 (blunted drill) - 600 images
    a. Upper side:300 images
    b. Bottom side: 300 images

To prepare images for recognition of the drill condition the elimination of the artifacts (unnecessary part of images around hole) was done first. The appropriate adaptive thresholding has been applied in this task [4,5]. Moreover every image was cropped to 170x170 pixels and conversion from RGB to grayscale has been applied. Such prepared images were used directly as the input data in deep learning.

3. DEEP LEARNING

Deep learning is sometimes called deep structured learning or deep machine learning [6,7,8,9]. We can treat this approach as of group algorithms which apply high-level abstraction models by using multiple hidden layers with very complex structures and a lot of weights and multiple non-linear transformations. Deep learning algorithms do not analyze pixel by pixel but rather consider the regions of pixels, for example filtering the subsequent regions of the size 5x5 pixels. One of the main advantages of deep learning approach is avoiding the stage of generation and selection of the appropriately defined diagnostic features characterizing the image in classification process. So, it means that there is no need to prepare hand craft features which are characteristic in classical approach to pattern recognition [10]. Fig. 6 depicts the basic differences between the traditional machine learning and deep learning approaches in pattern recognition of the hole images. We have applied here the deep learning in the form of convolutional neural network proposed by authors of [9], implemented in Matlab [5] environment.

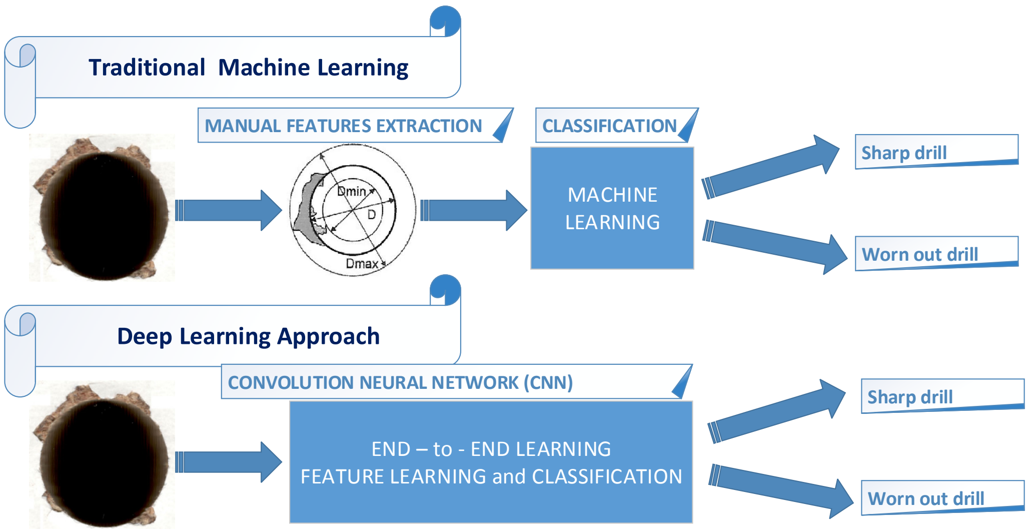

Figure 6. Comparison of traditional machine learning and deep learning approaches to recognition of hole images.

4. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural network (CNN) consists of multiple layers containing small groups of neurons [8]. Each neuron of the group receives inputs from a set of units located in a small neighborhood in the previous layer and is responsible for processing the small region of input images, called receptive fields. They will be called filters. The neurons with local receptive fields can extract the elementary visual features, such as oriented edges, end points, corners, etc. These features are then combined by the subsequent layers to detect features of the higher order. We have applied size of the receptive field equals 5x5 pixels and 32 filters in the layer. The outputs of these filters are then tiled so that their input regions overlap. In this way a better representation of the original image is obtained. This type of processing is repeated in the succeeding layers.

In each region we compute a dot product of the weights and the input signals and adds a bias term. The filter moves along the input image vertically and horizontally repeating the same computation for each region. The step size with which it moves is called a stride. We have applied the stride size equal one in convolutional layer and value of two in pooling layer. Fig. 7 presents the general structure of the convolution neural network used in experiments. It consists of successive 3 convolution ReLu (Rectified Linear Unit) layers, followed by the pooling layers for feature learning and the fully connected softmax used as a classifier.

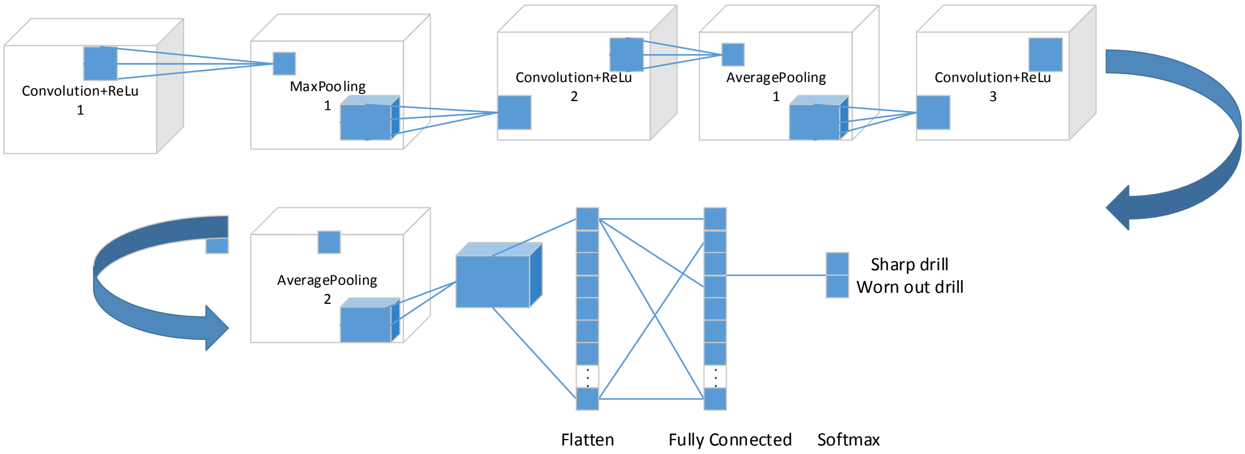

Figure 7. Structure of the convolutional neural network used in experiments.

The convolution layer is composed of filters. The number of weights used in a filter is equal $h \times w \times c$, where h is the height and w the width of the filter. The value of c is the number of color channels in the input (if the input is a color image, the number of channels is three, for grey scale images c=1). The total number of parameters in a convolutional layer is $(h \times w \times c + 1) \times$ (*No of filters*), where 1 is responsible for the bias. In our approach we have applied h=5, w=5 and c=1 with the *No of filters* equal 32 and the boundary padding equal two. It means that in our model the output of a convolutional layer consists of $32 \times 32 \times 32$ elements. Rectified Linear Unit layer, performs a threshold operation to each element, where any input value x results in max(0,x). Thanks to such form of nonlinearity we avoid saturation of the units and accelerate the learning process. Moreover, no input normalization to prevent unit from saturation is needed.

Pooling layer summarizes the outputs of the neighboring groups of neurons in the filter. It consists of a group of pooling units, each summarizing a neighborhood centered at the location of the pooling unit. This layer allows to calculate maximum (maxPooling2dLayer) or average (averagePooling2dLayer) value of the chosen region from previous layer. In our approach we have applied both types of pooling in different convolutional layers.

The output of the last, fully connected layer is fed to 2-way softmax, which produces the final class recognition (class 1 - drill sharp, class 2 – drill worn out) . Softmax layer calculates the output value based on the multinomial logistic regression objective, maximizing the average across training cases of the log probability of the correct class label, using the following class probability formula [9]

$$P(c_r \mid x) = \frac{P(x \mid c_r)P(c_r)}{\sum_{j=1}^{k} P(x \mid c_j)P(c_j)} = \frac{\exp(a_r)}{\sum_{j=1}^{k}\exp(a_j)} \tag{1}$$

where

$$a_r = \ln\left(P(x \mid c_r)P(c_r)\right) \tag{2}$$

$$0 \le P(c_r \mid x) \le 1 \tag{3}$$

$$\sum_{j=1}^{k} P(c_j \mid x) = 1 \tag{4}$$

where $P(x|c_r)$ is the conditional probability of the sample x given class r and $P(c_r)$ is the prior class probability. The class of the highest probability is regarded as the winner.

5. NUMERICAL RESULTS OF EXPERIMENTS

In the numerical experiments we have applied 90% of randomly chosen data for learning process and the remaining 10% for testing purposes. The first trials performed on the basis of 900 originally acquired images resulted in not acceptable accuracy of class recognition (66.6%) of the testing data. This unacceptable accuracy is the result of too small data set used in learning process. Hence we decided to expand the database by successive rotating each image first by 30 degrees and then in the next experiments by 10 degrees. In this way the database was expanded from 900 images to respectively, 11700 in the first case and to 33300 images in the second case. All numerical calculations have been performed on GPU applying CUDA architecture 5.0. The results of class recognition are presented in Table 1. As we can see increasing the number of sample images in the data set has allowed obtaining much better accuracy rate. The higher is this number the better quality of solution.

No of images	Accuracy [%]
900	66.6%
11700	89%
33300	95.5%

Table1. The results of numerical experiments of class recognition using deep learning at different sizes of database

These results have been compared to much more complex classical approach to drill state recognition. The SVM classifier [11] was employed to recognize the classes of drills using the diagnostic features generated from the signals of five sensors measuring the feed force, cutting torque, noise, vibration and acoustic emission. The diagnostic features have been extracted on the basis of statistics of time representation, Fourier transformation and wavelet decomposition. The best accuracy of class recognition using the same data set was equal 94%. It means that convolutional neural network has not only reduced the complexity of process recognition, but resulted also in the increase of accuracy.

6. CONCLUSIONS

The paper presents an application of a deep learning for the recognition of the drill condition on the basis of image analysis of the holes drilled in a chipboard. We have proved that analysis of the images of the holes, made by the drill, allows assessing the drill condition. Thanks to such solution we can avoid using very expensive measuring devices used in classical approach to TCM. Deep learning in the form of the convolutional neural network, applied in recognition of the images, was found very efficient tool in image analysis. The main advantage of such solution is the simplified form of image processing at very good class recognition rate. Such approach to the problem avoids the long process of extracting the specially designed numerical descriptors of the images and makes the recognition process more universal and applicable to different types of images.

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