Mechatronics xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Mechatronics

journal homepage: www.elsevier.com/locate/mechatronics

Compressive sensing and sparse decomposition in precision machining process monitoring: From theory to applications

Kunpeng Zhu [a,*], Xin Lin [b,a], Kexuan Li [c,a], Lili Jiang [d,a]

[a] Institute of Advanced Manufacturing Technology, Hefei Institutes of Physical Science, Chinese Academy of Science, Huihong Building, Changwu Middle Road 801, Changzhou 213164, Jiangsu, China
[b] Department of Automation, University of Science and Technology of China, Hefei 230026, China
[c] Department of Precision Machinery and Precision Instrumentation, University of Science and Technology of China, Hefei 230026, China
[d] Department of Electrical Engineering and Automation, Hefei University of Technology, Hefei 230009, China

ARTICLE INFO

Article history:
Received 30 November 2014
Revised 23 March 2015
Accepted 27 April 2015
Available online xxxx

Keywords:
Sparse decomposition
Precision machining
Condition monitoring

ABSTRACT

Precision machining has been claimed to be the backbone to modern industry. It has been widely applied to the key parts' production in the aerospace, medical and automotive industries. One of the main problems related to precision machining productivity and safety is the machining condition. By utilizing the acquired information from sensory measurements to direct the further actions, the signal processing bridges the gap between human instruction and full automation. Traditional signal acquisition and processing methods are mainly based on Shannon's Sampling theory, Fourier methods or wavelet analysis. While these techniques meet challenges in precision machining environment, such as machining at high speed, low signal to noise ratio, and high sampling rate. These factors limit their applications especially the online monitoring implementation. The newly developed compressive sensing theory and sparse decomposition techniques provide a possible solution to these problems, while limited studies have been investigated. This paper serves as an introduction to the theory and shows the theory's potentials in machining condition monitoring by reviewing related literatures and demonstrating case studies from real experiments.

1. Introduction

1.1. The background

Precision machining is an advanced manufacturing technology that can machine hard metallic materials with complex geometry at high precision, and it has been widely applied to aerospace, medical and automotive industries [1]. It bridges the gap between traditional CNC machining and the micro-machining technologies. In modern precision machining an effective condition monitoring system has a major influence in machining economics: it can improve productivity, ensure workpiece quality and environmental safety [2,3]. For the successful implementation of a machining monitoring system, sensor signal should be reliable and sensitive to machining conditions. Both direct and indirect monitoring methods have been developed. The direct methods have advantages of measuring actual geometric changes arising from tools [4,5], while direct measurements are very difficult to implement due to continuous contact between the tool and the workpiece during machining. The indirect methods have the advantages of less complexity and suitability for practical application [6]. As a result indirect methods such as forces, vibrations, and acoustic emission have been the most commonly used signals and more successfully achieved for condition monitoring by many researchers.

In the indirect measurements, force is one of the most important signals in machining process monitoring. It has been reported by researchers that cutting forces contain reliable information on cutting conditions and the most effective for tool condition monitoring [7–9]. The advantage of AE is that the signal measured is a source of engagement where the chip is formed, as were introduced in [10,11]. Vibration has also been one of the most widely studied signals for monitoring due to its convenient implementation; see for examples in [12,13]. Hsieh et al. [13] detected tool wear with an accelerometer and showed that the vibration signals could be implemented in a neural network and used for micro-milling monitoring. Generally the vibration is brought by the cutting force variations, and as a result the vibration is less

* Corresponding author.
E-mail addresses: kunpengz@hotmail.com (K. Zhu), xinlmm@mail.ustc.edu.cn (X. Lin), kexuan@mail.ustc.edu.cn (K. Li), lilijiang112358@hotmail.com (L. Jiang).

http://dx.doi.org/10.1016/j.mechatronics.2015.04.017
0957-4158/

sensitive than force in the monitoring [7]. The method based on motor current is considered one of the least disruptive and economical methods to estimate feed force and tool state. Li [14] and Sevilla-Camacho et al. [15] presented the approaches to detect the tool wear rate with current signal. It was carried by measuring both feed and motor current and then accomplished by using a regression analysis to classify the different tool states. Temperature-based method is also applied to machining monitoring. It involves some form of thermal imaging system that monitors the chip temperature, while this technique is hard to be implemented in a real cutting process, because it does not take account of the changes in the boundary conditions such as tool geometry and the use of coolant [16,17]. Vision method can be used in two different ways, either with a camera monitoring the tool tip or the work surface [18]. Oguamanam et al. [19] developed a system extracting five image-based features, which were used in classifying the tool as good, worn or broken in the light of single-point cutting tools. Other studies were also tried to fuse some of these measurements to get more robust results [20].

While the above mentioned measurements have gained a lot of success, they meet difficulties in online precision machining process monitoring. In precision machining, the machine generally operates at high rotation speed, the signal to noise ratio is low and the sampling rate is very high for an online monitoring application possible. For example to capture acoustic emission (AE) measurements, the Nyquist sampling rate [21] is so high (>Mb) that a huge number of samples need to be processed in a short time which makes it impossible for online monitoring. On the other side, in the current condition monitoring schemes, it operates with the signal preprocessing, feature extraction and classifier design sequentially, and results in low speed processing and high complexity. Different stages working independently may result in bad estimation results. The newly developed compressive sensing theory can solve these problems in the framework of sparse decomposition, both on low measurement sampling and simplified state estimation scheme.

1.2. The methods

Compressive sensing (or compressed sensing) [22] is relieved from the Shannon sampling theory [21], by claiming that if a signal is compressible or sparse in some transformed space, then the original signal could be recovered with high probability with much lower sampling rate than the Nyquist rate. According to this theory, the sampling rate is not decided by the bandwidth but the content and structure of the signal. The theory has been lately developed by Candès et al. [22], Donoho [23], Candès and Tao [24], and has shown its great success in the engineering applications [25]. Theoretically, every signal is compressive, and as a result if we could find its corresponding sparse representation space, the sampling can then be compressed. This theory has brought great progress in the signal sampling methods and will be applied and benefit a lot of engineering areas as could expect. Sparse decomposition is the central idea and prerequisite step to compressive sensing. The idea of sparse decomposition is to represent a signal with linear combination of atoms in an overcomplete dictionary, so that the representation is sparse. It was first attempted by Olshausen and Field [26], in and later elaborated by Lewicki and Sejnowski [27] in image analysis. Sparse coding has received a great deal of attentions in recent years, from signal classification to image recognition [28,29].

The compressive sensing methods, with the associated sparse decomposition theory, are promising that they could extract useful information for condition monitoring. Unfortunately, the compressive sensing theory work to date is predominantly oriented toward other applications with traditionally stronger ties to the optimization, numerical linear algebra and signal processing community, or toward mathematical theories which are far beyond the scopes of mechanical engineering. The purpose of this paper is to bring the academic researchers and the industrial users together to identify the promising signal processing technologies that meet the demands of machining condition monitoring. However, an exhaustive presentation of these vast topics would be beyond the scopes and possibilities of a single paper. While there are limited literatures on this topic, this paper is more an introduction to the theory and applications than an exhaustive review of related literatures. The compressive sensing and sparse decomposition theory introduced in this paper are expressed with least mathematics, with emphasizing on the ideas and applications in machining processing monitoring.

The outline of the paper is the following: First, some core concepts of signal processing are introduced including signal space, linear representation, and sampling, which forms the basis of later sections. Then, this paper introduces the ideas of compressive sensing and sparse decomposition, their mathematical rationale and investigates their research progress. It then focuses on the sparse representation and the state-of-the-art applications in machining condition monitoring. Some open questions in the applications are also raised.

2. Compressive sensing theory and signal's sparse decomposition

2.1. Basics of signal theory and Shannon's sampling theory

For a fundamental understanding of compressive sensing and sparse decomposition, the basic knowledge of analysis is needed, such as the operators in Hilbert space, frame theory and optimization theory. These advanced theories are beyond the limit of this paper, and only concepts most closely related to sparse decomposition are introduced herein. The theories presented herein are not mathematical rigorous but aimed for easy understanding. Interest readers may refer to [29,30] for more details.

2.1.1. Signal space and linear representation

In a broad sense, a signal $f(t)(t \in R)$ is any time-varying function of time variable t. A signal space is a collection of these signals (functions) that satisfies a certain mathematical structure. The signal spaces with finite energy and finite power structures are particular interested in signal processing. Most signals encountered in technical applications belong to these two classes.

If $f(t)$ is an energy signal, $\int_{-\infty}^{\infty} |f(t)|^2 dt < \infty$, or $f(t) \in L_2(R)$, then it is considered belonging to the Hilbert space. [The Hilbert space can be simply regarded as a generalization of the three-dimensional Euclidean space, in which the definitions of distance and angle are extended as norm and inner product respectively.] The inner product of two signals $f(t)$ and $y(t)$ is defined as,

$$\text{inner product} = \langle f(t), y(t) \rangle = \int_{-\infty}^{\infty} f(t) y^*(t) dt \tag{1}$$

where $y^*(t)$ is the complex conjugate of $y(t)$, and $y^*(t) = y(t)$ if $y(t)$ is real.

The signal $f(t)$ and $y(t)$ are said to be orthogonal if their inner product $\langle f(t), y(t) \rangle = 0$, and if also each vector is a unit vector, the vector set is called orthonormal. And in the Hilbert space, one can always find a set of functions $\{f_i(t)\}_{i=1}^{\infty}$ in $L_2(R)$ that are orthonormal, i.e., $\langle f_i(t), f_j(t) \rangle = 0$, when $i \neq j$, such that for any $s(t) \in L_2(R)$,

$$s(t) = \sum_{i=1}^{\infty} s_i f_i(t) \tag{2}$$