PREDICTION OF TOOL WEAR USING MACHINE VISION APPROACH

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ABSTRACT: Tool wear prediction plays a crucial role in the machining industry for proper planning and optimization of cutting conditions. Nevertheless, tool wear assessment method using sensor signals has its drawbacks in the industry application. The objective of this study is to apply Artificial Neural Network (ANN) prediction model and machine vision system to predict flank wear in turning operation based on the texture images of machined surface captured by complementary metal oxide semiconductor (CMOS) camera in-cycle. The image pre-processing technique was utilized to enhance the quality of surface texture images acquired from the experiment and the texture descriptors were extracted from the processed images using gray-level co-occurrence matrix (GLCM). Three ANN prediction models with different input variables were developed using MATLAB software. The findings showed that the ANN prediction model with input variables of contrast, entropy, cutting speed, and feed rate outperformed the other ANN prediction model. The prediction accuracy of this model in estimating flank wear reached up to 93.18%. A very good fit and the relationship could be found in this model with $R^2$ of 0.9863 for flank wear.

KEYWORDS: flank wear, machine vision, GLCM, ANN, Levenberg-Marquardt

1 INTRODUCTION

In the manufacturing industry, the surface quality of the machined part is one of the customer’s primary concerns where the important measure of surface quality on workpiece is surface roughness. The surface roughness of the machined part is the factor that is directly influenced by tool wear and which drives the decision for tool change (Siddhpura & Paurobally, 2013). Tool wear is a common and unavoidable phenomenon in the machining process, which describes as the progressive failure of cutting tools due to regular operation. The direct contact or rubbing of the cutting tool with the workpiece in the machining process will induce tool wear and consequently deteriorate the surface finish and dimensional accuracy. Since tool wear is an unpleasant situation in the manufacturing industry, the degree of tool wear must be kept under monitor during machine operation. Studies showed that the computer numerical control (CNC) system equipped with a monitoring system can reduce 75% of machine downtime, improve 10% to 60% of production rate and even increase machine utilization above 50% (Rehorn et al. 2005) as well can save up to 30% processing cost (Chen, 2011). Therefore, it is important to monitor the cutting tool condition to replace the cutting tool in time before the occurrence of excessive tool wear and tool breakage.

Tool condition monitoring systems generally can be divided into two main categories, which are direct and indirect methods. The direct method for observing the cutting tool condition usually involves optical measurement of tool wear, such as tool makers’ microscope, optical microscope, or scanning electron microscope. However, these techniques have an obvious shortcoming which is time consuming and can be only done offline, which requires that the cutting operation be stopped and dismantling of the cutting tool from the tool post for inspection or measurement. Another direct method that allows the tool wear could be observed in the process method is using a charge-coupled device (CCD) camera where the tool wear image can be captured during the machining operation (Dutta et al., 2013a).

On the contrary, the indirect method involves the measured parameters or signals such as acoustic emission, cutting force, and vibration of the machining process to assess the degree of tool wear.
(Mohanraj et al., 2020). Indirect method using sensor has several limitations in measurement of tool wear due to its high sensitivity to the industrial environment. In recent years, tool condition monitoring using machine vision approach coupled with image processing techniques has been an interest area of researchers. Several researchers have started implementing this method to analyze tool wear indirectly with reference to the surface texture of machined parts. This is because the machined surface image contains details about the state of the cutting tool by tool imprint on the workpiece surface (Al-Kindi & Zughaer, 2012). Previous studies are mostly focusing on analyzing the feed marks created by the cutting process on the surface of machined parts captured in the forms of the digital image. The feed marks or irregularity of the machined surface will create low spots (valleys) and high spots (ridges) on the machined surface. Machine vision techniques employ the visualization of the pattern of ridge-valley and use the descriptors extracted from surface texture images over an area as input of the prediction model for evaluating the surface roughness (Chethan et al., 2018). Some researchers attempted to predict the extent of tool wear by extracting different features, for instance, contrast and homogeneity from machined surface images (Dutta et al., 2012), (Dutta et al., 2015), (Dutta et al., 2016). The objective of the research is to develop machine vision to predict the tool wear based on the machined surface using artificial neural network.

2 MATERIALS AND METHODS

2.1 Experiment setup

The turning process is carried out on Harrison Alpha 400 NC lathe machine and the AISI 1045 carbon steel workpiece material was turned with carbide inserts TNGG220408R-UM (Sumitomo Electric) under dry cutting conditions. In this experiment, there are three factors (cutting speed, feed rate, and depth of cut) at three levels (low, center, and high) were used as tabulated in Table 1 and every possible combination of factors and factors level were considered. Therefore, the experiment can be expressed as a $3^3$ design and a total of 27 experimental runs were performed in this study. After finishing the turning process, the flank wear was measured by using Nikon MM-60 Toolmaker’s Microscope according to ISO 3685:1993.

2.2 Image Acquisition and Image Pre-processing

The image acquisition system consists of a complementary metal oxide semiconductor (CMOS) camera, camera holder, light source, and computer. Figure 1 shows the schematic diagram of the image acquisition system. The CMOS camera is fitted on the camera holder and connected to the computer with built in software of Daheng Galaxy Viewer via universal serial bus (USB) connector. In addition, both CMOS camera and light source are made fixed with respect to the machined workpiece to capture the images of the machined surface. The Red Green Blue (RGB) images or colour images of the turned surface of workpiece captured by the camera under different cutting parameters during the turning process were imported into the computer and further underwent image processing.

The obtained RGB images which contained too much unnecessary information were then converted into gray scale images with the range of gray scale level from 0 to 255 using matrix laboratory (MATLAB) library command ‘rgb2gray’ to suppress undesired distortions. Next, the focus regions of obtained gray scale images were cropped to the same size with 512 by 512 pixels to remove

<table>
<thead>
<tr>
<th>No</th>
<th>Parameter</th>
<th>Unit</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cutting Speed</td>
<td>m/min</td>
<td>1 (Low)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2 (Cen-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ter)</td>
</tr>
<tr>
<td>2</td>
<td>Feed Rate</td>
<td>mm/rev</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Depth of Cut</td>
<td>mm</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>
the unwanted area. After that, the cropped images were enhanced by using local Laplacian filtering to provide a clearer pattern of ridge-valley of the machined surface. Next, the high-pass filter (sharpening) was applied to the image to emphasize fine details of the image and make the image appear sharper. The sharpened images were then further processed by using adaptive histogram equalization. The adaptive histogram equalization technique improves the local contrast and enhances the edge in each region by redistributing the intensity value of the image uniformly. Lastly, the images were sharpening over again to obtain a clearer and sharper image. The images of machined surface texture after local Laplacian filtering, sharpening, and adaptive histogram equalization provides better details and contrast quality of images. Figure 2 shows the machined surface texture images before and after pre-processing.

2.3 Feature Extraction

After the image processing step, machined surface texture analysis using gray level co-occurrence matrix (GLCM) is introduced to extract relevant descriptors from the texture images acquired. The statistical descriptors such as contrast, energy, entropy, and homogeneity were extracted from the turned surface images by using MATLAB software. Contrast defines the level of dissimilarity between co-occurrence of pair of pixel values over the texture image. The expression of contrast descriptor is stated in Equation.1.

\[
\text{Contrast} = \sum_i \sum_j (i - j)^2 p(i, j)
\]

Where i and j are the gray level values (tone) in the image, while \(p(i, j)\) is the likelihood of occurrence of pixel pairs having gray level values i and j in the image at particular pixel pair spacing (pps) and a pixel pair direction (θ).

3 ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is a mathematical model that has strong ability to learn complex and non-linear relationships between multiple variables with high precision. The feedforward ANN tool wear prediction model with Levenberg-Marquardt backpropagation training algorithm was chosen to be used in this study.

![Fig. 2 Machined surface texture image (a) before and (b) after pre-processing](image)

The development of an ANN prediction model was started by importing the training and testing dataset into MATLAB software. 80% of the dataset was used for training while the remaining 20% of the dataset was used for testing the accuracy of the developed prediction model. To build an ANN model, there are several parameters of the neural network are required to be set, which included the number of hidden layers, number of neurons, training algorithm, activation function, maximum iterations, tolerance error, and minimum MSE gradient. These hyperparameters of the network were optimized by trial and error method until the best network structure was obtained. There were three ANN prediction models with different input variables were developed by using MATLAB R2019b as listed in Table 2. The ANN prediction models were developed and trained to predict flank wear and the prediction performance of the ANN models were evaluated by using mean absolute percentage error (MAPE) and coefficient of determination (R2) as shown in Equation.5 and Equation.6, respectively.

\[
\text{MAPE} = \frac{1}{N} \sum_i \left| \frac{Y_i - X_i}{Y_i} \right| \times 100\%
\]

\[
R^2 = 1 - \frac{\sum(Y_i - \bar{Y})^2}{\sum(Y_i - \bar{Y})^2}
\]

where N is the number of the dataset, \(X_i\) is the predicted values for flank wear and surface
roughness, \( Y_i \) is the experimental values for flank wear and surface roughness, and \( \overline{Y} \) is mean of the experimental values for flank wear and surface roughness.

4 RESULTS AND DISCUSSION

To evaluate the correlation of GLCM descriptors, which are contrast, energy, entropy, and homogeneity with flank wear values, the GLCM descriptors are plotted against experimental flank wear values as shown in Fig. 3. As can be seen from the figures, contrast is the best linear correlation texture feature with flank wear, where the coefficient of determination \( (R^2) \) value is 0.8911. This can be proven by Dutta et al. (2013b), where the contrast feature shows consistently a good linear correlation with average flank wear value for all the experiments with the range of \( R^2 \) value from 0.9241 to 0.9882. Homogeneity with \( R^2 \) value of 0.7376 also shows a good correlation with flank wear, while the energy and entropy demonstrate a low extent of correlation with tool flank wear with \( R^2 \) value of 0.5925 for energy and 0.5995 for entropy. The results obtained are consistent with the research findings of Dutta et al. (2013b), where the energy and entropy features do not correlate well with flank wear for some of the experiments. In conclusion, it can be said that the contrast is highly correlated with flank wear while the energy is the least correlated feature to flank wear among four texture descriptors.

### TABLE 2. Summary table for the ANN prediction models

<table>
<thead>
<tr>
<th>Model</th>
<th>Input</th>
</tr>
</thead>
<tbody>
<tr>
<td>1\textsuperscript{st} ANN Prediction Model</td>
<td>Contrast, Energy, Entropy, Homogeneity</td>
</tr>
<tr>
<td>2\textsuperscript{nd} ANN Prediction Model</td>
<td>Contrast, Entropy, Homogeneity</td>
</tr>
<tr>
<td>3\textsuperscript{rd} ANN Prediction Model</td>
<td>Cutting Speed, Feed Rate, Contrast, Entropy</td>
</tr>
</tbody>
</table>

Table 3 shows the ANOVA table for flank wear which is used to determine the significance of machining parameters on flank wear. From Table 3, it can be concluded that the cutting speed is the principal factor affecting the flank wear, with a percentage contribution of 29.64%, followed by feed rate and depth of cut with percentage contribution of 24.17% and 10.49%, respectively. This result is consistent with the research findings of Liu et al. (2019). The ANOVA results obtained by Liu et al. (2019) show that the cutting speed is the most significant parameter for flank wear, with a percentage contribution of 46.752%, followed by feed rate (28.120%) and depth of cut has little effect on flank wear with percentage contribution of 6.810% only.

Table 4 tabulates the coefficient of determination and MAPE for the 1\textsuperscript{st}, 2\textsuperscript{nd}, and 3\textsuperscript{rd} ANN prediction model in terms of flank wear. Based on Table 4 and Fig. 4, the 1\textsuperscript{st} ANN prediction model using four extracted features as the input of prediction model has the poorest fitting relationship with flank wear \( (R^2 = 0.8851) \) and the highest MAPE between experimental and predicted flank wear value, which is 13.72%. This might be due to the presence of insignificant extracted features for flank wear in this prediction model as abovementioned.

By filtering out the energy feature, it can be seen that the prediction result for the 2\textsuperscript{nd} ANN prediction model has been improved. The 2\textsuperscript{nd} ANN prediction model shows a better coefficient of determination for flank wear with \( R^2 \) value of 0.9747 as illustrated in Fig. 5. There is also a significant improvement of prediction accuracy for flank wear, which is shown in Table 4 that the MAPE between experimental and predicted values for flank wear has decreased from 13.72% to 10.84%. Therefore, it can be concluded that the 2\textsuperscript{nd} ANN prediction model is capable of predicting flank wear more accurately as compared to the 1\textsuperscript{st} ANN prediction model.

The 3\textsuperscript{rd} ANN prediction model yields the lowest prediction error among all the prediction models. As shown in Table 4, the MAPE of flank wear prediction for 3\textsuperscript{rd} model is 6.82\%. In other words, the 3\textsuperscript{rd} model has the ability to predict the flank wear with accuracy of 93.18\%. Moreover, this model exhibits a very strong direct relationship with flank wear \( (R^2 = 0.9863) \) as shown in Fig. 6. This exhibits that the 3\textsuperscript{rd} ANN prediction model has the highest capability to predict flank wear.

### TABLE 3. ANOVA table for flank wear

<table>
<thead>
<tr>
<th>Source of validation</th>
<th>Degrees of freedom</th>
<th>Sum of squares</th>
<th>Mean square</th>
<th>F-value</th>
<th>Contribution (%)</th>
<th>P-value</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth of Cut</td>
<td>2</td>
<td>0.02794</td>
<td>0.01397</td>
<td>2.94</td>
<td>10.49</td>
<td>0.0760</td>
<td>Not significant</td>
</tr>
</tbody>
</table>
Fig. 3 Relation between (a) contrast (b) energy (c) entropy (d) homogeneity and flank wear

TABLE 4. $R^2$ value and MAPE for 1st, 2nd, and 3rd ANN prediction model

<table>
<thead>
<tr>
<th>ANN Model</th>
<th>Flank Wear</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2$</td>
</tr>
<tr>
<td>1ST MODEL</td>
<td>0.8851</td>
</tr>
<tr>
<td>2ND MODEL</td>
<td>0.9747</td>
</tr>
<tr>
<td>3RD MODEL</td>
<td>0.9863</td>
</tr>
</tbody>
</table>

Fig. 4 Predicted versus experimental flank wear for 1st model
CONCLUSION

In a conclusion, this study successfully implemented the feed-forward ANN prediction model with Levenberg-Marquardt backpropagation algorithm to predict flank wear and surface roughness. The third ANN prediction model showed the best prediction performance among all the developed models, where the prediction accuracy of flank wear using this model can reach up to 93.18%. Furthermore, the third ANN prediction model also demonstrates a very good relationship and fit with $R^2$ of 0.9863 for flank wear.

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