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Multisensory fusion based virtual tool wear sensing for ubiquitous manufacturing

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ABSTRACT

Pervasiveness of ubiquitous computing advances the manufacturing scheme into a ubiquitous manufacturing era which poses significant challenges on sensing technology and system reliability. To improve manufacturing system reliability, this paper presents a new virtual tool wear sensing technique based on multisensory data fusion and artificial intelligence model for tool condition monitoring. It infers the difficult-to-measure tool wear parameters (e.g. tool wear width) by fusing in-process multisensory data (e.g. force, vibration, etc.) with dimension reduction technique and support vector regression model. Different state-of-the-art dimension reduction techniques including kernel principal component analysis, locally linear embedding, isometric feature mapping, and minimum redundancy maximum relevant method have been investigated for feature fusion in a virtual sensing model, and the kernel principal component analysis performs best in terms of sensing accuracy. The effectiveness of the developed virtual tool wear sensing technique is experimentally validated in a set of machining tool run-to-failure tests on a computer numerical control milling machine. The results show that the estimated tool wear width through virtual sensing is comparable to that measured offline by a microscope instrument in terms of accuracy, moreover, in a more cost-effective manner.

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1. Introduction

Ubiquitous computing enables a variety of information technologies and communication services connect with the distributed computational resources via internet [1]. With the advancement of ubiquitous computing and radio frequency identification technology (RFID), it promotes product design and manufacturing into a new paradigm, named UbiDM (design and manufacture via ubiquitous computing technology) [2,3]. It changes the manufacturing scheme from mass-production/consumption to a new customized and sustainable manufacturing mode. To achieve this, advanced sensing techniques and computing intelligence are needed to improve system flexibility and inventory turnover, minimise wastage, improve product quality and enhance on-time delivery [4,5]. However, such benefits highly rely on the reliability of a manufacturing system, thus system reliability becomes a crucial important aspect in ubiquitous manufacturing.

Machining tool is a major element in a manufacturing system and its failure (e.g. typically tool wear and breakage) can attribute up to 20% of machine downtime [6]. To enhance the system reliability, much research effort has been put on machining tool condition monitoring which mainly incorporates sensing data acquisition, signal denoising and processing, feature extraction and selection, fault diagnosis and prognosis, and maintenance decision making [7]. Increasing demand for system reliability has accelerated the integration of sensors into manufacturing system for timely acquisition of working status of machinery. With the advancement of ubiquitous computing, ubiquitous sensing emerges as an active research area. It has been investigated in real-time shop-floor scheduling [8], environment monitoring [9], electrical household appliance [10], and human healthcare [11].

In the context of tool condition monitoring, a variety of sensing techniques have been instrumented to acquire machining tool conditions. According to the correlation between sensing parameters and tool conditions [7], these sensing techniques can be categorized into direct sensing and indirect sensing methods. Direct sensing techniques measure actual quantities that directly indicate tool conditions, e.g. tool wear width. Traditionally, tool wear was measured using a tool-maker's microscope under laboratory conditions. This requires a human inspector to determine the worn region based on the textural difference between the worn and unworn surfaces [12]. In-situ direct sensing techniques, such as CCD cameras, radioactive isotopes, laser beams, and electrical resistances, have been investigated with high degree of

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Table 1
Comparison between direct sensing and indirect sensing techniques.

Category	Sensing techniques	Pros	Cons
Direct sensing	Microscope, CCD camera, Electrical resistances, Radioactive isotopes	Accurate, direct indicators of tool conditions	High cost, limited by operating environment, mainly for offline or intermittent monitoring
Indirect sensing	Cutting force, vibration, sound, acoustic emission, temperature, spindle power, displacement	Less complex, low cost, suitable for continuous monitoring in practical applications	Indirect indicators of tool conditions

accuracy in laboratory settings to observe fundamental measurable phenomena during machining processes [13–15]. However, such direct sensing techniques usually involve high cost, and present some practical limitations caused by accessing problems during machining, inference with chips, and the usage of cutting fluid. Thus they are mainly for intermittent operations.

On the contrary, indirect sensing techniques measure the auxiliary in-process quantities (e.g., force, vibration, and acoustic emission, etc.) that indirectly indicate tool conditions. Tool wear causes the increases of friction and heat generation, thus consequently causes the changes of in-process parameters, such as cutting force [16], vibration [17], acoustic emission [18], strain [19], eddy-current displacement [20], and spindle motor current [21], etc. Comparing to direct sensing, indirect sensing methods are less costly and enables continuous detection of all changes (e.g. tool breakage, tool wear, etc.) to signal measurements. The Pros and Cons of direct sensing and indirect sensing methods are summarized in Table 1.

To sum up, direct sensing measures direct indicators of tool conditions, but it is usually performed offline and thus interrupts normal machine operations. On the other hand, indirect sensing can continuously measure in-process parameters, but the obtained information is indirect indicators of tool conditions. To bridge the gap between direct sensing and indirect sensing, virtual sensing, as a complement to physical sensing, has emerged as a viable, noninvasive, and cost effective method to infer difficult-to-measure or expensive-to-measure parameters in dynamic systems based on computational models [22]. It has been investigated for active noise and vibration control [23], industrial process control [24], building operation optimization [25], lead-through robot programming [26], product quality of semiconductor industry [27], and tool condition monitoring [28,29].

There is an extensive literature on developing virtual sensing models with a focus of artificial intelligence models. In [28], an artificial neural network model is investigated to infer the state of insert wear from translational vibration measurements on a milling machine. Bayesian network is studied for tool breakage detection utilizing the in-process electrical power signal [29]. A classifying artificial neural network ensemble approach is investigated to estimate simulation workload in cloud manufacturing [30]. Given the high cost and practical constraints to obtain data samples in practice, support vector regression with good generalization capability attracts much research interest. It requires less data samples comparing with artificial neural network, and has been investigated for tool wear estimation in [31–33].

Due to the interference of complex operating conditions and the limited applicability of a single sensor, multiple modalities of sensors have been instrumented to measure different aspects of tool conditions. However, the increased amount of data samples inevitably brings data redundancy and model overfitting problems. To address these issues, this paper presents a multisensory fusion based virtual tool wear sensing method on a support vector regression basis. Different dimension reduction methods including kernel principal component analysis (KPCA), locally linear embedding (LLE), isometric feature mapping (ISOMAP), minimum redundancy maximum relevance (mRMR) have been investigated for feature selection and fusion. The fused features from force and vibration in-process measurements are then fed into support vector regression model to infer the actual quantities of tool conditions. The performance of different feature fusion methods is compared using experimental studies on a computer numerical control (CNC) milling machine.

The main contribution of this study rests on the following: 1) a multisensory fusion based virtual tool wear sensing framework is presented to bridge the gap between direct sensing and indirect sensing methods; and 2) different dimension reduction techniques are evaluated for virtual tool wear sensing, and the technique of KPCA with the best performance is identified by an experimental study. The rest of the paper is constructed as follows. After introducing the theoretical background of sensing fusion techniques and support vector regression in Section 2, details of the multisensory fusion based virtual sensing method is discussed in Section 3. The effectiveness of the presented technique is experimentally demonstrated in Section 4 based on direct and indirect sensing data acquired using a ball nose tungsten carbide cutter on a CNC milling machine. Finally, conclusions are drawn in Section 5.

2. Theoretical framework

2.1. Data fusion techniques

2.1.1. Kernel principal component analysis

Kernel principal component analysis (KPCA) is a nonlinear version of principal component analysis (PCA) and has been widely used for feature selection and fusion applications. The key idea of KPCA is to define a nonlinear mapping function $\phi(\bullet)$ which transforms the sample data into a high-dimensional data space, and the transformed sample data is then analyzed using traditional principal component analysis [34]. It transforms a set of observations of possible correlated variables into a set of uncorrelated variables called principal components. The first principal component has the largest variance, and each succeeding principal component has comparative lower variance orthogonal to the preceding principal components. The first several principal components can represent the original data with minimal mean squared approximation error, and thus KPCA can be used in dimensionality reduction.

Mathematically, given a set of input vectors $(X_i(1), X_i(2), \ldots, X_i(m))^T$, $i = 1, 2, \ldots, p$, the sample data X_i is mapped into $\phi(X_i)$ via the nonlinear kernel function $\phi(\bullet)$, i.e. $X_i \to \phi(X_i)$. With the assumption of centered data $\frac{1}{p}\sum_{i=1}^{p}\phi(X_i) = 0$, the principal components are obtained by solving eigenvalue problem in KPCA.

$$\lambda_i u_i = C u_i \tag{1}$$

where C is the sample covariance matrix of $\phi(X_i)$, λ_i is one of the eigenvalues of covariance matrix C, and u_i is the corresponding eigenvector. The covariance matrix is constructed as:

$$C = \frac{1}{p}\sum_{i=1}^{p}\phi(X_i)\phi(X_i)^T \tag{2}$$

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