Chapter 1
Signals and Signal Processing in Manufacturing

The term "signal" refers to a physical quantity that carries certain type of information and serves as a means for communication. As an example, the output of an accelerometer in the form of a voltage that varies with time is a signal that carries information about the vibration of the structure (e.g., a machine tool) on which the accelerometer is installed. Such a signal can serve as a means for communicating the operation status of the machine tool to the machine operator.

1.1 Classification of Signals

In general, any signal can be broadly classified as being either deterministic or nondeterministic (Bendat and Piersol 2000). Deterministic signals are those that can be defined explicitly by mathematical functions. An example is the vibration caused by imbalance in a rolling bearing, when the bearing's gravitational center does not coincide with the rotational center. Nondeterministic signals, in comparison, are random in nature and are described in statistical terms. An example is the acoustic emission signals generated during a machining process. In real-world applications, whether a measured signal is deterministic or nondeterministic depends on its reproducibility. A signal that can be generated repeatedly with identical results is considered to be deterministic, otherwise it is nondeterministic.

1.1.1 Deterministic Signal

There are two types of deterministic signals: periodic and transient. They are briefly explained and illustrated in the following.

1.1.1.1 Periodic Signal

A periodic signal is defined as a function that repeats itself exactly after a certain period of time, or cycle. Such a signal is mathematically expressed as

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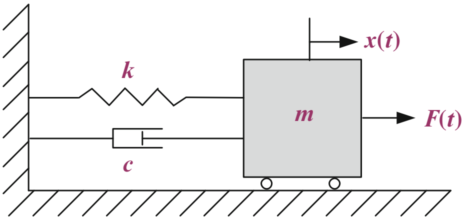


Fig. 1.1 A single-degree-of-freedom (SDOF) mass-spring-damper system

$$x(t) = x(t + nT) \quad n \in \mathbb{Z} \tag{1.1}$$

In the above equation, $\mathbb{Z}$ represents the integer set, n is an integer, and $T > 0$ represents the period. The simplest example of a periodic signal is the sinusoidal signal.

In practice, many physical systems can produce such a type of signal. A typical scenario is a single-degree-of-freedom (SDOF) mass-spring-damper system (Rao 2003). As illustrated in Fig. 1.1, the mass m is attached to the wall through a spring k and a damper c, and can vibrate in the horizontal direction. The motion (or displacement) of the mass-spring-damping system under input $F(t)$ is expressed as

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) = F(t) \tag{1.2}$$

where $x(t)$ is the displacement of the mass, $\dot{x}(t)$ the velocity of the mass, and $\ddot{x}(t)$ the acceleration of the mass.

Let us suppose that the system is under free vibration, with the external forcing input $F(t)$ being zero. Also assume that the damping coefficient $c = 0$. If the system is initially pulled away from the equilibrium position by a distance A_0 and released with the initial velocity equal to zero, so that

$$x(t = 0) = A_0 \quad \dot{x}(t = 0) = 0 \tag{1.3}$$

then the solution of (1.2) will generate a periodic signal with the period $T = 2\pi/\omega_n$. This will be a cosine function, as illustrated in Table 1.1a

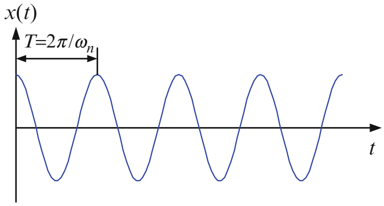
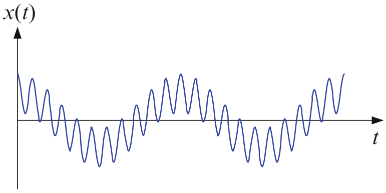
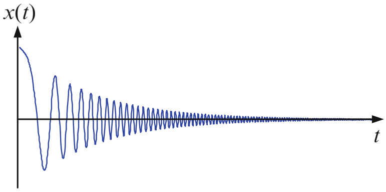
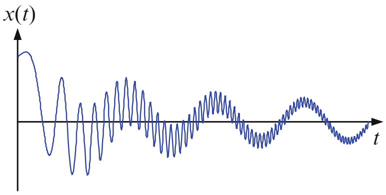
A complex periodic signal can also be generated from the same system (Fig. 1.1) with $c = 0$, when the system is subject to a harmonic forcing input, $F(t) = F\cos(\omega t)$.

As illustrated in Table 1.1b, the complete response can be expressed as the sum of cosine waveforms of two different frequencies.

1.1.1.2 Transient Signal

A transient signal is defined as a function that lasts a short period of time. Such a signal can be generated by the system shown in Fig. 1.1, with the damping coefficient $c \neq 0$ and free vibration, as illustrated in Table 1.1c.

Table 1.1 Example of deterministic signals

Mathematical function	Waveform
(a) A simple periodic signal Condition $c = 0$ $F(t) = 0$ Solution $x(t) = A_0 \cos(\omega_n t)$	
(b) A complex periodic signal Condition $c = 0$ $F(t) = F\cos(\omega t)$ Solution $x(t) = A_1 \cos(\omega_n t) + A_2 \cos(\omega t)$	
(c) A transient signal Condition $c \neq 0$ $F(t) = 0$ Solution $x(t) = A_0 \mathrm{e}^{-\zeta\omega_n t} \cos(\omega_d t)$	
(d) A mixed deterministic signal Condition $c \neq 0$ $F(t) = F\cos(\omega t)$ Solution $x(t) = A_0 \mathrm{e}^{-\zeta\omega_n t} \cos(\omega_d t) + A_3 \cos(\omega t)$	

Note: $\omega_n = \sqrt{\frac{k}{m}}, \omega_d = \sqrt{1-\zeta^2}\omega_n$, and $\zeta = \frac{c}{2m\omega_n} < 1,\ A_1 = A_0 - \frac{F}{k-m\omega^2},\ A_2 = \frac{F}{k-m\omega^2},\ A_3 = \frac{F}{\sqrt{(k-m\omega^2)^2 + c^2\omega^2}}$

Periodic and transient signals are often mixed together in real-world applications. Such a signal can be generated, for example, by the system shown in Fig. 1.1 with the damping coefficient $c \neq 0$, under a harmonic force, as illustrated in Table 1.1d.

1.1.2 Nondeterministic Signal

Nondeterministic signals, also called random signals, do not follow explicit mathematical expressions. They can be generally divided into two categories: stationary and nonstationary.

1.1.2.1 Stationary Signal

A signal $x(t)$ is considered *stationary* when none of its statistical properties change with time. Generally, wide-sense stationary (Bendat and Piersol 2000) is used to characterize the signal. This requires that it satisfies the following conditions on its mean function:

$$E\{x(t_1)\} = m_x(t_1) = m_x(t_1 + \tau) \quad \tau \in \mathbb{Z} \tag{1.4}$$

and the autocorrelation function:

$$E\{x(t_1), x(t_1 + \tau)\} = R_{xx}(t_1, t_1 + \tau) = R_{xx}(0, \tau) \quad \tau \in \mathbf{R} \tag{1.5}$$

In the above equations, the symbol τ is the real number, $\mathbf{R}$ is defined as the real number set, and R_{xx} is the autocorrelation function of the signal $x(t)$. Equation (1.4) indicates that the mean function $m_x(t)$ must be time-invariant or remain unchanged as time goes by. As shown in (1.5), the autocorrelation function of the signal depends only on the time difference τ. The mean function and autocorrelation function of a signal can be obtained by time-averaging over a short time interval T as follows:

$$E\{x(t_1)\} = \frac{1}{T}\int_{t_1}^{t_1+T} x(t)dt \tag{1.6}$$

and

$$E\{x(t_1), x(t_1 + \tau)\} = \frac{1}{T}\int_{t_1}^{t_1+T} x(t)x(t + \tau)dt \tag{1.7}$$

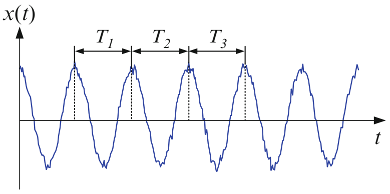
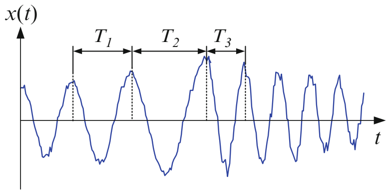
Table 1.2a illustrates an example of a stationary signal, which satisfies the two conditions expressed in (1.5) and (1.6).

1.1.2.2 Nonstationary Signal

A signal whose statistical properties change with time is called a nonstationary signal. As a result, a nonstationary signal does not satisfy the conditions specified in (1.4) and (1.5). Table 1.2b illustrates a nonstationary signal.

It should be noted that signal classification method as described above is not rigid and exclusive. No signals encountered in the real-world are exactly deterministic. Furthermore, there exist other means to classify a signal. For example, a signal can be considered as being either linear or nonlinear, as defined by the superposition principle. An SDOF mass-spring system is considered linear, if a linear relationship exists between the force input to the system and its corresponding displacement

Table 1.2 Example of nondeterministic signals

(a) Stationary signal	(b) Nonstationary signal
	
$T_1 = T_2 = T_3$	$T_1 \neq T_2 \neq T_3$

output. In real-world applications, a signal may contain some or several of the components described above.

1.2 Signals in Manufacturing

Signals are ubiquitously present in manufacturing machines and systems. For example, metal removal is essential to many manufacturing processes, as seen in turning, milling, and drilling (Schey 1999). During such a process, interactions between the cutting edge of the tool and the workpiece lead to removal of fragments of varying volumes, producing whereby time-varying or transient components in the vibration signals. Figure 1.2 illustrates the waveform of a vibration signal measured on a CNC milling machine center (shown in Fig. 1.3) when it is in production.

Another manufacturing process where transient signals may present is sheet metal stamping. The physical setup of a sheet metal stamping operation consists of three main components, namely, the die, the binder, and the punch (Suchy 2006), as shown in Fig. 1.4. During a stamping operation, the periphery of the sheet metal workpiece is held between the binder and die flange. As the punch moves down, the workpiece is pressed into the die, causing plastic deformation in the workpiece material. The flow of the workpiece material into the die is regulated by the binder force (Ahmetoglu et al. 1992; Koyama et al. 2004).

To characterize the stamping process, tonnage measurement has been conducted by placing accelerometers on the columns of the stamping machine. In Fig. 1.5, the output of an accelerometer is shown, in which four different phases of the forming operations are characterized: press idle, travel, contact, and free vibration. When the press is idle, the punch runs down until the binder touches the workpiece at point A. Then travel starts, and the signal amplitude increases as the stamping force increases, until it reaches point B where the punch touches the workpiece. After that, contact between the punch and workpiece is established, and metal forming starts. The signal quickly increases to its maximum at point C, as the punch pushes the sheet metal into the die. At point D, the forming process is completed, and the amplitude of the

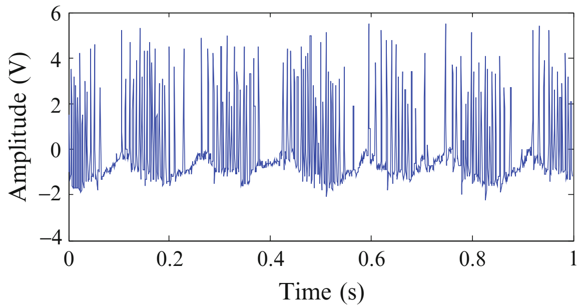


Fig. 1.2 Vibration signal measured during a milling process

Fig. 1.3 A CNC milling machine center (Haas Automation, Inc., http://www.haascnc.com)

vibration signal quickly drops to zero. After point E, vibration of the stamping machine diminishes with time, until the next stamping operation starts.

For nonmetallic material processing, injection molding is widely employed because of its capability in mass production of plastic parts. Figure 1.6 illustrates a typical injection molding machine. The injection molding process generally consists of four stages (Potsch and Michaeli 1995; Bryce 1996; Johannaber 2008): (1) plastication, where the raw material is melted in the barrel, (2) injection, during which the melted polymer is injected into the mold cavity, (3) packing, holding, and cooling, when additional polymer melt is forced into the cavity under high pressure to compensate for the volumetric shrinkage until the part is sufficiently solidified, and (4) ejection, where the mold opens and the part is ejected out of the mold by the push pins.

During each injection molding cycle, pressure within the mold cavity varies, as illustrated in Fig. 1.7. Such time-variation serves as a measure for identifying

Fig. 1.4 A typical stamping machine (BowStar Biz Management Ltd)

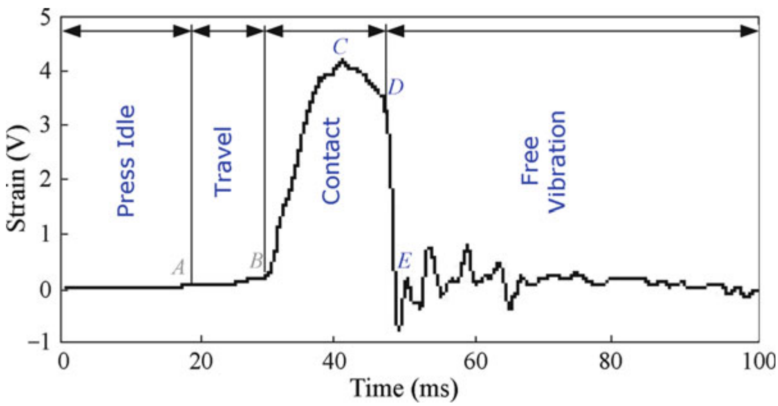


Fig. 1.5 A typical tonnage signal during stamping process

Fig. 1.6 A typical injection molding machine (Ferromatik Milacron)

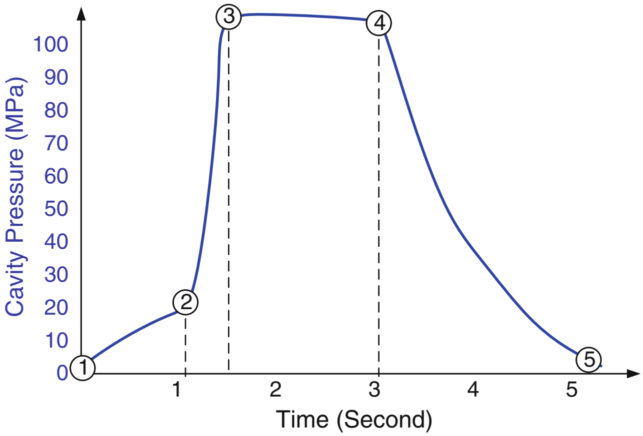


Fig. 1.7 Pressure signal measured during an injection molding process

and characterizing the various stages of the molding process. At point ① where the plasticized polymer enters the cavity, pressure starts to increase from zero in an approximately linear gradient relative to the duration of filling time. When the melt reaches the end of the cavity at point ②, the material is compacted to ensure reproduction of the mold cavity contour. Such a process is indicated by a fast pressure ramping rate as shown in the curve from ② to ③. During the holding phase from ③ to ④, a constant holding pressure is applied to the melt to compensate for the contraction of the polymer by injecting additional material into the cavity. As the molded part starts to cool down and solidify, viscosity of the material increases and the flow channel becomes constricted. As a result, pressure drop is seen from the sensor data as indicated by the section from ④ to ⑤.

The close association between signals and manufacturing, in addition to the various processes as illustrated above, is also seen in various components that have been employed in various machine equipment. One representative is the rolling bearings, which have been widely applied to providing loading support and rotational freedom in manufacturing, transportation, aerospace, and defense (e.g., machine tools, trains, helicopters, power generator, etc.). Because of faulty installation, inappropriate lubrication, and other unpredictable adverse conditions during bearing operations, premature failure of bearings may occur, for example, in the form of surface spalling on the bearing raceways. As a result, impulsive signals will be generated every time when the rolling elements interact with the defects. These impulsive signals subsequently excite the machine system, leading to forced vibrations. Figure 1.8 illustrates a customized spindle system where bearings are installed. Vibration signals measured at two stages during a run-to-failure experiment on the spindle system are shown in Fig. 1.9.

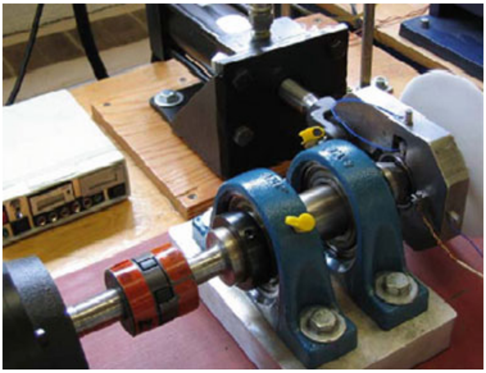


Fig. 1.8 A customized spindle-bearing test system

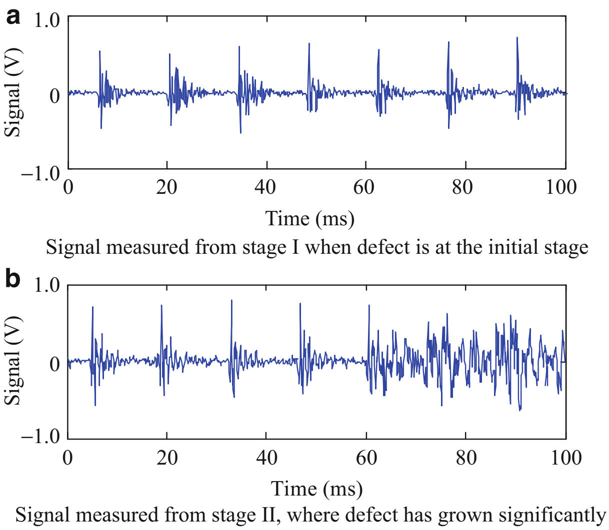


Fig. 1.9 The vibration signals from bearing run-to-failure test. (**a**) Signal measured from stage I when defect is at the initial stage and (**b**) signal measured from stage II, where defect has grown significantly

Gearbox, as illustrated in Fig. 1.10, has been employed in a wide range of machinery and control systems, because of its ability in transferring both power and motion with high efficiency. When a defect is developed in a gear, the vibration signal of the gearbox will contain amplitude and phase modulations that are periodic with respect to the rotation of the gear. Figure 1.11 shows an example of vibration signals measured on a gearbox under different running conditions.

Fig. 1.10 An automobile transmission gearbox (Topic Media PTY LTD)

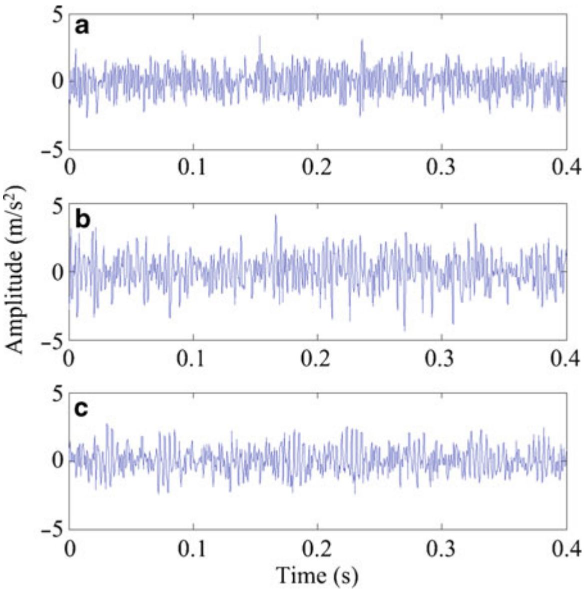


Fig. 1.11 Acceleration signals measured on a gearbox: (**a**) normal condition, (**b**) slight fault condition, and (**c**) severe fault condition

1.3 Role of Signal Processing for Manufacturing

Growing demand for high-quality and low-cost production has increased the need for condition monitoring, health diagnosis, and enhanced controls in manufacturing equipment and processes (Tönshoff et al. 1988; Byrne et al. 1996; Ganesan et al. 2004; Liang et al. 2004). Accordingly, sensor-based information acquisition and processing systems have gained increasing attention from the research community worldwide (Teti 1996; DimlaSnr 2000; Tseng and Chou 2002; Frankowiak et al. 2005). The goal of these efforts is to obtain information in real-time about the operation status of the machines and use the information for the following purposes:

1. Identification of machine faults at the incipient stage such that proper corrective measures can be taken before the faults have progressed to cause significant structural damage and costly downtime, thus enabling *adaptive* instead of fixed-time maintenance and production scheduling
2. More accurate control of the quality of products being manufactured, which is directly related to the working conditions of the machine

In addition to monitoring individual machines, data gathered from the sensors provide insight into the manufacturing process itself, and can be used to assist in high-level decision-making for production optimization.

Signals encountered in manufacturing machines typically consist of three major components:

1. A periodic component resulting from the cyclic interactions between the interfacing elements of the machine, such as vibrations caused by the interaction between the rolling elements and the raceway
2. A transient component caused by "one-time" events, such as the sudden breakage of a drilling bit or the inception of a crack inside a workpiece
3. Broadband background noise

Detection of the existence of these signals in real-time during the manufacturing process and extracting relevant information from the signals in a timely manner are of significant interest and importance, as they are precursors of potential machine defect and product quality deterioration that will negatively impact the manufacturing processes. On the other hand, detection of such signals can be challenging, as these signals are generally short in duration and weak in amplitude. Often times, they can be buried under strong background noises, making their detection difficult (Gu et al. 2002; Padovese 2004; Shi et al. 2004). Furthermore, the one-shot nature of these signals makes the assumption for stationary signals invalid, thus reducing the effectiveness of conventional signal processing techniques. For example, while Fourier transform has been extensively used in conjunction with filtering techniques, its effective utilization depends upon signals containing distinct characteristic frequency components of sufficient energy content, within a limited frequency band. If the feature components spread over a wide spectrum, it would be difficult to use Fourier transform to differentiate them from disturbing or masking components, especially when the feature components are weak in magnitude. This has been shown in condition-monitoring studies of bearings with an incipient defect (Mori et al. 1996).

Time-frequency and time-scale techniques have been the subject of extensive research over the past decade for nonstationary signal analysis. Typical representatives include the short-time Fourier transform (STFT) and wavelet transform (Li and Ma 1997; Satish 1998). STFT was developed to address the limitation of the Fourier transform, which is rooted in its basis functions extending over an infinite period of time. As a result, Fourier transform is not well adapted to nonstationary transient signals with short durations. A solution to this problem is to perform a "time localized" Fourier transform within a sliding window, as in the case of STFT (Chui 1992). Popular choices for the window function include the Hamming, the Hann, and the Gaussian functions. When a Gaussian window is chosen, the STFT is called a Gabor transform (Gabor 1946). A one-sided Gaussian window has been used for detection of transient signals in a workpiece (Friedlander and Porat 1989). The disadvantage of the STFT is that its *time resolution* (the smallest separation in time of two signal components that can be discriminated) and *bandwidth* cannot be chosen to be simultaneously small, according to the uncertainty principle (Cohen 1989). The time-bandwidth product of the STFT must be greater than or equal to the inverse of 4π. The equal sign holds only when the window function is a Gaussian function. This means that the time-frequency resolution over the entire time-frequency plane is fixed, once the window function is chosen. As a result, a trade-off must be made between the time resolution and frequency resolution, when the STFT is applied to transient signal analysis.

To overcome the resolution limitation of the Gabor transform, the wavelet transform has been increasingly investigated for nonstationary signal analysis (Mallat 1989; Daubechies 1990, 1992; Rioul and Vetterli 1991). In contrast to the Gabor transform with fixed windows, the wavelet transform uses short windows at high frequencies and long windows at low frequencies (Rioul and Vetterli 1991). Such a nature leads to the wavelet transform being called the *constant relative-bandwidth* frequency analysis. Unlike the Fourier transform, which expresses a signal as the sum of a series of single-frequency sine and cosine functions, the wavelet transform decomposes a signal into a set of *basis* functions. These basis functions are obtained from a single base wavelet function by a two-step operation: *scaling* (through *dilation* and *contraction* of the base wavelet along the time axis, as will be explained in Chap. 2), and *time shift* (i.e., *translation* along the time axis). Essentially, the wavelet transform process measures the "similarity" between the signal being analyzed and the base wavelet. Through variations of the scales and time shifts of the base wavelet function, features hidden within the signal can be extracted, without requiring the signal to have a dominant frequency band.

Research on manufacturing machine and process monitoring and diagnosis using the wavelet transform has attracted increasing attention worldwide. For example, the adaptive capability has made wavelet transform a good analytical tool for decomposing gearbox vibration signals. Studies have demonstrated its ability to detect incipient failures as well as differentiating different types of defects (Wang and McFadden 1993, 1995; Zheng et al. 2002). The discrete wavelet transform has been applied to analyzing spindle motor current for tool failure diagnosis in end-milling, under varying cutting conditions (Lee and Tarng 1999). Similar studies of wavelet transform for machine tool monitoring have been reported (Fu et al. 1998; Li et al. 2000). For detecting localized bearing defects and/or estimating the defect severity level, the advantage of wavelet transform has been extensively investigated (Wang and Gao 2003; Lou and Loparo 2004; Yan and Gao 2005; Chiementin et al. 2007; Wang et al. 2009), and the results have shown its superior performance over the conventional, Fourier-based approaches. Other applications of wavelet transform, including singularity detection (Sun and Tang 2002), denoising and extraction of weak signals (Altmann and Mathew 2001; Lin 2001), vibration signal compression (Tanaka et al. 1997; Staszewski 1998), and system and parameter identification (Robertson et al. 1998; Kim et al. 2001), have also been reported.

It can be concluded that the wavelet transform provides a powerful mathematical tool for the analysis, characterization, and classification of nonstationary signals typically seen in manufacturing. The adaptive, multiresolution capability of the wavelet transform makes it well suited for decomposing signals of varying time and frequency resolutions that are characteristic of the underlying defect mechanisms associated with a machine, a dynamical structure, or a manufacturing process. Such capability makes the wavelet transform an enabling tool for advancing the science base of signal processing in manufacturing. It is such significance and the associated potential impact that motivate this book, and it is the intention of the book to provide graduate students and practicing engineers with a systematic, comprehensive, yet easily accessible coverage of the fundamental theory and representative applications of wavelet transform in the broad and vibrant field of manufacturing research.

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