ACTA TECHNICA CORVINIENSIS – Bulletin of Engineering
Tome XV [2022] | Fascicule 1 [January – March]

[1.]Chinglung CHANG

AN ONLINE TOOL DIE MONITORING SYSTEM FOR THE STAMPING PROCESS: AN APPLICATION OF DEEP METRIC LEARNING

[1]Fu Jen Catholic University, Graduate Institute of Business Administration, Taipei City, TAIWAN

Abstract: Effectively monitoring the conditions of the tool die in the production line's stamping process is essential, as operators can only inspect the conditions when the product is produced. Convolutional neural networks (CNNs) have demonstrated promising results for classifying complex signals including accelerometer signals, but their practicality have been restricted due to a lack of flexibility in adding new classes and a low accuracy when faced with low sample numbers per class. This study applies deep metric learning (DML) methods to enhance the CNN method. It develops a tool die monitoring system to apply when monitoring the stamping process. It applies signal extraction from sensors and signal classification using DML methods. The system provides information by which operators can monitor tool tie conditions and thus avoid unexpected tool die damage, machine downtime, and unplanned repairs. It further results in a reduction of tool and scrap costs through early failure detection. Manufacturing quality can thus be guaranteed, and productivity can be improved.
Keywords: stamping, monitoring, deep metric learning, Siamese network, triplet network

INTRODUCTION

The stamping process is essential in the manufacturing industry, where a breakdown or unplanned maintenance could lead to a severe disruption of productivity. The need for a highly efficient stamping process has led to an increase in stamping force. However, this has come at the expense of the lifespan and durability of the tool die. One way to combat this is by creating a new design or using new materials in the design of the tool die to make it more robust. Another method is to improve the monitoring of tool conditions. The current common method for assessing the stamping tool die conditions still relies heavily on workers' manual and visual inspection for wear and tear on the tool. However, by the time such conditions are noticed, it is already too late as the product has already started to be affected. It is therefore necessary to develop a system that can eliminate the dependency on human workers and rather provide continuous monitoring of tool wear.

Incorporating sensors such as accelerometers into the milling process is a robust and effective way to achieve real-time process monitoring (Kulis, 2013). However, extracting useful information from sensors is still challenging. Differentiating only one wear condition compared with a standard is not difficult, but when many wear conditions need to be classified, it becomes difficult to investigate the signal and identify the information source.

Signal processing is widely applied to better understand what information lies inside those signals. Signal processing can extract time-based or frequency-based features such as maximum peak, average value, root mean square, standard deviation, crest factor, variance, kurtosis, and skewness (Wu, Hoi, Xia, Zhao, and Wang, 2013). However, there are specific drawbacks to this method. For example, because all features are extracted manually, it can require a lot of man-hours (Workman, Souvenir, and Jacobs, 2015). Furthermore, these manually extracted features tend to not adapt well to evolving conditions and scenarios. More recently, deep learning has been applied to address these issues (Lin, Cui, Belongie, and Hays, 2015). Convolution neural network (CNN) employs nodes as a type of filter that allows this architecture to extract features from complex and non-linear data. Deep metric learning (DML) is developed by mimicking the ability of humans. When learning, humans can differentiate visual objects by looking at similar features. Humans are good at extracting and generalizing visual features. DML tries to do the same thing by training the CNN as a feature extraction (encoder) that can respectively extract similar and dissimilar features from objects into embedded features. The ability to learn from such similarities gives DML the advantage of flexibly adding new classes without requiring model retraining.

The purpose of this study is to develop a system (tool die monitoring system, TDMS) to monitor the conditions of tool dies in a stamping process through signal extraction from sensors and signal classification applying DML methods. The information provided by the TDMS would help production operators know of potential issues before the tool dies wear out or break down and thus improve production quality and efficiency.

RELATED WORK

There are several studies related to the monitoring of stamping tool conditions using signal processing and conventional machine learning methods. Ge, Du, and Xu (2004) apply an auto regressive model to determine discrete time series stamping signals and conduct feature selection by applying a hidden Markov model for classification. Bassiuny, Li, and Du (2007) extract features from strain signals by applying empirical mode decomposition, where the extracted features are tracked using the Hilbert marginal spectrum. They apply linear vector quantization to identify faulty processes. Some studies also use audio signals to monitor stamping processes. Ubhayaratne, Pereira, Xiang, and Rolfe (2017) develop a low-cost monitoring system using sound. They develop a method of semi-blind signal extraction to eliminate noise from surrounding machines. They find the frequency band 2-6 kHz contains the most important wear-related information. Shanbhag, Rolfe, and Pereira (2020) investigate galling wear using acoustic emission generated by tool wear fractures. They find that the acoustic emission mean-frequency can be used for condition monitoring to identify galling and non-galling conditions. Ge, Du, Zhang, and Xu (2004) further use a support vector machine combined with a kernel function to monitor the stamping process. Zhang, Li, Zhou, and Wagner (2018) use a 4-level wavelet decomposition method to extract strain signal features. A semi-supervised clustering algorithm is then applied to the features to detect punching failures. The method is effective for failure detection in punching processes.

The use of CNN based on 1-dimensional (1D) data signals has also gained popularity for the monitoring of other processes. Zhang, Sun, Guo, Gao, Hong, and Song (2020) diagnose bearing faults. They apply 2D-CNN to transformed 1D vibratory bearing data to automatically extract features and classify bearing conditions. Eren, Ince, and Kiranyaz (2019) directly apply 1D-CNN to vibratory bearing data which allows for a much more compact architecture than the 2D-CNN and requires less data preprocessing.

Recent development of few-shot learning based on the DML method with all its advantages over traditional CNN have shown to provide successful applications in fault diagnosis. Zhang, Li, Cui, Yang, Dong, and Hu (2019) develop a deep neural network based on the Siamese neural network to classify rolling bearing conditions. It shows good results while being more flexible, providing more robust signals, and requiring a lower number of samples than the traditional CNN method. Wang, Wang, Kong, Wang, Li, and Zhou (2020) develop a metric-based meta-learning method called *reinforce relation network* to transfer scenarios from experimental situations to actual working situations as related to bearing fault diagnosis.

DML is also known as similarity-based learning and is a branch of machine learning. It can also be applied to image recognition (Weinberger and Saul, 2009), visual search (Wang, Song, Leung et al., 2014), and image-based geo-localization (Vo and Hays, 2017). The distance between samples is used to determine the similarity of samples (Davis, Kulis, Jain, Sra, and Dhillon, 2007). More similar samples have a closer distance. Before the popularity of deep learning, one of the popular algorithms from similarity-based learning was the nearest neighbor rule. The Euclidian distance or Mahala Nobis distance are widely applied in the rule. However, the Mahala Nobis metric faces a linear transformation issue; it is incapable of transforming non-linear data (Bellet, Habrard, and Sebban, 2014). Supervised DML, which is one of DML's two categories, the other being unsupervised DML (Kulis, 2013), has the capability of non-linear transformation by activating the non-linear structure function.

Based on artificial neural networks, a Siamese network (Bromley, Guyon, LeCun, Säckinger, and Shah, 1993) describes a network that has two identical sub-networks joined together at output. During the training phase, these two sub-networks extract features from samples and provide signatures. The joining network then measures the distance between these two samples. A Siamese network is similar to a supervised DML in that the identical sub-networks can be applied to feature mapping (Chopra, Hadsell, and LeCun, 2005). Schultz and Joachims (2003) propose a method for learning distance metrics from relative comparisons. Hoffer and Ailon (2018) take a similar concept from Chechik, Sharma, Shalit, and Bengio (2009) and Wang et al. (2014) and propose a triplet network to learn metric embedding and corresponding similarity functions. However, it is inefficient and sometime computationally impossible to compute all the triplet types across the whole training set. Moreover, it might result in poor training as mislabeled and poor samples could dominate the hard negatives and easy negatives. Schroff, Kalenichenko, and Philbin (2015) propose triplet selections to constrain an embedding space to be within a dimensional hyperspace and propose triplet selection for a faster convergence in the training process.

METHODOLOGY

Signal acquisition and signal classification are two parts of the methodology applied to develop this study's TDMS. Signal acquisition covers data preprocessing and signal extraction. Data preprocessing transforms raw information into data that the system can understand. The signal from the sensors in this study only occur when the stamping machine is in activity. The vibration signal data does not match the signal length, and thus it cannot be used for CNN input. Standardizing the data is therefore required. A root mean squared algorithm is thus applied to extract only certain signal data, as determined through a template matching technique. First, both the template signals and incoming signals are transformed into their root mean squared form with the same resolution. Second, the template signal is then selected. The selection process is manual and comprised of several templates for every class. Third, the template signal slides along the incoming signal, where in each sliding window the similarity is measured using distance d between the template and incoming signal. If the distance d is below the threshold θ, this study starts to search for the local minima until $d>\theta$. Several distance metrics are investigated to determine which is the most suitable. Finally, if the above conditions match, the incoming signal is extracted. An auto threshold is used to automatically calculate the threshold θ needed for the signal extraction to determine the local minima for the distance metric. Two distance metrics, standard deviation, and variance, are used to determine the auto threshold, respectively.

Signal classification covers the model architecture through DML (Kaya and Bilge, 2019). Siamese and triplet networks are the main models applied in this study. A sequential 1D CNN is used as the feature extractor for each main model. The

Siamese network has two types of loss: contrastive and cross-entropy. A contrastive loss requires the distance between two embeddings to calculate the loss function. A cross-entropy loss applies a probability calculation, where after the distance metric is calculated, a sigmoid activation function is used to produce the probability of similarity. The triplet network has three types of triplet selections: Hard-soft-margin, hard, and semi-hard negatives. Online triplet mining is used since it provides an efficient method of training the triplet network.

RESULTS AND DISCUSSION

Figure 1 presents the setup of the TDMS. An acoustic emission sensor is installed on the back plate of the machine to detect frequency, speed, and vibration, with frequency from 20Hz to 20MHz, sensitivity from 0.087v/ με to 0.092V/ με, and range from 1000mm to 1500mm. An industrial server with the specifications of Intel® Core™ i7/ 16GB, DDR4, 2933MHz, and 1 TB 7200 rpm 3.5" hard drive collects the data from the sensors and sends it to TDMS.

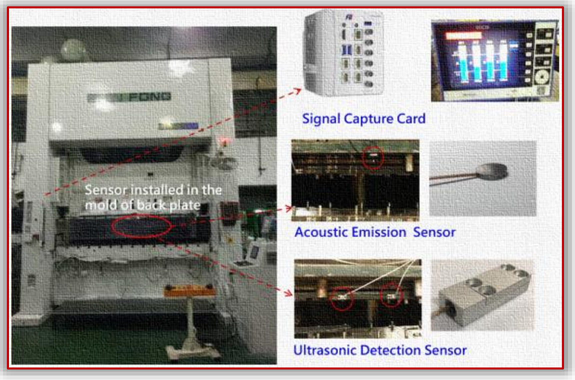

Figure 1. Setup of the TDMS

This study applies TensorFlow 2.4 on top of Python 3.8 to develop the TDMS. The TDMS runs in an Anaconda environment and Nvidia GPU is utilized to train the model. Signal extraction and classification are the main functions that the TDMS executes.

Signal extraction: During signal extraction, distance metrics that measure the similarity between the template and incoming signals are used for signal comparison and analyzation. Metric performance is measured using the following steps: First, the presence and/or absence of stamping signals and noise signals are determined. Second, the time required by each metrics to do the same signal extraction process is computed. All metrics can detect the presence of a stamping signal to some degree. Kurtosis, root-mean-square deviation, skewness, and mean show distinguished values whenever a signal is present. Third, the auto-thresholding performance is examined and analyzed to determine how effective the auto-thresholding values are regarding locating the start of the local minima in the root-mean-square deviation and mean values, respectively. The parameters included in this test are sensitivity, miss rate, and positive predicted value.

Signal classification: The models are evaluated using different numbers of training samples to simulate the lack of training data observed in real world stamping process scenarios. Each class is evaluated according to individual sample sets. These sets are then respectively divided into training and test sets containing 60% and 40% of the samples. Each sample set is randomly sampled five times, and each random sample is trained and tested four times. In total, every sample set undergoes 20 training processes to generate new models. To determine the efficacy of each loss function to enable each feature extractor to distinguish between different classes, embedding projections are produced for every feature extractor as shown in Figure 2. This is the comparison of principal component analysis from embedding projections for all trained and untrained feature extractors.

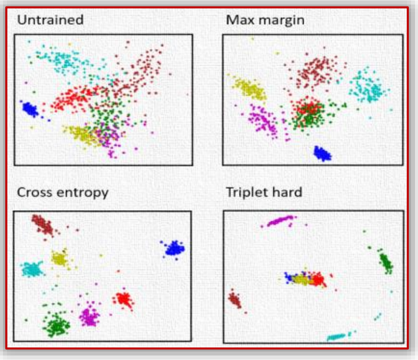

Figure 2. Comparison of feature extractors

Through signals from the sensors, the TDMS monitors the abnormalities such as material jumping and crashing into the machine. The TDMS sends out data to timely trigger an alarm and the machine shuts down. The operators can solve abnormal issues directly based on the information from the TDMS. The TDMS applies ultrasonic sensors to monitor machine tonnage, improve product yield, and reduce machine adjustment time. Real-time acquisition of stamping pressure data enables the detection of abnormal stamping motions. Anomaly issues trigger the stamping machine to be stopped in time to avoid continuing making defect products as shown in Figure 3.

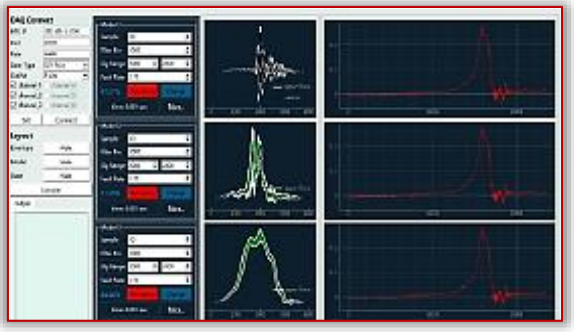

Figure 3. Tool die monitoring system

When an operator solves the anomaly issue, both production output and machine utilization rate can be increased. The TDMS supports stamping production in achieving the highest productivity and manufacturing quality. Information provided by the TDMS is essential for ensuring efficient machines, tools, and quality monitoring whenever millions of parts are produced monthly.

This system is suitable for common situations in the processes that are likely to cause product defects. In stamping processes, foreign objects in the mold (wrenches, screwdrivers, and other tools left by the mold repair team), burrs generated during the stamping process (metal square sheets), metal skips, metal wool, and raw materials with foreign objects can all be detected accurately. The system can automatically collect, build, and optimize the model, and the stamping process can be detected without affecting production. Through this system, production efficiency and utilization rate can be improved, product quality can be ensured, mold repair and time costs can be reduced, production yield can be greatly improved, and the dependence on inspectors can be reduced.

CONCLUSION

This study develops a tool die monitoring system for the stamping process. Signals from sensors, as raw data, first go to data preprocessing for data extraction either in the same class or cross-class signal. The DML method is then applied for signal classification and recognition. The results then go into the TDMS to visualize the die status for production operators. Auto-thresholding can be used as an effective base thresholding value for signal extraction. The TDMS provides information by which operators can monitor tool tie conditions and thus unexpected tool die damage, machine downtime, and unplanned repairs can be avoided. It furthermore facilitates a reduction of tool and scrap costs through early failure detection, leading to the guarantee of manufacturing quality and the improvement of productivity.

References

[1] Bassiuny, A. M.; Li, X. and Du, R.: Fault diagnosis of stamping process based on empirical mode decomposition and learning vector quantization, International Journal of Machine Tools and Manufacture, 47 (15), 2298–2306, 2007
[2] Bellet, A.; Habrard, A. and Sebban, M.: A survey on metric learning for feature vectors and structured data, 2014
[3] Bromley, J.; Guyon, I.; LeCun, Y.; Säckinger, E. and Shah, R.: Signature verification using a 'Siamese' time delay neural network, in Proceedings of the 6th International Conference on Neural Information Processing Systems, San Francisco, CA, 737–744, 1993.
[4] Chechik, G.; Sharma, V.; Shalit, U. and Bengio, S.: Large scale online learning of image similarity through ranking, in Pattern Recognition and Image Analysis, 5524, 11–14, 2009
[5] Chopra, S.; Hadsell, R. and LeCun, Y.: Learning a similarity metric discriminatively, with application to face verification, in 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Diego, CA, 1, 539–546, 2005
[6] Davis, J. V.; Kulis, B.; Jain, P.; Sra, S. and Dhillon, I. S.: Information-theoretic metric learning, in Proceedings of the 24th international conference on Machine learning, Corvalis, Oregon, 209–216, 2007
[7] Eren, L.; Ince, T. and Kiranyaz, S.; A generic intelligent bearing fault diagnosis system using compact adaptive 1D CNN classifier, Journal of Signal Processing Systems, 91 (2), 179–189, 2019
[8] Ge, M.; Du, R. and Xu, Y.: Hidden Markov Model based fault diagnosis for stamping processes, Mechanical Systems and Signal Processing, 18 (2), 391–408, 2004
[9] Ge, M.; Du, R.; Zhang, G. and Xu, Y.: Fault diagnosis using support vector machine with an application in sheet metal stamping operations, Mechanical Systems and Signal Processing, 18 (1), 143–159, 2004
[10] Hoffer E. and Ailon, N.: Deep metric learning using triplet network, arXiv:1412.6622 [cs, stat], 2018
[11] Kaya, M. and Bîlge, H. Ş.: Deep metric learning: A survey, Symmetry, 11 (9), 2019
[12] Kulis, B.: Metric learning: A survey, FNT in Machine Learning, 5 (4), 287–364, 2013
[13] Lin, T.-Y.; Cui, Y.; Belongie, S. and Hays, J.: Learning deep representations for ground-to-aerial geolocalization, in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 5007–5015, 2015
[14] Schroff, F.; Kalenichenko, D. and Philbin, J.: FaceNet: A unified embedding for face recognition and clustering, in 2015 IEEE Conference on Computer Vision and Pattern Recognition, 815–823, 2015
[15] Schultz M. and Joachims, T.: Learning a distance metric from relative comparisons, in Advances in Neural Information Processing Systems 16, Vancouver and Whistler, British Columbia, 2003.
[16] Shanbhag, V. V.; Rolfe, B. F. and Pereira, M. P.: Investigation of galling wear using acoustic emission frequency characteristics, Lubricants, 8 (3), 2020
[17] Ubhayaratne, I.; Pereira, M. P.; Xiang, Y. and Rolfe, B. F.: Audio signal analysis for tool wear monitoring in sheet metal stamping, Mechanical Systems and Signal Processing, 85 (2), 809–826, 2017
[18] Vo, N. and Hays, J.: Localizing and orienting street views using overhead imagery, arXiv:1608.00161 [cs.CV], 2017
[19] Wang, J.; Song, Y.; Leung, T.; Rosenberg, C.; Wang, J; Philbin, J.; Chen, B. and Wu, Y.: Learning fine-grained image similarity with deep ranking, arXiv:1404.4661 [cs.CV], 2014
[20] Wang, S.; Wang, D.; Kong, D.; Wang, J.; Li, W. and Zhou, S.: Few-shot rolling bearing fault diagnosis with metric-based meta learning, Sensors, 20 (22), 6437, 2020
[21] Weinberger, K. Q. and Saul, L. K.: Distance metric learning for large margin nearest neighbor classification, Journal of Machine Learning Research, 10, 207-244, 2009.
[22] Workman, S.; Souvenir, R. and Jacobs, N.: Wide-area image geolocalization with aerial reference imagery, arXiv:1510.03743 [cs.CV], 2015
[23] Wu, P.; Hoi, S. C. H.; Xia, H.; Zhao, P.; Wang, D.; Miao, C.: Online multimodal deep similarity learning with application to image retrieval, in Proceedings of the 21st ACM international conference on Multimedia, 153-162, 2013
[24] Zhang, A.; Li, S.; Cui, Y.; Yang, W.; Dong, R. and Hu, J.: Limited data rolling bearing fault diagnosis with few-shot learning, IEEE Access, 7, 110895–110904, 2019
[25] Zhang, G.; Li, C.; Zhou, H. and Wagner, T.: Punching process monitoring using wavelet transform based feature extraction and semi-supervised clustering, Procedia Manufacturing, 26 (1), 1204–1212, 2018
[26] Zhang, J.; Sun, Y.; Guo, L.; Gao, H.; Hong, X. and Song, H.: A new bearing fault diagnosis method based on modified convolutional neural networks, Chinese Journal of Aeronautics, 33 (2), 439–447, 2020

ACTA TECHNICA CORVINIENSIS
Bulletin of Engineering

ISSN: 2067-3809