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Monitoring and prediction in centering process of optical glass lenses using long short-term memory with acoustic emission sensor

Shiau-Cheng Shiu[1], Yu-Chen Liang[1], Chun-Wei Liu[1]

[1]*Department of Power Mechanical Engineering, National Tsing Hua University*

s109033802@m109.nthu.edu.tw

Abstract

To proactively address the occurrence of these issues, the monitoring and prediction methodology of centering process within batch production was developed in this study. The experimental phase encompassed the utilization of 20 quartz lenses for centering batch production, with real-time monitoring of material removal employing an acoustic emission (AE) sensor. Based on the AE signal processing, the long short-term memory (LSTM) algorithm was applied to forecast the trajectory of AE signal trends. Moreover, convolutional neural network (CNN) was integrated into LSTM (CNN-LSTM) to enhance the prediction speed. By virtue of this predictive capability, an assessment of the future conditions within the centering process was made feasible. The analysis of more than 32,000 data points was derived from batch production. A highly accurate predictive model was built in this study, as indicated by coefficient of determination (R^2) 0.9067, root mean square error (RMSE) of 0.0577, and mean absolute error (MAE) of 0.0400. By establishing appropriate thresholds and calculating deviations between real AE signals and predicted values, the defects within the centering process can be effectively detected.

Keywords: centering process, optical glass lens, acoustic emission sensor, long short-term memory(LSTM)

1. Introduction

Optical positioning accuracy is critical to the manufacturing of nanometer scale semiconductors. To achieve such feat, high performance optical glass lenses with excellent optical quality are required. Glass lenses normally go through a key manufacturing process known as centering to optimize optical positioning accuracies.

It is common for glass lenses that came off of surface grinding with their optical axis and geometric center axis misaligned. Thus, centering is crucial step in correcting optical axis error. However, the batch production of centering process is affected by the operators fixing the lenses, the original dimensions of lenses or the stability in machine working. These uncertain factors would randomly cause unexpected defects such as edge cracks. The further negative effect would be on the lens appearance and optical performance.

Acoustic emission (AE) sensors are proven useful in monitoring the status of a manufacturing process. D. Choi et al. created a real time monitoring system that used AE signal during cutting to identify tool breakage [1]. It is found that a drop in AE signal can be tied to tool breakage. Z. Wu et al. experimented with multi-sensor signals including AE signal to identify features related to tool wear [2]. From experiment, AE sensor combined with accelerometer sensor provided the best accuracy to tool wear prediction. W. N. Lopes proposed a method to monitor the dressing operation of aluminum oxide grinding wheel [3]. T. Segreto at al. proposed a method of using AE and other sensors to monitor a robot-assisted polishing process for online assessment of workpiece surface roughness [4]. This study not only used AE sensor to monitor the centering condition of hard-and-brittle material, but also predict the AE signal to forecast the process condition.

In the research of processing prediction, it can be seen that different models will be selected according to different situations. Based on the time series forecasting model of the wavelet process neural network, Bitzel Cortez et al. used the long short-term memory (LSTM) model and other machine learning models to compare the accuracy of emergency event prediction, and found that LSTM is more accurate than the machine learning model in time series prediction [5]. Combining convolutional neural network (CNN) with other algorithms can significantly reduce model computation time and improve overall efficiency. R. Yan et al. built a multi-time and multi-site prediction model, which compared CNN-LSTM with other algorithms [6]. X. Shao et al. proposed a novel domain fusion deep model based on CNN, LSTM, and discrete wavelet transform (DWT) [7]. M. F. Alsharekh et al. developed a residual convolutional neural network (R-CNN) structure and combined it with a multi-layer-LSTM architecture to create an innovative prediction framework [8]. In consideration of the strict changes in the short-time AE signal, this study tried LSTM to predict the AE signals in centering process. Furthermore, CNN was integrated into LSTM to improve the prediction efficiency.

In this study, LSTM was used with AE sensor to monitor and predict the condition of optical glass lens centering process.

2. Methodology

2.1. Centering process

Centering process aligns the geometrical axis to the optical axis by alignment and edge grinding. After fixing the glass lens between two bell-shaped clamps and aligning the optical axis to the rotary axis, the edge of optical glass lens is ground to adjust the size and align the geometrical axis, as shown in Figure 1.

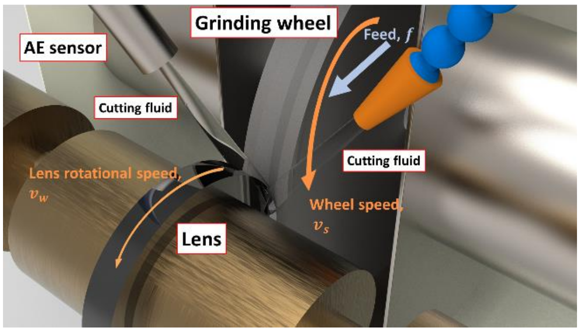


Figure 1. Mechanism of centering process

Centering is cylindrical grinding process of hard-and-brittle material. The material removal rate (MRR) is derived by the following equation:

$$MRR = dWv_w = dW\omega_w(r_w + \tfrac{1}{2}ft) \quad (1)$$

where d is the depth of cut that changes over time t due to feed rate f, W is the width of cut, v_w is the speed of grinding point on the lens, ω_w is the rotation speed of the lens and r_w is the lens radius.

During centering process, the grinding energy is a key factor affecting the quality of a glass lens's edge. The specific energy is related to the grinding power P and can be calculated using the following equation [9]:

$$u = \frac{P}{MRR} = \frac{F_t v_s}{dW\omega_w(r_w + \frac{1}{2}ft)} \quad (2)$$

where u is the grinding energy, F_t is the tangential grinding force, v_s is the grinding wheel speed.

During centering process, the grinding energy is transmitted from the grinding wheel through grinding force to the lens edge, resulting in material removal. Furthermore, while the micro-structure of material is broken, the grinding energy dissipates into the enviroments as heat and wave. AE signal is the stress wave that mainly transferred from the grinding energy. It is assumed to be related to the amount of grinding energy.

2.2. Acoustic emission (AE)

AE signal is elastic stress wave which is generated from irreversible structural changes. It is high-frequency signal and indicates the condition of a material.

A hydrophone AE sensor was adopted in this study to monitor the grinding point in centering process. It was installed in the outlet of the cutting fluid. The AE signal was collected through cutting fluid instead of mechanical contact. The vibration of working machine was then isolated from the sensor. On the other hand, the flow of cutting fluid influenced the noise of signals.

2.3. AE signal process for real-time monitoring

The frequency band of AE sensor was set 300-350 kHz, which was the most sensitive band to centering process. To process and analyze the data in real time, the sampling rate of raw AE signal was limited in 20Hz.

To catch the trend and seanal features of the AE signals more efficiently, The data collected without centering processing was cut away. Only the AE signals of centering processing were fed into the following prediction models.

2.4. Long short-term memory (LSTM)

LSTM is a type of time recurrent neural network suitable for processing manufacturing processes with longer prediction time intervals. Data with indefinite time length can be memorized by LSTM. The proposed model comprises three LSTM layers, each of which includes 128 hidden units. Moreover, a dense layer with hidden units equivalent to the length of the prediction horizon is appended as the final layer.

To reach the required computation speed and accuracy in real-time monitoring of real manufacturing process, convolutional neural network (CNN) was employed to improve the computation efficiency. CNN is a feedforward neural network. It can effectively read and classify the signal features. By integrating CNN into LSTM, the features in AE signals are extracted in a short time and treated as references for further signal prediction.

In the hybrid model, CNN consists of two convolutional layers with 64 filters and a max-pooling layer with a pool size of 2, as shown in Figure 2. The activation function used is the ReLU function, which makes the model computationally simple and fast.

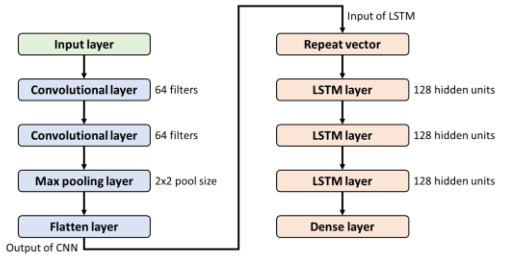


Figure 2. Structure of proposed CNN-LSTM

Each prediction model was trained and verified on sets of preprocessed signals. Three metrics—the coefficient of determination (R^2), RMS error (RMSE), and mean absolute error (MAE)—were used to evaluate model accuracy.

3. Experimental setup

BE-WF-502N horizonal centering machine from Shonan Optics was used in this study. The machine was equipped with a #230 and 150-mm diameter single-layer electroplated diamond grinding wheel. 20 quartz lenses with diameters of 39 mm were randomly chosen from a batch of 300 lenses on a production line. The industrial computer with CPU 4-core i5-7500, RAM 16GB and SSD 256GB was adopted as edge computing to execute AE signal collection, data preprocess and prediction. The experimental setup is depicted in Figure 3.

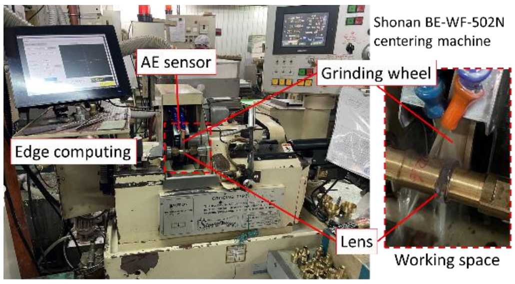


Figure 3. Experimental setup of centering process

A lens in centering process was ground for totally 75 seconds, including 45 seconds of feeding and 30 seconds of spark out. During centering process, the feed rate was 0.02 mm/s in feeding stage and 0 mm/s in spark out stage. The grinding wheel rotational speed was 3,000 rpm and the lens rotational speed was 2 rpm.

The AE signal collected from the centering process of a glass lens is shown in Figure 4.

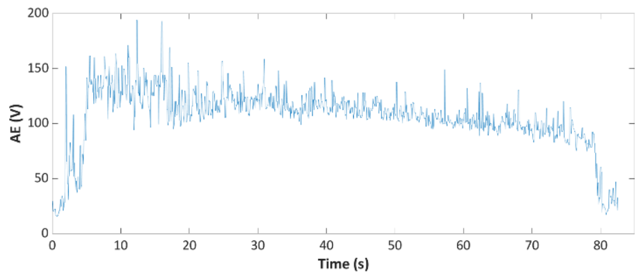


Figure 4. AE signal of a glass lens centering process

4. Results and discussion

According manual inspection, the lenses corresponding to the signals with these features were scraped due to defects. Signal feature 1 was a momentary spike in the signal's amplitude. Correspondingly, an edge crack occurs as the grinding stress concentrates on the corner between the edge and surface. An obvious edge crack was on the corresponding lens. Signal features 2 and 3 were substantially higher signal amplitudes than typical with a clear decrease in gradient as processing continued. The corresponding lenses had poor circularity but no edge cracks. This phenomenon may be caused by the large blank sizes of these lenses before processing. Signal feature 4 was a momentary decrease in the signal amplitude and corresponded to a small edge crack on the lens. Unlike signal feature 1, feature 4 was found to appear when the grinding wheel reached an existing crack instead of when it generated a new crack. Signal features 5 was momentary spikes in the signal. Multiple fine edge cracks were on the corresponding lenses.

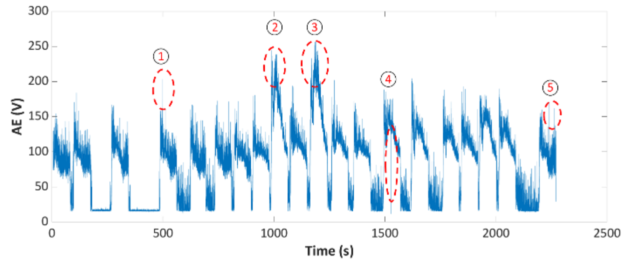


Figure 5. The AE signals from the centering process of 20 quartz lenses

After data process, the overall 30,000 AE signals, collected from centering processes of the 20 quartz lenses were used to train LSTM and CNN-LSTM prediction models. The signals were normalized and divided into training (20%) and testing (80%) sets; after training, the models were evaluated. The results are presented in Table 1.

The prediction accuracy of LSTM was higher, with an R^2 of 0.956660, RMSE of 0.039323, and MAE of 0.022571. On the other hand, the calculation speed of CNN-LSTM was higher than did LSTM and an acceptable R^2 of 0.906716. In steady-state processing, 20 data points are generated per second. The LSTM model required 300 s per calculation. This indicates that LSTM model predicts the next AE signals of 300 s for 300 s. The objective of applying prediction model can not be realized. The CNN-LSTM model required only 20 s. Hence, CNN-LSTM is more suitable for manufacturing processes with short cycle times.

The training and testing results of CNN-LSTM is presented in Figure 2.

Table 1 AE signal prediction results of LSTM and CNN-LSTM

Model	R^2	RMSE	MAE	Time
LSTM	0.9566	0.0393	0.0226	300 s
CNN-LSTM	0.9067	0.0577	0.0400	20 s

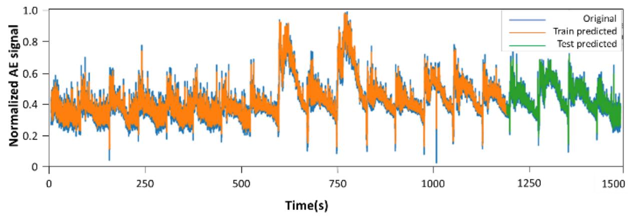


Figure 6. Prediction result by CNN-LSTM compared with original signal

Figure 7 is the graphical user interface (GUI) of the monitoring and prediction system developed in this research. The system has been applied in the actual production line.

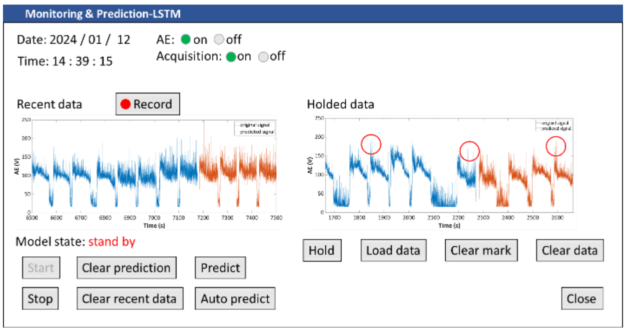


Figure 7. GUI of monitoring and prediction system

Finally, a batch production was carried out to verify the monitoring and prediction system. 50 quartz lenses were prepared for the centering processes. The system kept recording with the AE signals collected during batch production. The defects of the lenses, including edge cracks and circularity errors, were then inspected after processes. During the process, the AE signal features that indicated lens defects were recorded to compare with the actual defects. The prediction result is depicted in Figure 8.

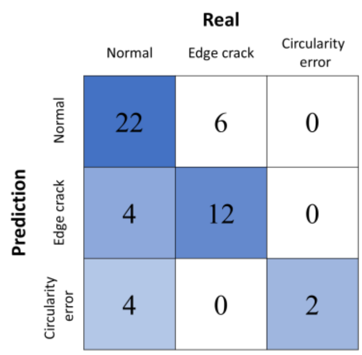
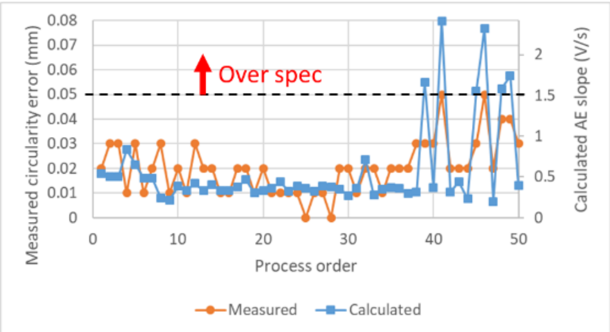


Figure 8. Prediction result of lens defects by monitoring system

According to the results, the defects can be well detected by AE signal features in time. The misidentified defects were predicted by the model with AE rms or slopes closed to the boundary of detection, as shown in Figure 9. The edge cracks and circularity errors were respectively predicted by the rms and slope of the AE signal. An edge crack with depth over 0.1 mm was identified as the AE rms was larger than 20 V, and circularity error over 0.1 mm was identified as the AE slope was larger than 1.5 V/s.

(a)



(b)

Figure 9. Comparison between calculated results and measured results

To verify the effectivity of the system, the method proposed by this study and the traditional method were defined and conducted. In the proposed method, the AE signal features were recorded, and the features were compared with the lens defects after all the centering processes and inspections were done. In the traditional method, inspection is conducted once after processing every 5 lenses and takes 10 minutes.

If a signal feature was marked in the proposed method, or lens defects were found once in traditional method, the total production time adds 2 minutes that represent an process adjustment. The results of comparison between the proposed method and the traditional method were shown in Table 2.

Table 2 Performance evaluation of monitoring system compared with traditional method

Method	This study	Traditional method
Total marked lenses / total scraped lenses	22	20
Marking accuracy	72%	-
Yield rate	88%	60%
Production time	90 mins	
Inspection time	-	100 mins
Process adjusting time	44 mins	20 mins
Total production time	134 mins	210 mins

Consequently, the proposed monitoring and prediction system in this study can effectively improve the yield rate and reduce the production time. Based on the verification results, the use of monitoring system enhanced the yield rate from 60% to 88% and reduced the total production time by 36.2%. Without batch inspection, much time was saved. Though the adjusting time in the proposed method was more than in the traditional method, the overall yield rate and production time were much better.

5. Conclusion

This study presented a real-time centering process monitoring system by analyzing signal trend and actual manufacturing condition. The real-time monitoring system predicts AE signal trends during centering and triggers fault to allow for parameter change, grinding wheel change or machine fault. The early warning prevents loss from damage to products, such as crack or circularity error, causing scrap. The algorithms LSTM and CNN-LSTM were applied to train an AE signal predicting model, whilst comparing the algorithms for their accuracy and computational time. Results show that LSTM has the highest accuracy at R^2 = 0.95666, but each prediction requires 300 seconds. On the other hand, CNN-LSTM only requires 20 seconds for each prediction while still maintaining an accuracy of R^2 = 0.906716. Compared to other algorithms, CNN-LSTM possesses the most suitable characteristic for real-time centering process monitoring with its short computational time.

A verification including 50 centering processes of quartz lenses was conducted. Based on the results, the proposed monitoring system by this study was evaluated and can effectively improve the yield rate and reduce the production time. The proposed monitoring and prediction system showed an improvement in yield rate from 60% to 88% and reduced the total production time by 36.2%.

This study proves the concept that it is possible to monitor and predict the grinding condition of centering process in real-time. It's a major step towards future smart machining in the glass lens grinding industry as machines will be able to deduce errors autonomously, moving the industry one step forward towards Industry 4.0. Further research on model optimization and implementation on CNC machines will be studied in the distant future.

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