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1.3
Sensors in Mechanical Manufacturing – Requirements, Demands, Boundary Conditions, Signal Processing, Communication Techniques, and Man-Machine Interfaces

T. Moriwaki, *Kobe University, Kobe, Japan*

1.3.1
Introduction

The role of sensor systems for mechanical manufacturing is generally composed of sensing, transformation/conversion, signal processing, and decision making, as shown in Figure 1.3-1. The output of the sensor system is either given to the operator via a human-machine interface or directly utilized to control the machine. Objectives, requirements, demands, boundary conditions, signal processing, communication techniques, and the human-machine interface of the sensor system are described in this section.

1.3.2
Role of Sensors and Objectives of Sensing

An automated manufacturing system, in particular a machining system, such as a cutting or grinding system, is basically composed of controller, machine tool and machining process, as illustrated schematically in Figure 1.3-2. The machining command is transformed into the control command of the actuators by the CNC

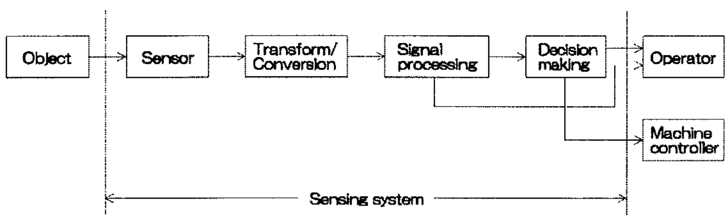


Fig. 1.3-1 Basic composition of sensor system for mechanical manufacturing

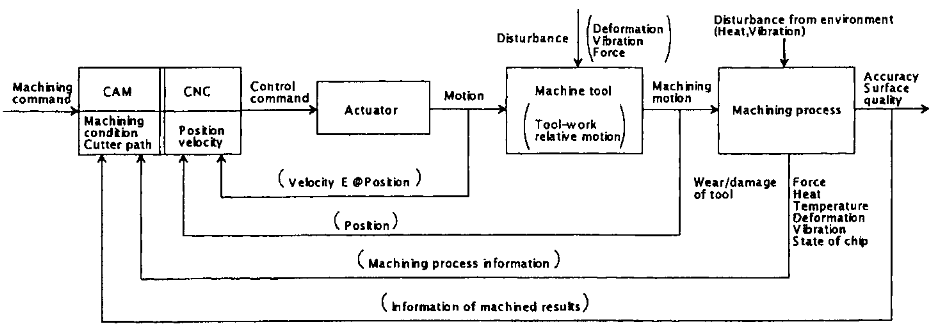


Fig. 1.3-2 Role of sensors in automated machining system

controller, which controls the motion of the actuators and generates the actual machining motion of the machine tool. The motion of the actuator, or the machining motion of the machine tool, is fed back to the controller so as to ensure that the relative motion between the tool and the work follows exactly the predetermined command motion. Motion sensors, such as an encoder, tacho-generator or linear scale, are generally employed for this purpose.

The machining process is generally carried out beyond this loop, where finished surfaces of the work are actually generated. Most conventional CNC machine tools currently available on the market are operated under the assumption that the machining process normally takes place once the tool work-relative motion is correctly given. Some advanced machine tools equipped with an AC (adaptive control) function utilize the feedback information of the machining process, such as the cutting force, to optimize the machining conditions or to stop the machine tool in case of an abnormal state such as tool breakage.

The machining process normally takes place under extreme conditions, such as high stress, high strain rate, and high temperature. Further, the machining process and the machine tool itself are exposed to various kinds of external disturbances including heat, vibration, and deformation. In order to keep the machining process normal and to guarantee the accuracy and quality of the work, it is necessary to monitor the machining process and control the machine tool based on the sensed information.

The objectives and the items to be sensed and monitored for general mechanical manufacturing are summarized in Table 1.3-1 together with the direct purposes of sensing and monitoring. Some items can be directly sensed with proper sensors, but they can be utilized to estimate other properties at the same time. For instance, the cutting force is sensed with a tool dynamometer to monitor the cutting state, but its information can be utilized to estimate the wear of the cutting tool simultaneously.

Almost all kinds of machining processes require sensing and monitoring to maintain high reliability of machining and to avoid abnormal states. Table 1.3-2 gives a summary of the answers to a questionnaire to machine tool users asking about the machining processes which require monitoring [1]. It is understood that monitoring is imperative especially when weak tools are used, such as in tapping, drilling, and end milling.

Tab. 1.3-1 Objects, items, and purposes of sensing

Object of sensing and monitoring	*Items to be sensed*	*Purpose of sensing and monitoring*
Work	State of work clamping Geometrical and dimensional accuracy Surface roughness Surface quality	Maintain high quality Avoid damage and loss of work
Machining process	Force (torque, thrust) Heat generation Temperature Vibration Noise and sound State of chip	Maintain normal machining process Predict and avoid abnormal state
Tool	Tool edge position Wear Damage including chipping, breakage, and others	Manage tool changing time, including dressing Avoid damage or deterioration of work
Machine tool, and auxiliary facility	Malfunction Vibration Deformation (elastic, thermal)	Maintain normal condition of machine tool and assure high accuracy
Environment	Ambient temperature change External vibration Condition of cutting fluid	Minimize environmental effect

Tab. 1.3-2 Machining processes which require sensing

Kind of machining	*Number of answers*	*Percentage*
Tapping	67	19.8
Drilling	66	19.2
End milling	55	16.8
Internal turning	51	15.1
External turning	30	8.9
Face milling	25	7.4
Parting	17	5.0
Thread cutting	13	3.9
Others*	15	4.4
Total	338	100

* Grinding, reaming, deep hole boring, etc.

1.3.3
Requirements for Sensors and Sensing Systems

The most important and basic part of the sensor is the transducer, which transforms the physical or sometimes chemical properties of the object into another physical quantity such as electric voltage that is easily processed. The properties of the object to be sensed are either one-dimensional, such as force and temperature, or multi-dimensional, such as image and distribution of the physical properties. The multi-dimensional properties are treated either as plural signals or a time series of signals after scanning.

The basic requirements for the transducers and sensor systems for mechanical manufacturing are summarized in Table 1.3-3. Figure 1.3-3 shows a schematic illustration of the characteristics of a typical transducer, such as a force transducer.

Tab. 1.3-3 Basic requirements for transducers and sensing systems

Performance/ accuracy	*Reliability*	*Adaptability*	*Economy*
Sensitivity	Low drift	Compact in size	Low cost
Resolution	Thermal stability	Light in weight	Easy to manufacture
Exactness	Stability against environment, such as cutting, fluid and heat	Easy operation	Easy to purchase
Precision	Low deterioration	Easy to be installed	Low power requirement
Linearity	Long life	Low effect of machining process and machine tool	Easy to calibrate
Hysteresis	Fail safe	Safety	Easy maintenance
Repeatability	Low emission of noise	Good connectivity to other equipment	
Signal-to-noise ratio			
Dynamic range			
Dynamic response			
Frequency response			
Cross talk			

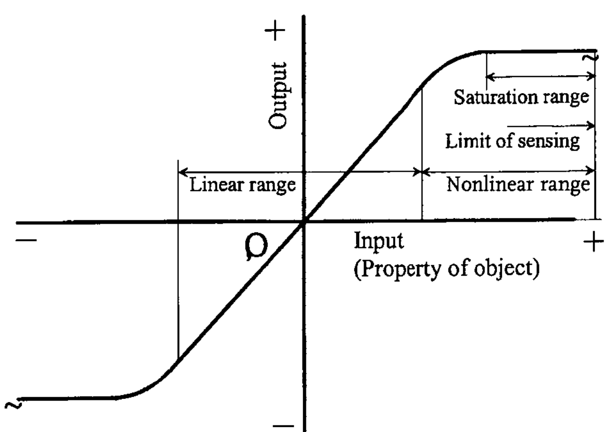


Fig. 1.3-3 Typical input-output relation of transducer

The figure represents the relation between the change in a property of the object, or the input and the output of the transducer. It is desirable that the transducer output represents the property of the object as exactly and precisely as possible. It is also essential for a transducer to output the same value at any time when the same amount of input is given. This characteristic is called repeatability. In most cases, the output increases or decreases in proportion to the input in the linear range, and then gradually saturates and becomes almost constant. When the amount of input exceeds the limit of sensing, the transducer becomes normally malfunctioning. The measurable range of the input is called the dynamic range of the sensor.

The ratio of output to input is called the sensitivity, and it is desirable that the sensitivity is high and the linear range of sensing is wide. The input-output relation is sometimes nonlinear depending on the principle of the transducer, as in the case of capacitive type proximeter (see Figure 1.3-4). Only a small range of linear input-output relation can be used in such a case when the accuracy requirement of sensing is high. When the nonlinear input-output relation is known exactly by calibration or by other methods in advance, the nonlinearity can be compensated afterwards by calculation. The nonlinear characteristics of thermocouples are well known, and the compensation circuits are installed in most thermometers for different types of thermocouples.

The input-output relation sometimes differs when the amount of input is increased and decreased, as shown in Figure 1.3-5. Such a characteristic is called hysteresis, and is sometimes encountered when a strain gage sensor is employed to measure the strain or the force. It is almost impossible to compensate for the hysteresis of the transducer, hence it is recommended to select transducers with small hysteresis.

The property of the object to be sensed in mechanical manufacturing is generally time varying or dynamic. The measurable dynamic range of the transducer is generally limited by the maximum velocity and acceleration of the output signal

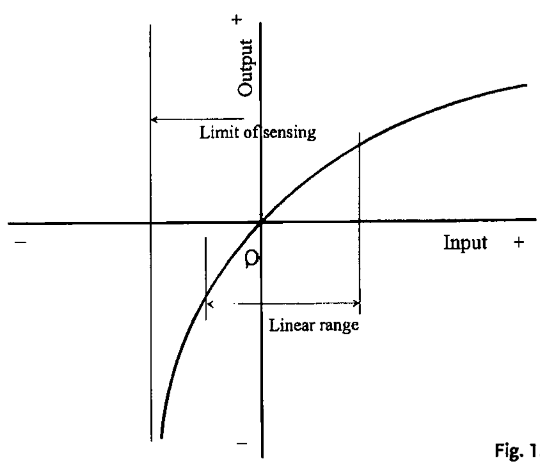


Fig. 1.3-4 Nonlinear input-output relation

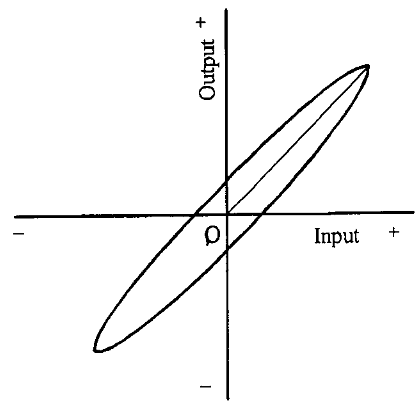


Fig. 1.3-5 Hysteresis in input-output relation

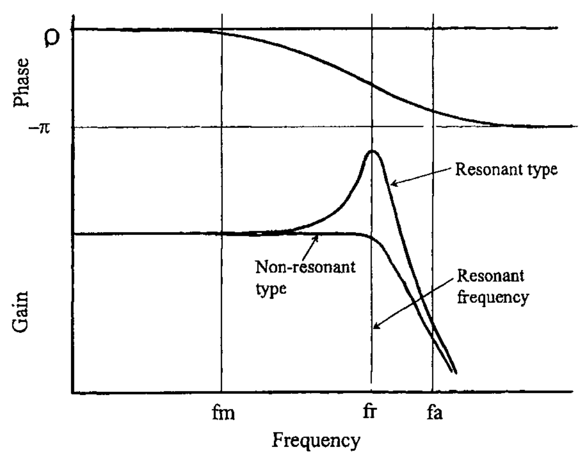


Fig. 1.3-6 Frequency response of typical transducers

and also by the maximum frequency to which the change in the input property can be exactly transformed to the output. Figure 1.3-6 shows typical frequency characteristics of the transducers in terms of the frequency response. The vertical axis shows the gain or the ratio of the magnitudes of the output to the input, and also the phase or the delay of the output signal to the input.

Some transducers show resonance characteristics, and the gain in terms of output/input becomes relatively larger at the resonant frequency. It should be noted that the phase is shifted for about $\lambda/2$ at the resonant frequency. The phase shift in the output signal cannot be avoided generally even with well-damped type or non-resonant type transducers, as shown in the figure.

The sinusoidal wave forms of the input and the output at some typical frequencies are shown in Figure 1.3-7 to illustrate the changes in the gain and the phase. When the phase information is essential to identify the state of the object, it is important to select a transducer with resonant frequency high enough compared with the frequency range of the phenomenon to be sensed.

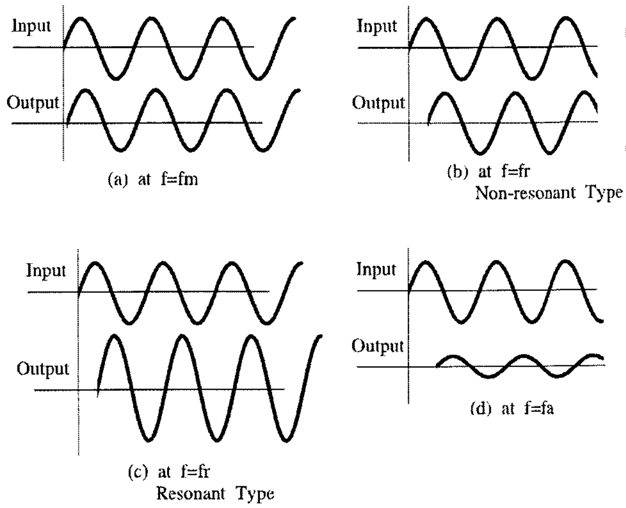


Fig. 1.3-7 Relation of input and output at some typical frequencies

As was mentioned before, the machining process normally takes place under high-stress, high-strain rate and high-temperature conditions with various kinds of external disturbances including the cutting and grinding fluids. It is therefore understood that high reliability and stability against various kinds of disturbances are the most important requirements for the sensors in addition to the basic performance and accuracy of the transducers. According to the answers given by industry engineers to the questionnaire concerning tool condition monitoring [2], the importance of technical criteria in selecting the sensors is in the order (1) reliability against malfunctioning, (2) reliability in signal transmission, (3) ease of installation, (4) life of the sensor, and (5) wear resistance of the sensor.

The importance of items in evaluating the monitoring system is also given in the order (1) reliability against malfunctions, (2) performance to cost ratio, (3) information obtained by the sensor, (4) speed of diagnosis, (5) adaptability to changes of process, (6) usable period, (7) ease of maintenance and repair, (8) level of automation, (9) ease of installation, (10) standard interface, (11) standardized user interface, (12) completeness of manuals, and (13) possibility of additional functions.

Table 1.3-4 summarizes items to be considered generally in selecting transducers and the sensors. It is basically desirable to implement on-line, in-process, continuous, non-contact, and direct sensing, but it is generally difficult to satisfy all of these requirements. The property of the object is directly sensed in the case of direct sensing, whereas in the case of indirect sensing it is estimated indirectly from other properties which can be easily measured and are related to the property to be measured. It should be noted that the property of object to be estimated indirectly must have a good correlation with the property to be measured. Indirect sensing is useful and is widely adopted when direct sensing is difficult.

Tab. 1.3-4 Items to be considered in selecting sensors

In-process sensing; between-process sensing; post-process sensing
On-line sensing; on-machine sensing; off-line sensing
Continuous sensing; intermittent sensing
Direct sensing; indirect sensing
Active sensing; passive sensing
Non-contact sensing; contact sensing
Proximity sensing; remote sensing
Single sensor; multi-sensor
Multi-functional sensor; single-purpose sensor

A typical indirect sensing is to estimate the wear and damage of a tool by sensing the cutting and grinding forces, the cutting temperature, the vibration, or the sound emitted. The wear and damage of the tool have a good correlation with those properties mentioned above, but they are also dependent on other conditions, such as the cutting and grinding conditions including the speed, the depth of cut and the feed, the cutting and grinding modes, the tool materials, etc. It is therefore necessary to have a good understanding of the correlation among the properties and the influencing factors.

1.3.4
Boundary Conditions

Sensing of the state of the machining process, the tool, the work, and the machine tool is not easy and it is restricted by many factors, as was mentioned earlier. Difficulties encountered in sensing, which are boundary and restrictive conditions for sensing, and their typical examples are summarized in Table 1.3-5. The most important requirements for sensing are to obtain the necessary information as accurately as possible under unfavorable conditions without disturbing the machining process, which normally takes place under high stress, high strain rate and high temperature.

It is always desirable to sense the properties of the object directly in-process and on-line, which is not generally easy to realize. When the cutting/grinding temperature and the acoustic emission (AE) signal are sensed, the sensors are normally attached apart from the cutting/grinding region, and hence the quality of necessary information deteriorates while the heat and the ultrasonic vibration are transmitted. It is more difficult to sense such signals when the transmission path is discontinuous, such as in the case of a rotating spindle or moving table. Fluid coupling is employed in the case of ultrasonic vibration.

The signal transmission is still difficult when the transducers are located on the rotating spindle or the moving table, even after the signals to be transmitted are converted to an electric signal by the transducers. The slip ring, wireless transmission with use of radio waves and the optical methods are commonly employed in such cases.

Tab. 1.3-5 Difficulties in sensing and examples

Items of difficulty	*Example*
In-process/on-line sensing is difficult	Geometrical and dimensional accuracy of work Surface roughness and quality of work Wear and damage of tool Thermal deformation of machine
Direct sensing is difficult	Tool wear and damage in continuous cutting Thermal deformation of machine
Distance between object and sensing position is large	Cutting/grinding point versus position where sensors can be placed
Installation of sensor should not affect machining process and rigidity of machining system	Reduction of rigidity of tool or machine elements to measure force by strain
Environment is not clean	Existence of cutting fluid Electrical noise due to power circuit
Signal is to be transmitted via rotating or moving element	Signal transmission from rotating spindle or fast-moving table Signal transmission via rotatable tool turret
Complicated correlation exists among many factors	Property of object to be sensed are affected by machining conditions, tool material, work material, etc.
Variety of machining method is large	Sensors are required to be effective for different machining methods, such as tapping, drilling, end milling, face milling, etc. on one machine

Another difficulty is that the sensors and the sensing systems are generally required to sense the properties of objects even though the combinations of the cutting/grinding methods, the machining conditions, the tool material, the work material, and even the machine itself are altered. In this sense, versatility is important for the sensors and the sensing systems.

1.3.5
Signal Processing and Conversion

1.3.5.1 Analog Signal Processing

The property of the object to be sensed is transformed into voltage, current, electrical charge, or other signal by the transducer. The signals other than the voltage signal are generally further transformed into a voltage signal which is easier to handle. The analog voltage signal is generally filtered to eliminate unnecessary frequency components and amplified prior to the digitization in order to be processed by computer.

There are basically two types of analog filters, the low-pass filter and the high-pass filter. The low-pass filter passes the signal containing the frequency components below the predetermined frequency, named the cut-off frequency, and prohibits the signal containing the frequency components above the cut-off frequency. The low-pass filter is commonly used when the high-frequency noise components, especially the electric noise components, are to be eliminated.

The high-pass filter passes the signal containing the frequency components above the cut-off frequency and prohibits the signal containing the frequency components below the cut-off frequency. The high-pass filter is commonly used when the AC (alternating current) components of the signal are utilized and the DC (direct current) components and the low-frequency components are eliminated. In other words, it is used when the dynamic components of the signal are utilized and the static or the low-frequency components are eliminated.

The combination of the low-pass and the high-pass filters constitutes the band-pass filter and the band-reject filter. The band-pass filter passes only the signal containing the frequency components within the specified frequency range, whereas the band-reject filter prohibits the signal containing the frequency components of that frequency range.

The band-pass filter is commonly used when the signal components of a particular frequency range are utilized, such as in the case when the signal components synchronizing to the rotational frequency of the spindle or the engagement of the milling cutter are to be monitored. The band-reject filter is used when the signal components of a particular frequency range are to be omitted.

The frequency characteristics of the filters are shown schematically in Figure 1.3-8 in terms of the output/input ratio. It should also be noted that the phase information is distorted when the signal is passed through the filters as shown in Figure 1.3-6.

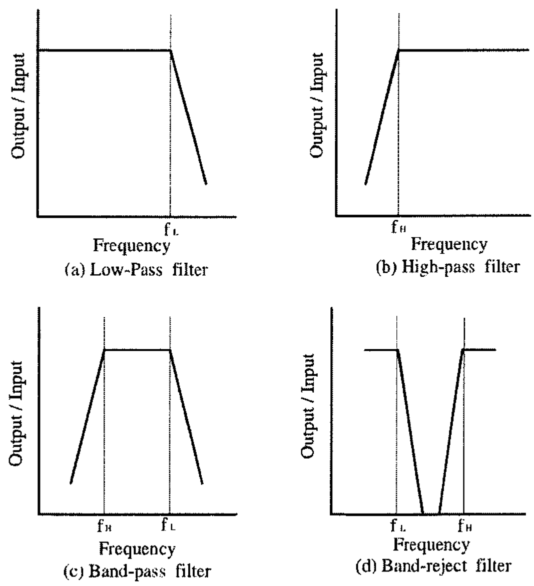


Fig. 1.3-8 Frequency characteristics of filters

Tab. 1.3-6 Typical processing and transformation of analog signal

Filtering (low-pass, high-pass, band-pass, band-reject)
Amplification
Differentiation
Integration
Logarithmic transformation

Tab. 1.3-7 Important parameters in AD conversion

Range of analog signal input
Number of digit (or resolution)
Sampling time Δt
Total number of sampled data M
Maximum frequency $f_{max} = 1/2\Delta t$
Frequency resolution $\Delta f = 1/M\Delta t$

The other transformation and processing of analog signals include the differentiation, integration, and logarithmic transformation, which are summarized in Table 1.3-6. The displacement signal can be transformed to a velocity signal by differentiation, and further to an acceleration signal, and vice versa. These signal transformations are often carried out after the signal is converted to a digital signal, which is explained below.

1.3.5.2 **AD Conversion**

The analog time series of electric signals is generally converted into digital values by the AD (analog-to-digital) converter prior to processing by computer. The important parameters of the AD converter are the input range, the number of digits of conversion, the sampling time, and the total number of sampled data (Table 1.3-7). The AD converter equally divides the voltage of the input range into the given digits and gives the corresponding number to the input voltage at a given sampling interval Δt. Comparison of the original analog signal and digitized samples is illustrated schematically in Figure 1.3-9.

When the input range of an 8-bit AD converter is ± 1 V, the signal from +1 V to −1 V is converted to digital numbers from +127 to −127. This means that the electric signal is digitized with a resolution of 7.9 mV, or 1/127 V. The signal of 0.1 V is converted to 13, 0.5 V to 64, and so forth. The commonly used digits other than 8 bits are 10 bits (± 511), 12 bits (± 2047) and 16 bits (± 8191). The AD conversion is always associated with the digitization error, but it can be ignored in practice if the number of digits is chosen to be high enough.

It is easily understood that the resolution of AD conversion is better if the number of digits is larger. However, it is useless to increase the resolution beyond the noise level of the original analog signal. The input signal is to be properly amplified prior to the AD conversion in such a way that the maximum voltage expected matches the input range of the AD converter.

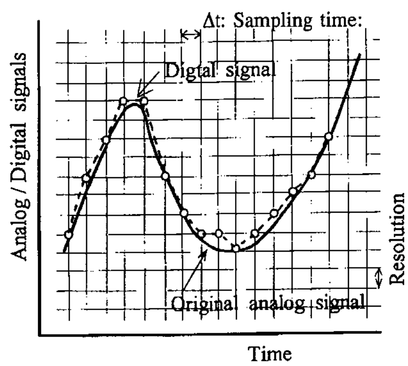


Fig. 1.3-9 Schematic illustration of AD conversion

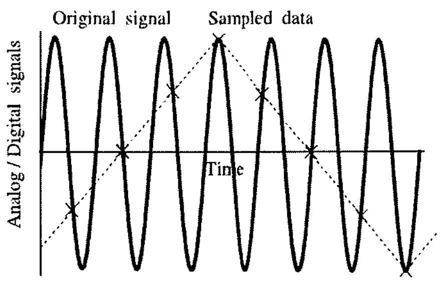


Fig. 1.3-10 Example of low sampling rate

The sampling time Δt gives the time interval of successive AD conversion. A sampling time of 1 ms means that the signal is converted at a sampling rate of 1000 samples per second, or a sampling frequency of 1 kHz. If the sampling time is shorter or the sampling frequency is higher, the original signal can be better represented in a digital form, but the total number of digital data M for a given time period becomes larger and may require a longer processing time.

The sampling time Δt gives the upper limit frequency f_{max} of the digitized signal to be analyzed, or

$$f_{max} = 1/(2\,\Delta t) \tag{1.3-1}$$

This means that the frequency range of the digitized signal is limited below $1/(2\,\Delta t)$ Hz, and the frequency components of the original analog signal beyond this frequency are included in the frequency components of the digitized signal which is lower than f_{max}. This is called Shannon's sampling theorem.

An example of the case of a low sampling rate as compared with the frequency component of the original analog signal is depicted in Figure 1.3-10. It is understood that an original sinusoidal analog signal sampled at a sampling frequency lower than its frequency is represented as a low-frequency signal in digitized form. The signal components with frequencies beyond f_{max} are thus represented as components at lower frequencies in digital form. This phenomenon is called aliasing or folding.

In order to avoid such problems, an analog low-pass filter is generally employed prior to AD conversion, the cut-off frequency of which is matched to the sampling time. Another method is to employ digital filtering, which is a digital calculation equivalent to analog filtering. The original analog signal is sampled at a sampling frequency high enough to avoid folding, processed by the digital processor to eliminate the high-frequency components and then sampled again at a predetermined sampling frequency which is much lower than the original sampling frequency.

When two or more analog signals are to be digitized simultaneously, it is important that the signal of each channel must be sampled at the same time without any delay. This is realized either by employing several AD converters operated in synchronization, or employing the sample and hold circuits, which practically freezes the levels of the analog signals while the single AD converter scans all the analog signals and converts them into digital data.

1.3.5.3 Digital Signal Processing

Once the sensor signal has been converted into digital data, the latter are processed in many ways to extract the features and to give the basis for the identification and the decision making in the following process. Most of the signal data coming from the sensor are time series data, and they are primarily processed in the time domain or in the frequency domain after Fourier transformation. The multi-dimensional data, such as the image data, are treated as they are, or some distinctive features extracted from the image are utilized. Some typical methods of signal processing are summarized in Table 1.3-8. The wavelet transform is a

Tab. 1.3-8 Typical signal processing methods and distinctive values

Domain of signal processing	*Method of signal processing*	*Distinctive value*
Time domain	Selection of distinctive feature	Peak value
	Time series analysis	Rms value
	Correlation analysis	Differentiated value
		Integrated value
		Duration
		Filtered value
		Moving average
		Frequency
		Accumulated frequency
		Auto-correlation
		Cross-correlation
		Difference in arrival time
Frequency domain	DFT (digital Fourier transform)	Band power
		Power spectrum
		Cross spectrum
		Cepstrum
		Phase (difference)
Others	Wavelet transform	Wavelet
	Image processing	Pattern (image data)

new method which deals with the changes in the frequency characteristics of the signal. Some typical signal processing methods are explained below.

Let the digitized time series data of analog signal $x(t)$ be represented as $x(i)$, where i is an integer and

$$t = i\Delta t \tag{1.3-2}$$

The moving average $MA(i)$ of $x(i)$ is given by

$$MA(i) = \frac{1}{K}\sum_{j=0}^{K-1} a(j)x(i-j) \tag{1.3-3}$$

where $a(j)$ are coefficients normally chosen to be 1. The range of integration is sometimes chosen to be from $j=-K$ to $j=K$.

The algorithm of digital filtering mentioned above is practically the same as Equation (1.3-3). The function of the filter can be low-pass or high-pass depending on the coefficients of $a(j)$.

For a given set of time series data of $x(i)$ ($i=0, 1, 2, \ldots, M-1$), the auto-correlation function of $x(i)$ is given by

$$C_{xx}(k) = \frac{1}{M}\sum_{i=0}^{M-k-1} x(k+i)x(i) \quad (k = 0, 1, \ldots, h) \tag{1.3-4}$$

The cross-correlation function between $x(i)$ and $y(i)$ is given in the same way by

$$C_{xy}(k) = \frac{1}{M}\sum_{i=0}^{M-k-1} x(k+i)y(i) \quad (k = 0, 1, \ldots, h) \tag{1.3-5}$$

$$C_{xy}(k) = \frac{1}{M}\sum_{i=-k}^{M-1} x(k+i)y(i) \qquad (k = -1, \ldots, -h) \tag{1.3-6}$$

The Fourier transform of $x(i)$ is given by

$$X(j2\pi k/M\Delta t) = \sum_{i=0}^{M-1} x(i)\exp(-j2\pi ki/M) \tag{1.3-7}$$

where $k = 0, 1, 2, \ldots, M/2$.

The discrete spectrum $X(j2\pi k/M\Delta t)$ is given at discrete frequencies $f=k/M\Delta t$. This means that the frequency resolution is given by dividing the maximum frequency f_{max} by $M/2$, as was shown in Equation (1.3-1) the maximum frequency is determined by the sampling time Δt and is given by $1/2\Delta t$. The frequency resolution Δf of the digitized data is then given by

$$\Delta f = 1/M\Delta t = 1/T \tag{1.3-8}$$

where T is the observation period of the signal.

In order to improve the frequency resolution and make Δf small, it is necessary to increase the number M or the observation period of the signal or to increase the sampling time Δt. The selection of sampling time Δt is restricted by the upper limit frequency or the maximum frequency, as explained before.

The Fourier spectrum $X(j2\pi k/M\Delta t)$ is a complex number, and it is divided into the real and the imaginary parts as

$$\mathrm{Re}(X) = A_k = \sum_{i=0}^{M-1} x(i)\cos(2\pi ki/M) \quad (k = 0, 1, \ldots, M/2) \tag{1.3-9}$$

$$\mathrm{Im}(X) = B_k = \sum_{i=0}^{M-1} x(i)\sin(2\pi ki/M) \quad (k = 1, 2, \ldots, M/2) \tag{1.3-10}$$

The relation between the original time series and the Fourier transform is shown schematically in Figure 1.3-11. The power spectrum P_k at a frequency $f = k/M\Delta t$ is given by

$$P_k = (A_k^2 + B_k^2)^{1/2} \tag{1.3-11}$$

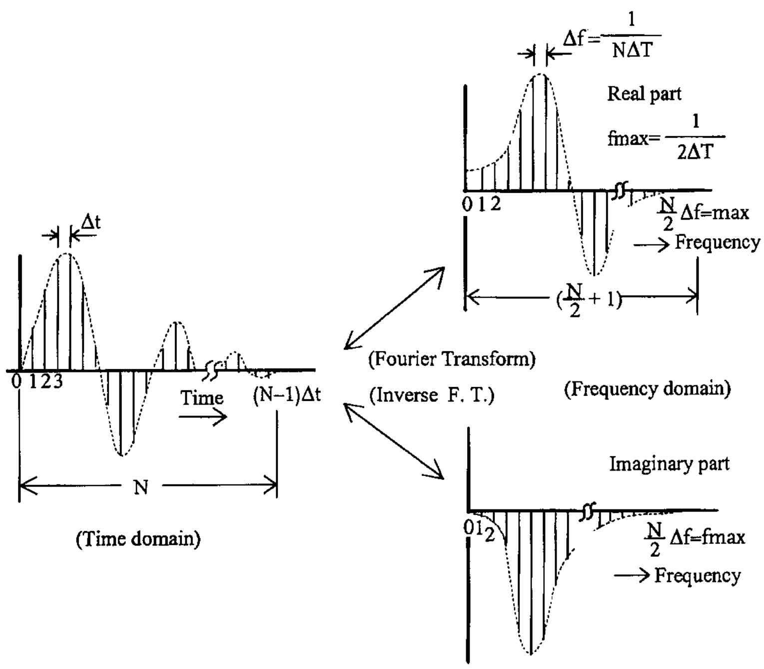


Fig. 1.3-11 Relation of time series data and its Fourier spectra

1.3.6
Identification and Decision Making

1.3.6.1 Strategy of Identification and Decision Making

The digitized sensor signals are used to extract their features, identify the state of the machining process and the conditions of the tool, the work, the machine, etc., and then make decisions to take necessary actions when it is necessary.

Figure 1.3-12 shows typical input-output relations between the input sensor signal and the output which is the status identified. In most cases, a single input signal is utilized to identify the specific state of the system, such as the condition of the tool as shown in case (a). Some sensor signals, such as the vibration signal or the force signal, contain information of various kinds of status, such as the tool wear, the chatter vibration, etc., and hence are utilized to identify those conditions as in case (b).

In order to increase the reliability of identification under varying conditions or to avoid the uncertainty in the identified results, it is useful to use several input signals instead of using a single input signal as in cases (c) and (d). Various kinds of algorithms or rules can be applied to the input signals. Such fusion of the input signals is becoming more popular to increase the quality of the identification.

The distinctive values of the processed signals, the extracted features or the identified parameters are mostly compared with the predetermined or given thresholds to identify the status by referring to these threshold values. In order to guarantee high accuracy of the identification, a reliable database must be prepared in advance based on the actual tests, etc. However, it is not easy to do so, as there are many combinations of the machining conditions, the tool, and the work, and this makes the identification difficult.

Another approach to identification is so-called model-based identification. Various kinds of analytical models or empirical models are employed which utilize

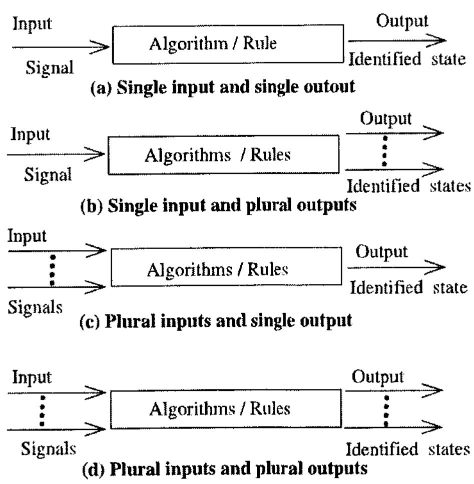


Fig. 1.3-12 Input-output relation of identification

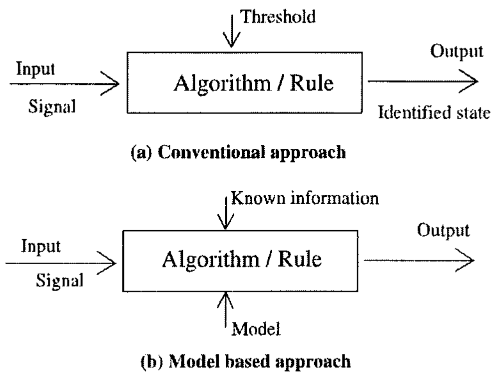


Fig. 1.3-13 Two approaches of identification

Tab. 1.3-9 Typical decisions made and actions to be taken

Emergency stop or feed stop, and	Continue operation but change
• change tool	• spindle speed
• dress grinding wheel	• feed speed
• change conditions (including NC program) to avoid chatter vibration, other damage, etc.	• cutter path to compensate tool wear, thermal deformation or other error source
• notify the operator	

the known information, such as the cutting conditions. For instance, the generalized model parameters are extracted from the input signals and are compared with the database, or the hypothetical output of the system is calculated which is to be compared with the actual signal data. It is expected that both the reliability and the versatility of identification will be increased by introducing the model-based approach. The differences between the above two approaches of identification are shown schematically in Figure 1.3-13.

The final decision is made based on the results of the identification. Typical decisions made or actions to be taken in the case of machining are summarized in Table 1.3-9. When the abnormal state is identified, the machine is either to be stopped or continues to operate depending on the nature of the abnormal state and the control capability of the machine.

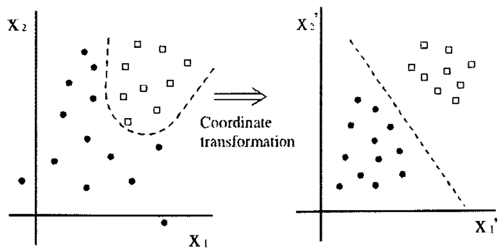
Various kinds of AI (artificial intelligence) technologies are applied to the identification and the decision making, which are briefly explained below.

1.3.6.2 **Pattern Recognition**

The pattern recognition method has been widely applied to identify the state of the machining process and the cutting tool, etc. [3–5].

It is based on the similarity between a sample to be identified and the patterns or classes that describe the target statuses. From a geometrical point of view, the monitoring indices, or the selected distinctive feature values extracted from the

Fig. 1.3-14 Separation of clusters by coordinate transformation



sensed signals, $x=(x_1, x_2, \ldots, x_m)$ span an m-dimensional space. In the span, each target status, h_j, is characterized by a pattern vector $p_j=(p_{j1}, p_{j2}, \ldots, p_{jm})$. The similarity between the sample with the feature values and a pattern is measured by the distance between the two vectors. The minimum distance is then used as the criterion for classifying the sample.

The clustering of the sample points, which belong to the particular patterns, is accomplished by a proper coordinate transformation in such a way that the mean square of the above mentioned distance becomes minimum. The transformed signal x' is given by

$$x' = [w]x \tag{1.3-12}$$

where $[w]$ is the transformation matrix.

Figure 1.3-14 shows schematically how the original sample points are classified into distinctive classes by a proper transformation in a two-dimensional space. The most appropriate coordinate transformation is obtained by learning with given sample data.

1.3.6.3 Neural Networks

The neural network is basically an imitation of the neural system of animals, and it has been applied to identify the state of the cutting tool [6], the machining process [7, 8], and also the thermal deformation of the machine tool [9], etc. The advantages of neural networks over pattern recognition are that it can easily constitute optimum nonlinear multi-input functions for pattern recognition and that the accuracy of pattern recognition is easily improved by learning.

A neural network may consist of several layers and each layer has a number of neurons as shown in Figure 1.3-15. The output O_j^L of the jth unit in the Lth layer to its input X_j^L is generally given by

$$O_j^L = h(X_j^L - \theta_j^L) \tag{1.3-13}$$

where θ_j^L is the threshold value. The well-known sigmoid monotonic input-output relation is generally adopted, which is given by

$$h(X_j^L - \theta_j^L) = \frac{1}{1 + 1/\exp(X_j^L - \theta_j^L)} \tag{1.3-14}$$

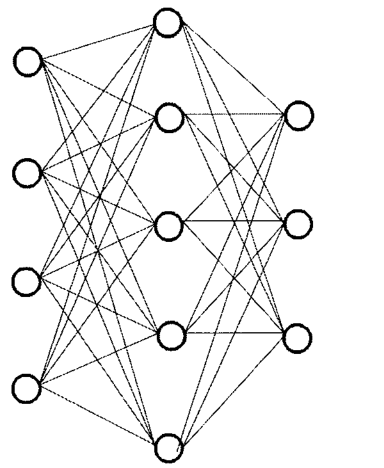


Fig. 1.3-15 Basic structure of neural network

The input X_j^L of the jth unit in the Lth layer, except the input layer, is given by the weighted sum of the outputs from the units in the previous layer, or

$$X_j^L = \sum_{i=1}^{m} W_{ji}^{L-1} O_i^{L-1} \tag{1.3-15}$$

where W_{ji}^{L-1} represents the weight which is given by the path from ith unit in the $(L-1)$th layer to the jth unit in the Lth layer, and m is the number of nodes in the $(L-1)$th layer.

The outputs of the network O_k are calculated based on the inputs following the paths of the network and the procedures mentioned above. The thresholds θ and the weights W are so determined that the sum of squares of the differences between the ideal outputs R_k and the calculated outputs O_k is minimized, or

$$X_j^L = \sum_{k=1}^{m} (R_k - O_k)^2 \tag{1.3-16}$$

is minimized. The thresholds and the weights are further modified through learning as the additional data are given to the network.

1.3.6.4 Fuzzy Reasoning

Fuzzy reasoning was first introduced by Zadeh [10] and has been applied to state identification and decision making when there exists fuzziness in the process, such as the grinding process [11].

Fuzzy reasoning is a reasoning method based on the fuzzy production rules. The fuzzy production rules are given in such a way as

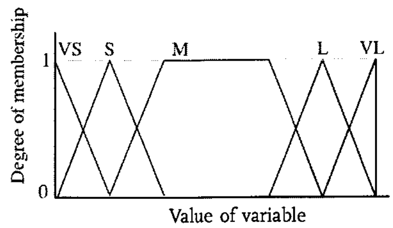


Fig. 1.3-16 Typical examples of membership functions

IF $(x_1$ is very small) and (x_2 is medium)

THEN (x_k is small)

In the fuzzy approach, uncertain events are described by means of a fuzzy degree or a membership function. If A is an uncertain event as a function of x, A can be described by

$$A = \{x|\mu_A(x)\} \tag{1.3-17}$$

where $\mu_A(x)$ the membership function. The membership function is a monotonous function $0 \leq \mu_A(x) \leq 1$, while '0' means certainly no and '1' means certainly yes. Some typical examples of the membership functions are shown in Figure 1.3-16, which represent the linguistic variables, such as VS (very small), S (small), M (medium), L (large) and VL (very large).

When a set of the input variables are given, the degrees of applicability of the rules are calculated according to the membership functions and they are applied to the production rules to give the quantified outputs. The detailed procedures of the fuzzy reasoning and examples of applications are given in Ref. [12].

Other AI technologies, such as expert systems, are employed for state identification, diagnosis, and decision making, but they are not explained in detail here.

1.3.7
Communication and Transmission Techniques

Communication and transmission of the signal within the sensing system are generally processed in digital form after digitization of the analog input signal. The analog transmission of the sensed signal prior to digitization requires special care, as the quality of the signal transmission directly influences the quality of sensing. The analog signal is easily deteriorated by the noise signal surrounding the transducers/sensors and the signal transmission cables. The high-frequency noise signals coming from the power circuits including the motors, the digital devices, etc., as well as those coming from the power supply can be major sources of noise signals.

The signal transmission requires special techniques when the signal is to be transmitted via relatively moving interfaces without contact. The slip ring, wireless transmission with use of radio waves and optical methods are generally employed in such cases.

The communication and transmission of digital signals and data can be easily conducted with the aid of current computer technology. A large amount of digital data can be transmitted between the I/O (input/output) devices and computers via an RS232C or RS422 serial interface at high speeds. Most computers and controllers are connected via the ether-net with the TCP/IP protocol, and the messages and the data can be easily transmitted with use of appropriate communication programs.

The internet services are available to transmit messages and data all over the world via a dedicated line or a commercial telephone line.

1.3.8
Human-Machine Interfaces

The outputs of the sensing system, which are the processed sensor signals, the identified states of the process or the system, or the decisions made, are transmitted to the machine controller and to the operator. At the same time, the operator has to input various kinds of commands to the sensing system. In this sense the human-machine interface plays an important role in the sensing system.

Typical I/O devices or media between the sensing system and the operators are listed in Table 1.3-10. The operators can input commands via dedicated switches or a keyboard, which is more versatile. A touch panel is widely adopted on the actual production floor, which is used to input commands by pressing the specified location on the screen displaying the various functions. The information from the pressed position on the screen is input into the computer via the touch sensor and transformed to a command input. Voice commands are not widely used in noisy environments.

Alarms are the most popular output to the operator when some malfunctions are identified in the system. The visual output, either a graphical presentation or a document, via the display, helps the operator to understand the situation. Oral output with use of a synthetic voice is also helpful.

Tab. 1.3-10 Typical input/output devices or media

Input devices/media	*Output devices/media*
Switch	Alarm (sound, light, etc.)
Keyboard	Voice (synthetic voice)
Touch panel	Display
Voice command	Printout

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