INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 20, Issue: 2, Month: April, Year: 2025
Article Number: 7028, https://doi.org/10.15837/ijccc.2025.2.7028

CCC Publications

Surface Roughness Determination With the Help of Artificial Neural Networks as Enabler of Metal Machining Process Controlling System

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Abstract

Implementation of control systems for metal machining process is leading to better quality of products, increase of productivity and decrease of environmental impact. These control systems are analyzing various types of data, acquired by sensors and IoT devices, to predict, to make classifications and to generate decisions. These imply all machining process phases. By analyzing the surface roughness, the machining process can be controlled, the decision if the resulting product can be accepted or should be rejected can be taken, and decisions regarding maintenance tasks can be generated, tasks that may imply the replacement of cutting tools. This way, the control system integrates predictive maintenance features which in-crease its complexity and value. In our research we propose a new classification algorithm to determine the surface roughness, classification that is later used as input to predictive and decision algorithms of the control system of the machining process. Traditional methods used to determine the surface roughness require highly skilled specialists and in-vestigations with the help of high-quality measuring equipment, both of which are not in the grasp of every company. The method we propose is intended to become an affordable and reliable tool for everybody. Thus, we decided to use a low-cost microscope to acquire the images that will be analyzed to determine the surface roughness. For classification we used Feed-Forward and Autoencoder Artificial Neural Networks on samples, splitting material roughness into three categories. Using this approach we achieved over 88% recognition of surface roughness categories.

Our best run gave us an average error of 0.79%. These results make this method a viable tool for control systems implementations for metal machining.

Keywords: Control systems, Artificial Neural Networks, Surface roughness, Surface roughness recognition, Surface roughness classification, Autoencoder.

1 Introduction

Implementation of control systems for metal machining process is leading to better quality of products, increase of productivity and decrease of environmental impact. These control systems are analyzing various types of data, acquired by sensors and IoT devices, to predict, to make classifications and to generate decisions. These imply all machining process phases.

Out of all types of data, surface roughness is one of the most essential property of a material during cutting phases, no matter if we are talking about milling, turning, wire cutting, or laser cutting. It is important that we obtain a value of Ra (roughness) that is minimal, right from the cutting process, no matter if we are going to further polish the surface for special treatments or not. However, in order to further prepare the materials that are going to be used for example as a target in processes as CVD (Chemical vapor deposition), PVD (Physical vapor deposition) or magnetron sputtering, the desired target surface must be as fine as possible (in the range of a few microns), in order to ensure that the substrate (evaporated) material adheres to the target, but also due to economic reasons such as high cost of the substrate material.

The research presented in this article is part of a larger and long term project having as goal to develop an automated an automated roughness control system. For example in [23] was studied surface roughness image acquisition and processing. In the studies were used quasi-fractal characteristics and fuzzy clustering methods to find a characteristic roughness parameter (for example Ra) on the bases of information contained in the image of the surface. The relevance of the research topic is demonstrated by the multitude of articles that address this topic. The research articles that are covering only roughness (Ra) prediction or recognition can be clustered based on cutting techniques, such as milling and turning [24], [4], [20], [17], [22], [10], [9], [3], [6], [18], [11], [5], [12], [15], [16], [21], laser cutting [25], [19], wire electrical discharge machining [2], [8]. Although most articles represent studies on well-established industrial processes, surface roughness prediction is also important in other less industrial and more complex technologies such as SPIF (Single Point Incremental Forming) [14].

By using an artificial neural network to analyze the data that comes directly from the machine by means of sensors or machine settings, such as vibrations, cutting speed, depth of cut, feed rate etc., the analysis process is sped up, and the best values are returned. Artificial intelligence analyzes hundreds of thousands of input data to predict or directly measure the roughness of a material. However, fuzzy logic methods have been implemented, although with a lower prediction or recognition percentile [1].

Our main goal is to establish a system that can measure the roughness of a material by analyzing an image acquired with the help of a digital microscope and classify it in different roughness classes to determine the best polishing technique to be used. The classification is done using Artificial Neural Networks. The complete system will be able to self-adjust according to the polished material and guide the user in polishing times and settings, but for now we have trained and tested a Neural Network just to recognize the roughness classes. In the process we used Feedforward Neural Networks and Neural Networks in the form of an autoencoder. There are some related studies that use Neural Networks to investigate failures and faults [13], [7], and in our case the roughness of the surface cand be identified as a fault and put through an automated identification.

The results so far are promising, and although we have used only 192 sets of data for training, validation and testing the mean error percentage using the autoencoder was only 0.79% in testing. In comparison, we found varying results in literature, which validate our findings and acknowledges the performance of our method: 19.48% on 57 values using image recognition with Keras DNN [20], 5.79% prediction for laser cutting [25], predicting roughness on incremental forming using feedforward backpropagation method 5.96% [14], predicting roughness in a turning process using backpropagation and 750 data sets resulted in 2.26% error in the training phase and 4.24% in validation phase [18], and for recognizing roughness based on RGB images using CNN with Keras and TensorFlow the best mean error was 3.2 micrometers [19] which in our case would have definitely considered it in another category of roughness. It has to be mentioned that in the case of laser or wire cutting or by milling and turning, the roughness of a material is relatively high when compared to polishing, sometimes as high as an order of magnitude.

2 Materials and methods

In order to train and test the AI algorithm on different classes of roughness we used a steel bar that was processed at a vertical milling machine as seen in (Figure 1).

Figure 1: Vertical milling machine

Three steel bars were obtained with varying roughness between 6.3 and 0.8 micrometers. Surface images of these three bars can be seen in (Figure 2).

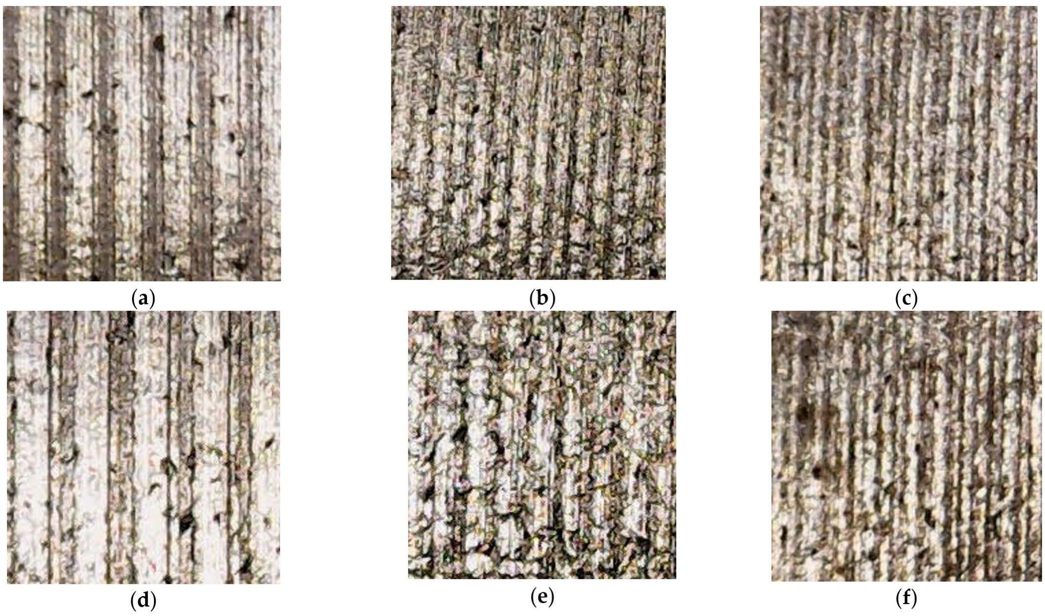


Figure 2: Pictures with three categories of roughness used in prediction and testing: (a, d) Ra 6.3 - 3.2 micrometers (class a); (b, e) Ra 3.2 - 1.6 micrometers (class b); (c, f) Ra 1.6 – 0.8 micrometers (class c) (magnification 50x).

The acquired surface images were used for training and validation. The acquisition process was performed using a low-cost and readily available digital microscope (Figure 3b). The acquire images were categorized based on the material surface roughness as measured with the help of a Surface Roughness Tester as seen in (Figure 3a).

(a) (b)

Figure 3: Pictures of equipment used: (a) Surface Roughness Tester; (b) Digital Microscope 50x.

The use of a low-cost and readily available digital microscope is vital due to the fact that our goal is to use a methodology that can be replicated or used in a low-cost laboratory, at home or in SMEs with the same results.

For experiments we used an average laptop, with 4 cores, 8 GB of RAM and integrated graphics and MATLAB software. Although the software can be pricey, the advantage is that the modelling of the network is easy and does not require much setup, optimization tools are integrated and there is no requirement for pro-graming skills such as for TensorFlow for example. One of our goals was to keep it as simple as possible for the final user.

Initially were acquired 64 images at a resolution of 480x640 pixels. Out of each acquired image were cropped 6 disjoint images having each a resolution of 200x200 pixels, resulting a set of 384 images.

This set of images was used to train the used for training, validation, and testing. Even that the used resolution of images is a low one of only 200x200 pixels, due to the fact that in those images were captured enough characteristics of the surface roughness, the obtained results were very good. Out of all available images, 70% were used for training, 15% were used for validation and 15% were used for testing.

In designing the models, the input layer was designed such that one input neuron to be used for every pixel of the input image, leading to an input layer consisting of 40000 neurons. For the hidden and output layers was decided to use two different types of Artificial Neural Networks (ANN) in order to have a comparison between the methods and choose the most appropriate one for our goal. The two used types of ANNs were Feedforward (Figure 4) and Autoencoder.

In the case of the Feedforward Neural Network several tests using 10 to 110 neurons on the hidden layer were made. At the beginning an architecture with three outputs was tested, in order to classify the three types of roughness classes, but the results were not satisfactory. Once obtained these not satisfactory results, the decision to explore the possibility of using two ANN in a cascade manner was made. Since this architecture delivered bet-ter results, it is the one described in this article.

As mentioned, the used architecture consists of two networks, each with its own usefulness: the first network differentiates the picture between the first class of roughness and the other two classes; the second network dif-ferentiates the picture between the second and the third class of roughness, as seen in (Figure 5).

In the case of using the Autoencoder type of ANN, the architecture consists of two layers of hidden neurons. In the experiments were used hidden layers having between 40 and 120 neurons. The neural network training tool window, alongside with settings for both ANNs, can be seen in (Figure 6).

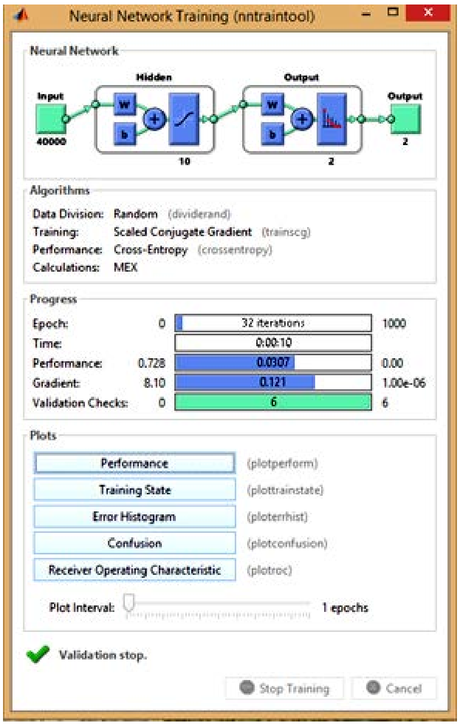


Figure 4: Neural Network Training Tool: Feedforward.

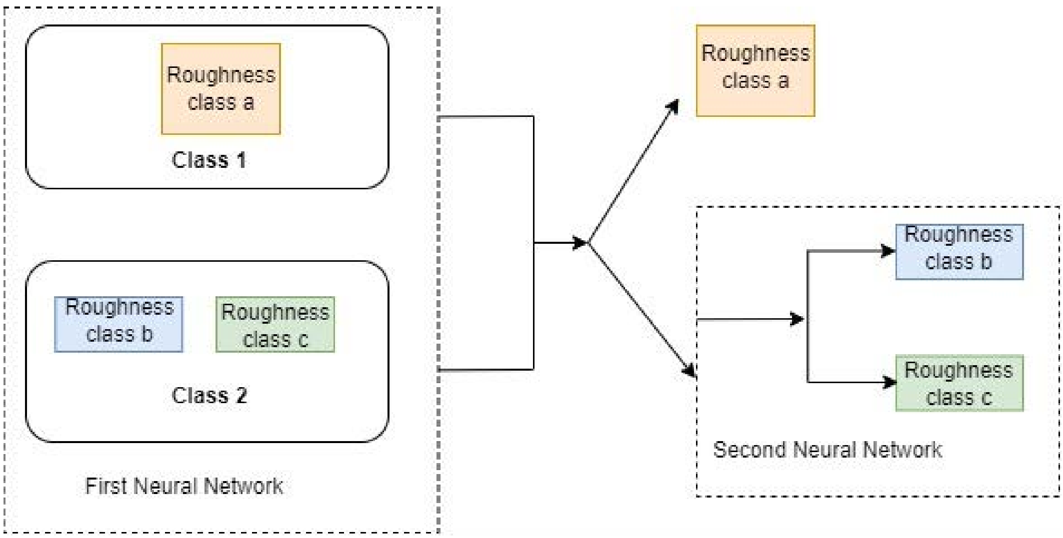


Figure 5: Diagram of how the Feed Forward Neural Network works.

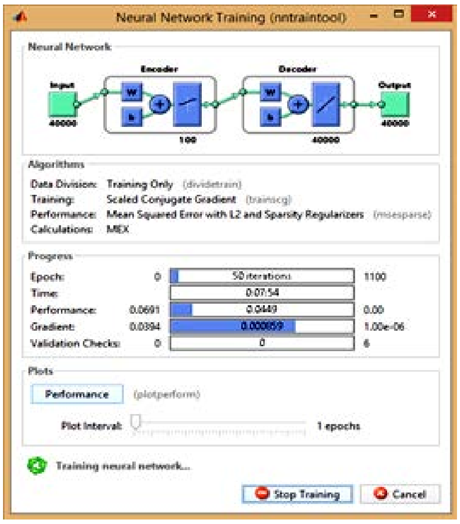


Figure 6: Neural Network Training Tool: Autoencoder.

3 Results

During the experiments, the Feedforward method, it was the least viable, as the confusion matrix had many errors. This can be seen in (Figure 7).

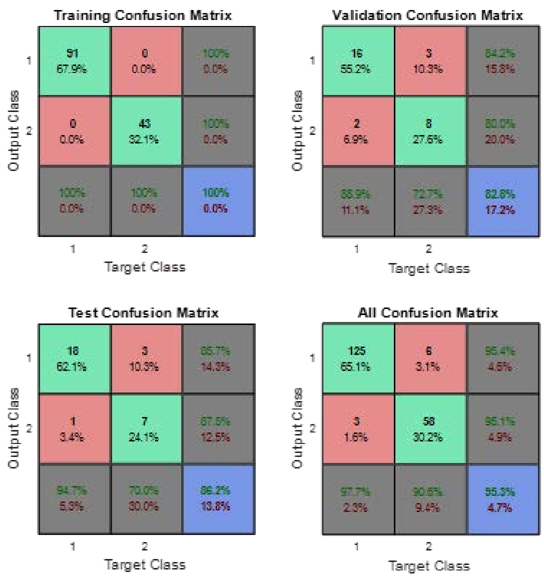


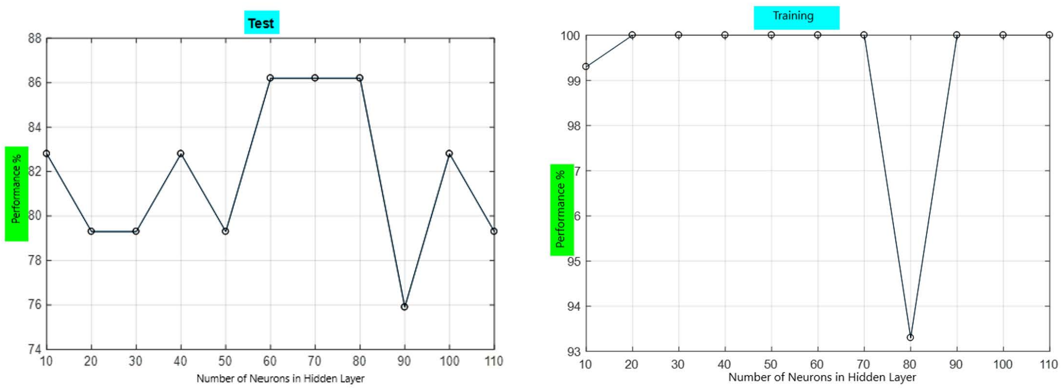
Figure 7: Confusion Matrix for Feedforward Neural Network.

Best performance was obtained in testing while using in hidden layer 60-80 neurons and in Training while using in hidden layer a number of 20-70 or 90-110 neurons, as it can be seen in (Figure 8).

On the other hand, the Autoencoder Network had very good results, with the best choice being 100 neurons on the first hidden layer and 60 neurons on the second hidden layer, as presented in (Figure 9). Each value in (Figure 9) is an arithme-tic average of 3 neural network outputs trained with the same number of neurons on the first hidden layer (hs1) and on the second layer (hds2).

4 Conclusions

Following the experiments results, we can conclude that the best method to analyze the surface roughness is using Neural Networks in the form of an autoencoder. Although training times are significantly high in comparison to Feedforward Neural Networks, the training can still be done with



(a) (b)

Figure 8: Performance of the first network for Feedforward Neural Network: (a) Testing; (b) Training.

Number of neurons on the second hidden layer (hds2)	Nr. of neurons	Number of neurons on the first hidden layer (hds1)				
		80	90	100	110	120
	40	8.73%	11.87%	3.97%	6.35%	9.52%
	50	8.73%	8.73%	11.11%	11.11%	10.31%
	60	9.52%	9.52%	0.79%	8.73%	7.14%
	70	11.90%	11.90%	7.14%	4.76%	11.87%
	80	11.11%	8.73%	7.14%	12.67%	7.93%

Figure 9: Autoencoder average errors in testing.

an average laptop in a few days' time and the results can be used in any low-cost laboratory especially for individual researchers and SMEs. The 0.79% average error for the Autoencoder can be further optimized. Anyway, considering the already achieved average error, makes it good enough for industry adoption at a wide scale. Having demonstrated the potential and viability of the technology, further it can be used to develop a fully functional system that ideally can replace laboratory technicians from the tedious work of inspecting and polishing surfaces.

In addition, insights can be provided into reducing some of the metallographic sample preparation steps, such as sanding with different grits of abrasive paper both by effectively reducing sanding time but also by reducing the number of different grit categories of abrasive paper - resulting in shorter preparation times and also lower costs for the necessary operations.

The newly introduced algorithm can also be applied to finishing operations, such as rectifying parts made of metallic materials, to reduce the number of passes required to obtain surfaces with the roughness prescribed in the drawing, helping to optimize the manufacturing process.

Funding

The APC was funded by University of Oradea.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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Cite this paper as:

Avram, F.T.; Tarca, D.I.; Noje, D.; Vesselenyi, T.; Tarca, R. (2024). Surface Roughness Determination With the Help of Artificial Neural Networks as Enabler of Metal Machining Process Controlling System, *International Journal of Computers Communications & Control*, 20(2), 7028, 2025.
https://doi.org/10.15837/ijccc.2025.2.7028