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Tool Condition Prediction by Process Monitoring using Semi-Supervised Learning

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In precision machining process, part fabrication quality often has a great deal to do with tool condition. For aerospace MRO (Maintenance, Repair and Overhaul) shopfloor, tool condition is particularly critical when the part-to-repair is of substantial size and machining cycle is prolonged, especially during finishing phase when tool change is not allowed due to elevated precision requirement. It is our endeavor to announce a tool change request only when change is possible, right before fabrication quality is to be compromised. Our approach predicts tool condition progression aiming to remind the operator of the best moment for a tool change in achieving both part quality assurance and tool cost saving. The work starts with process data collection in realtime including vibration, current, spindle load, feed rate, etc., and the actual tool wear (flank wear) condition measured from a microscope. Since the tool condition can only be inspected after prolonged machining cycles, the amount of labeled tool wear samples is limited. Hence, a 2-views semi-supervised approach is chosen to utilize information from both labeled and unlabeled datasets. Experimental results support the capabilities of the proposed model in predicting tool condition for a turning process in MRO shopfloor.

1. Introduction

In metal material cutting processes, condition of cutting tools plays a vital role in overall quality as well as yield performance. Unexpected tool failure can greatly increase manufacturing losses (materials, time to re-work, machine downtime, etc.). For aerospace MRO (Maintenance, Repair and Overhaul) shopfloor, awareness of tool condition is particularly critical especially during finishing phase. Here, parts-to-repair are of substantial sizes comparing with cutting tool and machining cycles prolong in several hours. In finishing phase, tool changing is not allowed due to elevated precision requirement and thus having a visibility of tool condition for such cutting is necessary.

Tool condition monitoring has been an interesting topic with several publications [1 - 4] in last decade. However, there are still some existing challenges while investigating tool condition during cutting process. One of the most common approaches for in-situ monitoring tool condition is to employ on-machine optical measurement with wear texture analyses. These configurations are usually with high cost and generally require assembly space. This is not always achievable in most MRO shopfloors due to large size of parts-to-repair. Another approach is to off-machine measure the tool condition via optical measurement, radioactive, or electrical resistance. Nevertheless, this technique faces a lot of difficulties for application require long cutting runtime without interrupts permitted.

Recently, a lot of studies have relied on in-direct tool-work interaction signals in real time for tool condition monitoring purpose [5 - 12]. In these studies, parameters from added sensors, e.g., force, vibration, acoustic emission (AE), current or power, sound, temperature, surface roughness, etc. are fed to AI model, e.g., artificial neural networks (ANN), fuzzy logic, neuro-fuzzy, generic algorithms, and support vector machines, to predict the tool's condition. Although these models have shown great potentials in many applications, there are still 2 main challenges to be solved:

- In real production scenarios, having multiple measurements of tool dimensions is generally difficult. Hence, training AI model for tool condition monitoring has to deal with limited labeled dataset.
- Major portion of sensors data are unlabeled and usually underutilized in conventional approaches. It would be desirable to better utilize unlabeled data during model training for performance improvement.

In this paper, we study the feasibility of a semi-supervised learning ML model for tool condition prediction task in milling process. Process parameters considered in this paper include spindle load, vibration, speed, acceleration, cutting depth and cutting cycle. For model training, a 2-view k-NN (k-nearest neighbor) approach is used to better utilize unlabeled data together with limited labeled data. Experiments are carried out and evaluation results confirm the proposed approach.

2. Tool Condition Modeling and Prediction

2.1 Experiment setup

The experimental work (Fig. 1) is carried out on the Makino F3 vertical 3 axes machining center. The Aluminum T6061 grade is selected for test material and a single 6 mm diameter carbide milling cutter with 4 cutting flutes has been used until the end of the tool life. Each machining cycle is carried out with the constant parameters: cutting speed= 150 m/min, federate= 0.025 f/ tooth, depth of cut – Radial, Ap= 2.4 mm & Axial, Ae= 1 mm. A total of 200 machining cycles with dry cut condition are conducted, and a total of 37 cutting tool flank wear are recorded for the entire machining cycles. The cutting tool flank wear, VB are inspected and measured using Keyence VHX- 1000 digital microscope.

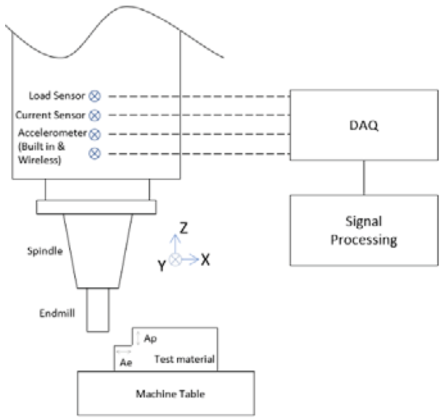

Figure 1. Experimental Setup of the milling process

2.2 Monitoring of process parameters

To monitor the milling process, we obtain position, speed, and acceleration of the spindle together with the spindle load. These parameters are read directly from CNC controller. In order to observe other features of machining process we additionally use a 3 axis (X, Y, Z) wireless vibration sensor that can stream data continuously to our laptop and 3 wireless current sensors to measure the 3 phases of the spindle current. The vibration sensor data is mounted on the spindle shaft to detect vibration caused by the interaction between the tool and the workpiece. The vibration data can be streamed at 1kHz. Also, a current sensor, rated at 100A, is clamped at the 3 phases of the spindle controller to measure the current drawn by the spindle. The electrical current data can be streamed at 5Hz continuously via MQTT.

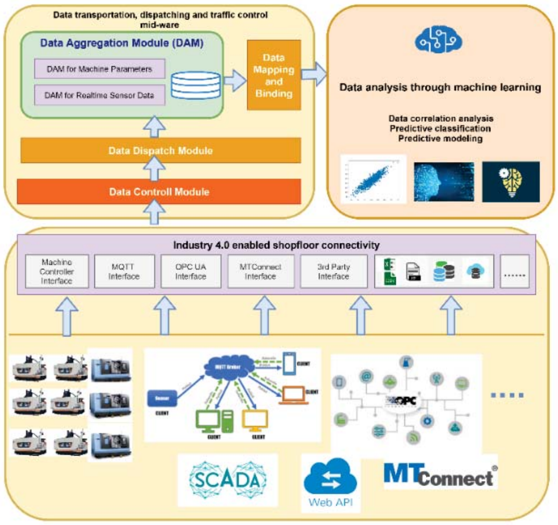

Figure 2. Middleware for data communication

All process parameters are collected and synchronized by a middleware before feeding to data analytic layer to ensure the quality of the data stream. The middleware in this paper is developed with three functional layers: Shopfloor Connectivity Layer, Data Traffic Control Layer and Data Aggregation & Dispatch Layer. Details of the developed middleware are in Fig. 2.

2.3 Data pre-processing and feature engineering

The mapped real-time monitored machining process and tool wear measurement from selected cycles yields a raw data sheet for correlation analysis. In the raw data sheet, target variable to predict is Tool Flank Wear. Candidate independent variables are limited to Cycle Number, Spindle Load, Vibration, Position X, Position Y and Position Z. Feedrate and spindle revolution per minutes (i.e. rpm) are out of concern because although they ramp up and decline naturally at every start and end of a machining cycle, they are considered as constant setting parameters throughout the experiment. Furthermore, all the spindle position variables are not meaningful on their own, instead we converted them into Speed and Acceleration with the help of timestamp recorded, to represent movement of the spindle in a better way. All of these have resulted in a list of complete independent variables as shown in Table *1*:

Table 1 List of independent variables for modelling

Cycle Number	Spindle Load	Vibration
Speed X-dir	Speed Y-dir	Speed Z-dir
Acceleration X-dir	Acceleration Y-dir	Acceleration Z-dir

As independent variables are recorded in time-series manner, we extract 9 features from all except Cycle Number, based on every machining cycle, to establish data model. Features include *absolute energy, autocorrelation of the specific lag (i.e. lag 1), kurtosis, the highest value, mean, the lowest value, skewness, standard deviation, variation coefficient* [13]. Upon feature engineering, the ultimate mapped data sheet consists of 73 process features (columns) and 176 usable machining cycles (rows), of which 37 cycles are labeled with flank wear measurement.

2.4 Semi-supervised regression by co-training

Since the dataset used in this paper consists of limited labeled data (37 samples), a semi-supervised regression approach is employed to take into account useful features from unlabeled data (139 samples). In this paper, we consider an approach introduced by Zhou and Li named as COREG for semi-supervised regression task. In COREG, two separate k-nearest neighbor (k-NN) regressors are selected as the based models. Then, predictions with appropriate confident level of each based model are used to pseudo labeled samples in unlabeled dataset of the other model. The selection of samples for pseudo labelling is considered by evaluating its influence on the performance of labeled dataset. The pseudo labeling is looped until the prediction confident drop below acceptable threshold. The final prediction of the trained model is made by averaging the estimation made by both regressors. Details about COREG can be found in [14] while the training loop can be shown in Fig. 3.

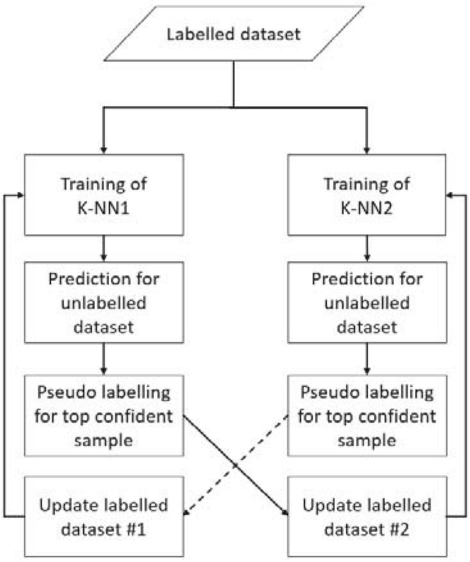

Figure 3 Workflow of COREG approach

2.5 Benchmark with other models

Let's take the conventional approach, supervised learning based on labeled dataset, be our baseline approach. In order not to disregard vast amount of unlabeled dataset, we then apply COREG so the entire dataset would be involved in modelling. Basically, we use the k-nearest neighbors algorithm (k-NN) as the base estimator for both baseline and co-training approach to ensure fair comparison. What we are interested to evaluate is whether the 2-views co-training regressor leveraged on both labeled and unlabeled datasets could outperform a single view k-NN regressor in term of prediction accuracy.

For **COREG**, we establish 2 views of input data, namely estimator1 and estimator2, for which the distance orders are set to be 2 and 5 respectively, to make the estimators sufficiently distinct and independent. The same distance order values are used for baseline approach – single view **kNN1** and **kNN2**. The number of neighbors to be considered for determining the prediction accuracy for COREG is 5, and unlabeled pool size to be updated by each training iteration is 20. A Python module CTRegressor is used to implement co-training approach [15]. Normalization of all the input data is conducted before training process, as a pre-requisition for k-NN to function properly. Cross validation is carried out (5-fold, repeated 20 times) for all 3 regressors to avoid biased model performance due to unfair training testing split.

Fig. 4 has depicted the averaged testing root mean squared error (RMSE) for each cross-validation experiment, over 20 iterations. When estimating tool wear against measured values, all three regressors experiences fluctuation at different iterations with shuffled train-test data split, which is expected. But in general, in most iterations, COREG yields lowest averaged testing RMSE, which means it performs the best in prediction tool wear compared to two other baseline regressors. However, one has to admit that advantage is not significant. We would assume by including more types of process parameters (such as multi-channel current, 3-phase vibration) with increased sample size, performance of COREG could be further justified.

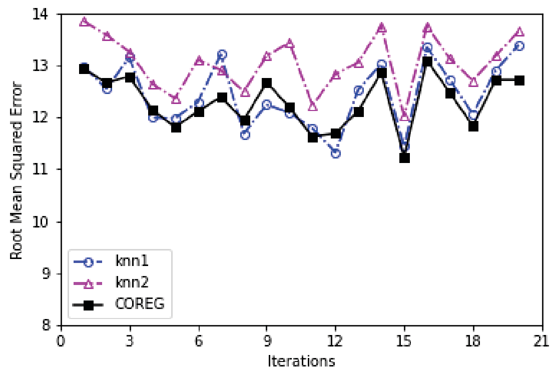

Figure 4 Comparison on testing Root Mean Squared Error (RMSE) among different regressors at different iterations

2.6 Tool condition prediction

With the best model built on COREG regressor (selected based on lowest test RMSE), we then predict the Tool Wear for all 176 machining cycles and mark the measured Tool Wear only for 37 machining cycles in the same graph (See Fig. 5). One thing to take note is that measured Tool Wear is not ever increasing along machining cycles, which is due to cutting tool cyclic build-up edge (BUE) formation and collapse, discussed in a prior research work [16]. Predicted value tries to catch up with this oscillation, therefore accuracy is affected. Practical recommendation to avoid BUE is to select sharper tool and adjust federate and speed accordingly, which is out of the scope of current study. This operational issue would need to be resolved before we can have cleaner flank wear measurement to retrain the model and predict.

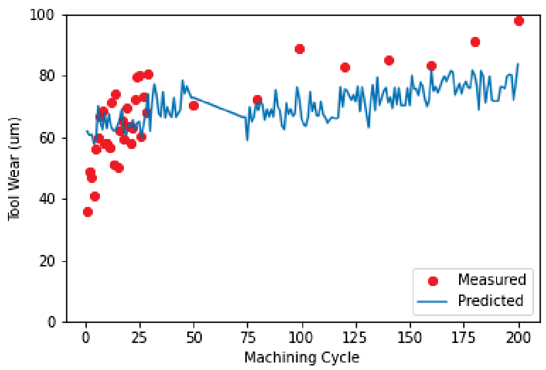

Figure 5 Tool wear predicted values (all machining cycles) versus measured values (only measured cycles)

3. Conclusions

In this paper, a semi-supervised learning approach was successfully employed for tool condition prediction task for milling process. Validation results confirm the effectiveness of proposed approach in benchmarking with conventional supervised learning approach. Further enhancement of the model can be made through incorporating more sensor signals of cutting process, and more accurate measurement of cutting tool flank wear. This is a significant advantage since frequent measurement of tool dimensions are generally not possible. With the well-trained model, operators can make a better decision whether to replace a new tool for important cutting passes, especially for the finishing phase.

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