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A multimodal intelligent monitoring system for turning processes

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ABSTRACT

Online process condition monitoring is an essential component of closed-loop process-level automation of machining operations. This paper describes the development of an intelligent monitoring system for turning processes, which consists of three units: a tool wear predictor, a chatter detector and a tool chipping detector. Features are extracted from the signals of multiple low-cost and low-intrusive sensors, and then normalized using a novel scheme to eliminate their dependence on cutting conditions, workpiece materials and cutting tools. A systematic feature selection procedure, coupled with automated signal preprocessing parameter selection, is presented to select the optimal feature set for each unit. The tool wear unit is built with type-2 fuzzy basis function networks to predict tool wear with uncertainty bounds, while the chatter unit and tool chipping unit are built with support vector machines to maximize the classification fidelity. Experimental results show that the monitoring system achieved high accuracy, generalized applicability and satisfactory robustness for all the three process conditions, by using two affordable sensors: a power meter and an accelerometer. The three monitoring schemes are integrated into a monitoring software so that they can be implemented in different environments with minimal calibration efforts.

1. Introduction

Smart factories in next-generation manufacturing call for automation at the process level for machining operations and machine tools [1], in pursuit of faster response to the rapidly-changing product design, boosted productivity, consistent product quality and lower labor cost in shop-floor operations. The closed-loop machining system aims to optimize the process performance and suppress adverse conditions by automatically adjusting operating parameters (e.g., feed, speed) based on the monitoring of relevant process variables. However, in-process direct measurements are not feasible for many process conditions, such as tool conditions and surface integrity. Therefore, indirectly inferring the unmeasurable process conditions by fusing multi-sensor data with artificial intelligence models is a promising paradigm that has been pursued in academia and industry for decades [2]. By sensing measurable process variables, such as cutting force [3,5], spindle power [8,9], vibration [5,6] and acoustic emission [6,7], and extracting descriptive features from collected signals, the process conditions of interest can be estimated using intelligent models, such as artificial neural networks [8–10], fuzzy systems [11], support vector machines [12,13], and random forests [14].

In this paper, to develop a comprehensive monitoring system for turning processes, three fault conditions are considered: tool wear, chatter and tool chipping. Tool wear is one of the most widely studied process conditions for monitoring, because tool wear always happens during machining and negatively impacts work quality and productivity [1,15]. Hence, estimating the tool wear and scheduling timely tool replacement before it exceeds a certain limit are essential for process-level automation. Chatter is a kind of strong self-excited vibration during machining mainly because of the regenerative effect [16], which results in poor surface finish and could damage the cutting tools or machine tools. Tool chipping refers to the breaking away of small pieces of tool material from the cutting edge [17], which leads to degraded surface finish. Chatter and tool chipping are regarded as catastrophic failures with which the machining cycle must be stopped immediately. Though they can be avoided mostly by choosing proper cutting parameters in process planning, chatter or tool chipping could still happen unexpectedly in actual operations due to the variability of machining environment. Therefore, in-process detection of chatter and tool chipping is desired to prevent defective products and damage to the machines.

By reviewing the literature, a significant amount of research can be found in the fields of tool wear monitoring [3–6,10–12], chatter detection [18–21] and tool chipping detection [22–24], in which the theoretical fundamentals were studied and exploratory applications were presented. Industrial implementation of process monitoring

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systems has also been explored: Altintas presented a process monitoring module integrated with a virtual machining system for tool breakage detection by sensing feed and spindle drive motor current, which has been implemented on a CNC machining center for use in production [25]. Zhu demonstrated a cyber-physical framework for tool condition monitoring with three case studies of implementations [26]. A microphone-based chatter monitoring device that could work with various CNC controllers is developed in [27]. However, the number of successful industrial implementation, especially for the tool wear monitoring systems, reported in the literature is limited. In the authors' opinion, the gap between laboratorial research and industrial implementation can be attributed to the missing of following enabling factors:

1) The sufficient generalization capacity [10]. To be used in a machining environment with high variability, the monitoring system should be generalizable to different machine tool set-ups, tool-workpiece combinations and cutting conditions. This requires the signal features and predictive models used in the system be independent of these factors. Also, for different machining setups, the signals and features that best describe the process conditions might be different. Therefore, a systematic feature selection procedure that combines the model-independent methods, which are computationally fast for large candidate pools, and model-dependent methods, which yield the best performance of predictive models [10,28], is highly desired. In addition, the signal preprocessing parameters, which will significantly influence a feature's correlation to process conditions, need to be considered during feature selection. However, such a generalizable scheme and a systematic feature selection procedure are not readily available in the literature, to the best of the authors' knowledge.
2) The practicability of instrumentation setup. For massive industrial applications, the sensors used for instrumentation must be affordable and not intrusive to original machine tool set-ups. A counter-example is the piezoelectric dynamometer used for cutting force measurement [25], which is expensive and interferes with typical machine tool set-ups, though the cutting force might be the most informative variable to indicate process conditions.
3) The consideration of process uncertainties. There are considerable uncertainties embedded in the machining processes [17], such as the variations of material properties, impact of cutting fluid, noise from the environment and uncertainties in tool wear measurements. Hence, even with the same operating conditions and process conditions, reproducing the same signal data is impossible. However consideration of process uncertainties in monitoring models has been addressed only in recent years: enhanced particle filter [29], extended Kalman filter [30], particle learning [31] and random forest with interval output [32] have been adopted to predict tool wear with uncertainty bounds. However, these models are mostly trained for a certain set of operating conditions and a robust process condition monitoring scheme that can be generalized to different operating conditions hasn't been established.

In this paper, an exemplary intelligent multisensor monitoring system is developed for turning processes, in which the above missing enabling factors are brought about. The tool wear monitoring scheme is adopted from [33]. The contribution of this paper is that the methodologies established in [33] are further extended to build the chatter and tool chipping monitoring schemes, which validated the effectiveness and versatility of the proposed feature normalization and systematic feature selection schemes, and an integrated monitoring system that is suitable for industrial implementation is developed. The monitoring system is highlighted with the followings innovations:

1) The signal features are normalized using a novel scheme to minimize their sensitivity to cutting tools, workpiece materials and cutting conditions. The normalization parameters can be calibrated with minimal experimental efforts and the calibration procedure is also provided.
2) The optimal feature set for each monitoring scheme and the optimal signal preprocessing parameters for each feature are selected using a hybrid and systematic procedure, which is efficient for large candidate feature/parameter pools and could maximize the performance of predictive models in each scheme.
3) The predictive models are built by considering process uncertainties. Interval type-2 fuzzy basis function networks [36] are adopted to quantify the uncertainty bounds associated with tool wear, while support vector machines (SVMs) with selected dimensionless features are constructed to maximize the classification margins for chatter and tool chipping.

Experimental results show that the developed tool wear predictor, chatter detector and tool chipping detector all possess high accuracy, generalized applicability and satisfactory robustness. These three schemes are integrated in a unified framework to compose a comprehensive process monitoring system and a software is developed to implement such a system.

2. Methodologies

The proposed process monitoring system extracts a set of selected features from properly processed sensor signals, normalizes the features to minimize their sensitivity to varying cutting conditions, and then feeds the normalized features into predictive models to forecast process conditions. The architecture of the proposed monitoring system is shown in Fig. 1. To construct such a system, three offline training modules are needed: normalization parameter calibration, optimal feature set selection, and predictive model training. This section will elaborate the methodologies used in the three modules.

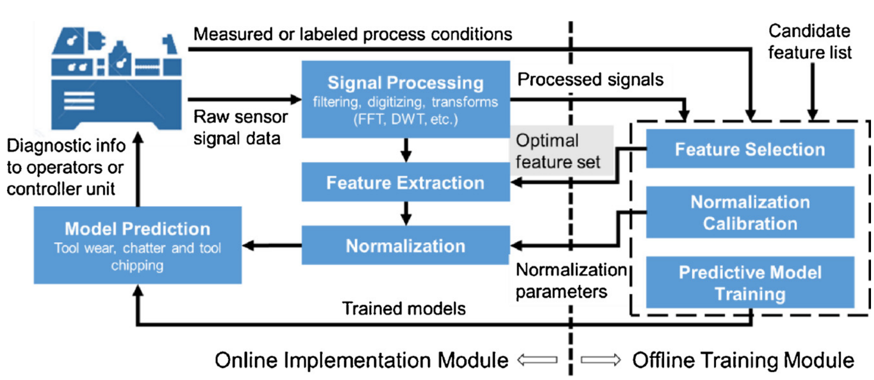

Fig. 1. Architecture of the process monitoring system.