Sensors in Manufacturing. Edited by H.K. Tönshoff, I. Inasaki

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1
Fundamentals

1.1
Roles of Sensors in Manufacturing and Application Ranges

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1.1.1
Manufacturing

Manufacturing can be said in a broad sense to be the process of converting raw materials into usable and saleable end products by various processes, machinery, and operations. The important function of manufacturing is, therefore, to add value to the raw materials. It is the backbone of any industrialized nation. Without manufacturing, few nations could afford the amenities that improve the quality of life. In fact, generally, the higher the level of manufacturing activity in a nation, the higher is the standard of living of its people. Manufacturing should also be competitive, not only locally but also on a global basis because of the shrinking of our world.

The manufacturing process involves a series of complex interactions among materials, machinery, energy, and people. It encompasses the design of products, various processes to change the geometry of bulk material to produce parts, heat treatment, metrology, inspection, assembly, and necessary planning activities. Marketing, logistics, and support services are relating to the manufacturing activity. The major goals of manufacturing technology are to improve productivity, increase product quality and uniformity, minimize cycle time, and reduce labor costs. The use of computers has had a significant impact on manufacturing activities covering a broad range of applications, including design of products, control and optimization of manufacturing processes, material handling, assembly, and inspection of products.

1.1.2
Unit Processes in Manufacturing

The central part of manufacturing activity is the conversion of raw material to component parts followed by the assembly of those parts to give the products. The processes involved in making individual parts using machinery, typically machine tools, are called unit processes. Typical unit processes are casting, sintering, forming, material removing processes, joining, surface treatment, heat treatment, and so on. Figure 1.1-1 shows various steps and unit processes involved in manufacturing which are dealt with in this book. The unit processes can be divided into three categories [1]:

- removing unnecessary material (–);
- moving material from one region to another (0);
- putting material together (+).

For example, cutting and abrasive processes are removal operations (–), forming, casting, and sintering are (0) operations, and joining is a (+) operation.

The goal of any unit process is to achieve high accuracy and productivity. Thanks to the significant developments in machine tools and machining technologies, the accuracy achievable has been increased as shown in Figure 1.1-2 [2]. The increase in productivity in terms of cutting speed is depicted in Figure 1.1-3 [2]. The development of new cutting tool materials has made it possible, together with the improvements in machine tool performance, to reach cutting speeds higher than 1000 m/min.

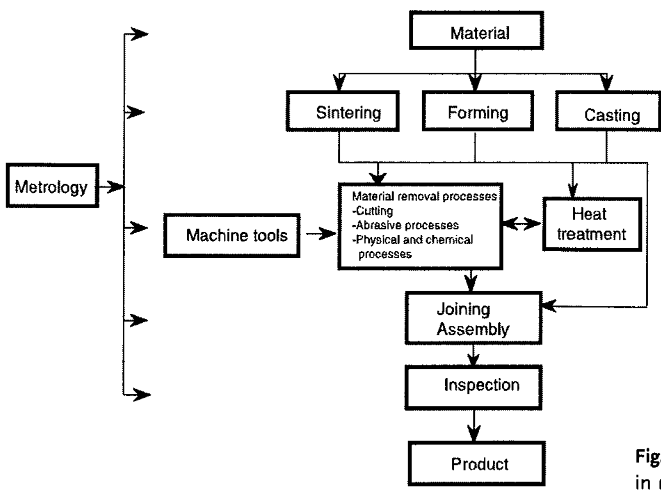


Fig. 1.1-1 Unit processes in manufacturing

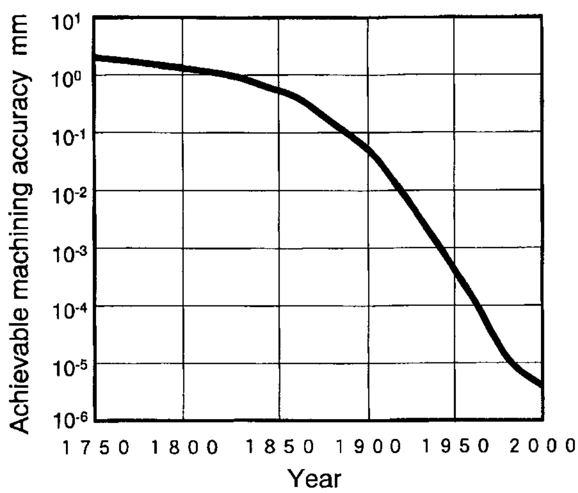


Fig. 1.1-2 Achievable machining accuracy [2]

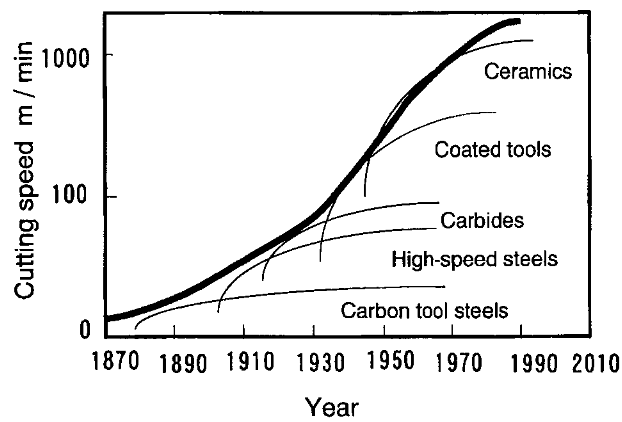


Fig. 1.1-3 Increase of cutting speed in turning [2]

1.1.3
Sensors

Any manufacturing unit process can be regarded as a conversion process of material, energy, and information (Figure 1.1-4). The process should be monitored carefully to produce an output that can meet the requirements. When the process is operated by humans, it is monitored with sense organs such as vision, hearing, smell, touch, and taste. Sometimes, information obtained through multiple sense organs is used to achieve decision making. In addition, the brain as the sensory center plays an important role in processing the information obtained with the sense organs. In order to achieve automatic monitoring, those sense organs must be replaced with sensors. Some sensors can sense signals that cannot be sensed with the human sense organs.

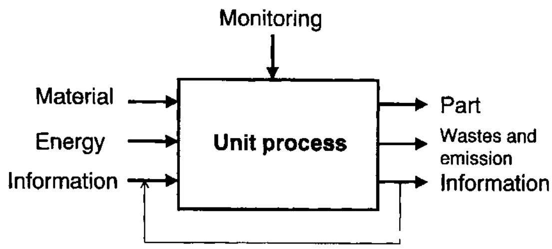


Fig. 1.1-4 Unit process as a conversion process

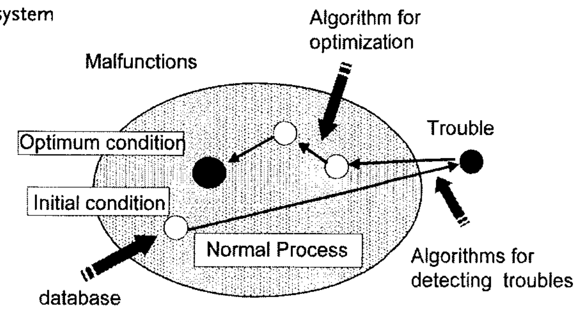
The word sensor came from the Latin *sentire*, meaning 'to perceive', and is defined as 'a device that detects a change in a physical stimulus and turns it into a signal which can be measured or recorded' [3]. In other words, an essential characteristic of the sensing process is the conversion of energy from one form to another. In practice, therefore, most sensors have sensing elements plus associated circuitry. For measurement purposes, the following six types of signal are important: radiant, mechanical, thermal, electrical, magnetic, and chemical [3].

1.1.4
Needs and Roles of Monitoring Systems

Considering the trends of manufacturing developments, the following reasons can be pointed out to explain why monitoring technology is becoming more and more important in modern manufacturing systems:

(1) Large-scale manufacturing systems should be operated with high reliability and availability because the downtime due to system failure has a significant influence on the manufacturing activity. To meet such a demand, individual unit processes should be securely operated with the aid of reliable and robust monitoring systems. Monitoring of large-scale systems is already beyond the capability of humans.
(2) Increasing labor costs and shortage of skilled operators necessitate operation of the manufacturing system with minimum human intervention, which requires the introduction of advanced monitoring systems.
(3) Ultra-precision manufacturing can only be achieved with the aid of advanced metrology and the technology of process monitoring.
(4) Use of sophisticated machine tools requires the integration of monitoring systems to prevent machine failure.
(5) Heavy-duty machining with high cutting and grinding speeds should be conducted with minimum human intervention from the safety point of view.
(6) Environmental awareness in today's manufacturing requires the monitoring of emissions from processes.

Fig. 1.1-5 Roles of monitoring system



The roles of the monitoring system can be summarized as shown in Figure 1.1-5. First, it should be capable of detecting any unexpected malfunctions which may occur in the unit processes. Second, information regarding the process parameters obtained with the monitoring system can be used for optimizing the process. For example, if the wear rate of the cutting tool can be obtained, it can be used for minimizing the machining cost or time by modifying the cutting speed and the feed rate to achieve adaptive control optimization [4]. Third, the monitoring system will make it possible to obtain the input-output causalities of the process, which is useful for establishing a databank regarding the particular process [5]. The databank is necessary when the initial setup parameters should be determined.

1.1.5 Trends

In addition to increasing needs of the monitoring system, the demand for improving the performance of the monitoring system, particularly its reliability and robustness, is also increasing. No sensing device possesses 100% reliability. A possible way to increase the reliability is to use multiple sensors, making the monitoring system redundant. The fusion of various information is also a very suitable means to obtain a more comprehensive view of the state and performance of the process. In addition, sensor fusion is a powerful tool for making the monitoring system more flexible so that the various types of malfunctions that occur in the process can be detected.

In the context of sensor fusion, there are two different types: the *replicated sensors system* and the *disparate sensors system* [5]. The integration of similar types of sensors, that is, a replicated sensor system, can contribute mainly to improving the reliability and robustness of the monitoring system, whereas the integration of different types of sensors, disparate sensors system, can make the monitoring system more flexible (Figure 1.1-6).

Significant developments in sensor device technology are contributing substantially being supported by fast data processing technology for realizing a monitoring system which can be applied practically in the manufacturing environment.

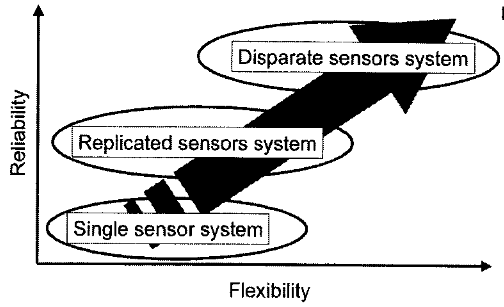


Fig. 1.1-6 Evolution of monitoring system

Soft computing techniques, such as fuzzy logic, artificial neural networks and genetic algorithms, which can to some extent imitate the human brain, can possibly contribute to making the monitoring system more intelligent.

1.1.6
References

1 Shaw, M.C., *Metal Cutting Principles;* Oxford: Oxford University Press, 1984.
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1.2
Principles of Sensors in Manufacturing

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1.2.1
Introduction

New demands are being placed on monitoring systems in the manufacturing environment because of recent developments and trends in machining technology and machine tool design (high-speed machining and hard turning, for example). Numerous different sensor types are available for monitoring aspects of the manufacturing and machining environments. The most common sensors in the industrial machining environment are force, power, and acoustic emission (AE) sensors. This section first reviews the classification and description of sensor types and the particular requirements of sensing in manufacturing by way of a background and then the state of sensor technology in general. The section finishes with some insight into the future trends in sensing technology, especially semiconductor-based sensors.

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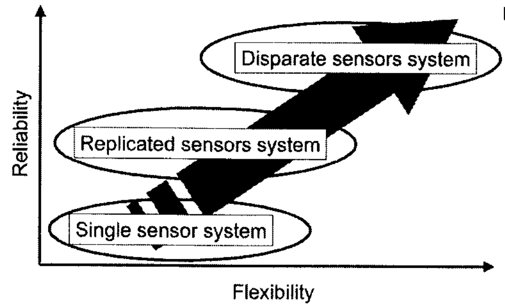

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In-process sensors constitute a significant technology, helping manufacturers to meet the challenges inherent in manufacturing a new generation of precision components. In-process sensors play different roles in manufacturing processes and can address the tooling, process, workpiece, or machine. First and foremost, they allow manufacturers to improve the control over critical process variables. This can result in the tightening of control limits of a process and as improvements in process productivity, forming the basis of precision machining (Figure 1.2-1). For example, the application of temperature sensors and appropriate control to traditional machine tools has been demonstrated to reduce thermal errors, the largest source of positioning errors in traditional and precision machine tools, and the work space errors they generate. Second, they serve as useful productivity tools in monitoring the process. For example, as already stated, they improve productivity by detecting process failure as is the case with acoustic sensors detecting catastrophic tool failure in cutting processes. They also reduce dead time in the process cycle by detecting the degree of engagement between the tool and the work, allowing for a greater percentage of machining time in each part cycle. As process speeds increase and equipment downtime becomes less tolerable, sensors become critical elements in the manufacturing system to insure high productivity and high-quality production.

With regard to sensor systems for manufacturing process monitoring, a distinction is to be made on the one hand between continuous and intermittent systems and on the other between direct and indirect measuring systems. In the case of continuously measuring sensor systems, the measured variable is available throughout the machining process; intermittently measuring systems record the measured variable only during intervals in the machining process. The distinction is sometimes referred to as pre-, inter-, or post-process measurement for intermit-

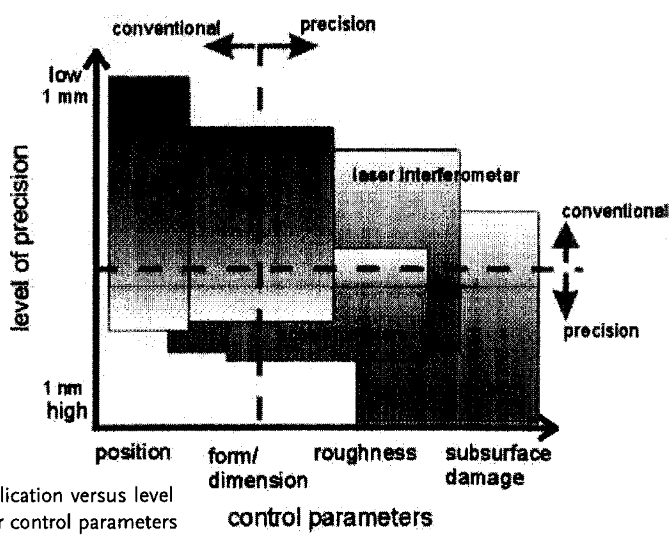


Fig. 1.2-1 Sensor application versus level of precision and error control parameters

tent systems and in-process for continuous systems. Obviously, other distinctions can apply. Direct measuring systems employ the actual quantity of the measured variable, eg, tool wear, whereas indirect measuring systems measure suitable auxiliary quantities, such as the cutting force components, and deduce the actual quantity via empirically determined correlations. Direct measuring processes possess a higher degree of accuracy, whereas indirect methods are less complex and more suitable for practical application. Continuous measurement permits the continuous detection of all changes to the measuring signal and ensures that sudden, unexpected process disturbances, such as tool breakage, are responded to in good time. Intermittent measurement is dependent on interruptions in the machining process or special measuring intervals, which generally entail time losses and, subsequently, high costs. Furthermore, tool breakage cannot be identified until after completion of the machining cycle when using these systems, which means that consequential damage cannot be prevented. Intermittent wear measurement nevertheless has its practical uses, provided that it does not result in additional idle time. It would be conceivable, for example, for measurement to be carried out in the magazine of the machine tool while the machining process is continued with a different tool. Intermittent wear-measuring methods can be implemented with mechanical, inductance-capacitance, hydraulic-pneumatic and opto-electronic probes or sensor systems.

Direct and continuous sensor measuring is the optimal combination with respect to accuracy and response time. For direct measurement of the wear land width, an opto-electronic system has been available, for example, whereby a wedgeshaped light gap below the cutting edge of the tool, which changes proportionally to the wear land width, is evaluated. The wear land width can also be measured directly by means of specially prepared cutting plates, the flanks of which are provided with strip conductors which act as electrical resistors. Another approach uses an image processing system based on a linear camera for on-line determination of the wear on a rotating inserted-tooth face mill. Non-productive time due to measurement is avoided and the system reacts quickly to tool breakage. There are, however, problems due to the short distance between the tool and the camera, which is mounted in the machine space to the side of the milling cutter, and due to chips and dirt on the inserts.

The indirect continuous measuring processes, which are able to determine the relevant disturbance, eg, tool wear, by measuring an auxiliary quantity and its changes, are generally less accurate than the direct methods. A valuable variable which can be measured for the purpose of indirect wear determination is the cutting temperature, which generally rises as the tool wear increases as a result of the increased friction and energy conversion. However, all the known measuring processes are pure laboratory methods for turning which are furthermore not feasible for milling and drilling, owing to the rotating tools. Continuous measurement of the electrical resistance between tool and workpiece is also not feasible for practical applications, on account of the required measures, such as insulation of the workpiece and tool, and to short circuits resulting from chips or cooling lubricant. Systems based on sound monitoring using microphones, for example, also have not yet reached industrial application owing to the problems caused by noise that is not generated by the machining process.

The philosophy of implementation of any sensing methodology for diagnostics or process monitoring can be divided into two simple approaches. In one approach, one uses a sensing technique for which the output bears some relationship to the characteristics of the process. After determining the sensor output and behavior for 'normal' machine operation or processing, one observes the behavior of the signal until it deviates from the normal, thus indicating a problem. In the other approach, one attempts to determine a model linking the sensor output to the process mechanics and then, with sensor information, uses the model to predict the behavior of the process. Both methods are useful in differing circumstances. The first is, perhaps, the most straightforward but liable to misinterpretation if some change in the process occurs that was not foreseen (that is, 'normal' is no longer normal). Thus some signal processing strategy is required.

The signal that is delivered by the sensor must be processed to detect disturbances. The simplest method is the use of a rigid threshold. If the threshold is crossed by the signal owing to some process change affecting the signal, collision or tool breakage can be detected. Since this method only works when all restrictions (depth of cut, workpiece material, etc.) remain constant, the use of a dynamic threshold is more appropriate in most cases. The monitoring system calculates an upper threshold from the original signal. The upper threshold time-lags the original signal. Slow changes of the signal can occur without violating the threshold. At the instant of breakage, however, the upper threshold is crossed and, following a plausibility check (the signal must remain above the upper threshold for a certain time duration), a breakage is confirmed and signaled. Because of the high bandwidth of the acoustic emission signal, fast response time to a breakage is insured. Of course, process changes not due to tool breakage (eg, some interrupted cuts) that affect the signal similarly to tool breakage will cause a false reading.

Another method is based upon the comparison of the actual signal with a stored signal. The monitoring system calculates the upper and lower threshold values from the stored signal. In the case of tool breakage, the upper threshold is violated. When the workpiece is missing, the lower threshold is consequently crossed. The disadvantage of this type of monitoring strategy is that a 'teach-in' cycle is necessary. Furthermore, the fact that the signals must be stored means that more system memory must be allocated. These methods have found applicability to both force and AE signal-based monitoring strategies.

These strategies work well for discrete events such as tool breakage but are often more difficult to employ for continuous process changes such as tool wear. The continuous variation of material properties, cutting conditions, etc., can mask wear-related signal features or, at least, limit the range of applicability or require extensive system training. A more successful technique is based on the tracking of parameters that are extracted from signal features that have been filtered to remove process-related variables (eg, cutting speed), eg, using parameters of an auto-regressive model (filter) of the AE signal to track continuous wear. The strategy works over a range of machining conditions.

The combination of different, inexpensive sensors today is ever increasing to overcome shortages of single sensor devices. There are two possible ways to achieve a multi-sensor approach. Either one sensor is used that allows the measurement of different variables or different sensors are attached to the machine tool to gain different variables. The challenge in this is both electronic integration of the sensor and integration of the information and decision making.

1.2.2
Basic Sensor Classification

We now review a basic classification of sensors based upon the principle of operation. Several excellent texts exist that offer detailed descriptions of a range of sensors and these have been summarized in the material below [1–3]. We distinguish here between *a transducer* and a *sensor* even though the terms are often used interchangeably.

A transducer is generally defined as a device that transmits energy from one system to another, often with a change in form of the energy. A good example is a piezoelectric crystal which will output a current or charge when mechanically actuated. A sensor, on the other hand, is a device which is 'sensitive' to (meaning responsive to or otherwise affected by) a physical stimulus (eg, light) and then transmits a resulting impulse for interpretation or control [4]. Clearly there is some overlap as in the case of a piezoelectric actuator (responding to a charge and outputting a motion or force) and a piezoelectric sensor (outputting a charge for a given force or motion input). In one case, the former, the piezo device acts as a transducer and in the other, the latter, as a sensor. The terms can often be used interchangeably without problem in most cases.

A sensor, according to Webster's Dictionary is 'a device that responds to a physical (or chemical) stimulus (such as heat, light, sound, pressure, magnetism, or a particular motion) and transmits a resulting impulse (as for measurement or operating control)'. Sensors are in this way devices which first perceive an input signal and then convert that input signal or energy to another output signal or energy for further use. We generally classify signal outputs into six types:

- mechanical;
- thermal (ie, kinetic energy of atoms and molecules);
- electrical;
- magnetic;
- radiant (including electromagnetic radio waves, micro waves, etc.); and
- chemical.

Sensors now exist, and are in common use, that can be classified as either 'sensors' *on* silicon as well as 'sensors *in* silicon' [1]. We shall discuss the basic characteristics of both types of silicon 'micro-sensors' but introduce some of the unique features of the latter which are becoming more and more utilized in manufacturing. The small size, multi-signal capability, and ease of integration into signal processing and control systems make them extremely practical. In addition, as a result of their relatively low cost, these are expected to be the 'sensors of choice' in the future.

The six types of signal outputs listed above reflect the 10 basic forms of energy that sensors convert from one form to another. These are listed in Table 1.2-1 [3, 5, 6]. In practice, these 10 forms of energy are condensed into the six signal types listed as we can consider atomic and molecular energy as part of chemical energy, gravitational and mechanical as one, mechanical, and we can ignore nuclear and mass energy. The six signal types (hence basic sensor types for our discussion) represent 'measurands' extracted from manufacturing processes that give us insight into the operation of the process. These measurands represent measurable elements of the process and, further, derive from the basic information conversion technique of the sensor. That is, depending on the sensor, we will probably have differing measurands from the process. However, the range of measurands available is obviously closely linked to the type of (operating principle) of the sensor employed. Table 1.2-2, adapted from [7], defines the relevant measurands from a range of sensing technologies. The 'mapping' of these measurand/sensing pairs on to a manufacturing process is the basis of developing a sensing strategy for a process or system. The measurands give us important information on the:

- process (the electrical stability of the process, in electrical discharge machining, for example),
- effects of outputs of the process (surface finish, dimension, for example), and
- state of associated consumables (cutting fluid contamination, lubricants, tooling, for example).

Tab. 1.2-1 Forms of energy converted by sensors

Energy form	***Definition***
Atomic	Related to the force between nuclei and electrons
Electrical	Electric fields, current, voltage, etc.
Gravitational	Related to the gravitation attraction between a mass and the Earth
Magnetic	Magnetic fields and related effects
Mass	Following relativity theory ($E=mc^2$)
Mechanical	Pertaining to motion, displacement/velocity, force, etc.
Molecular	Binding energy in molecules
Nuclear	Binding energy in electrons
Radiant	Related to electromagnetic radiowaves, microwaves, infrared, visible light, ultraviolet, x-rays and γ-rays
Thermal	Related to the kinetic energy of atoms and molecules

Tab. 1.2-2 Process measurands associated with sensor signal types (after [7])

Signal output type	*Associated process measurands*
Mechanical (includes acoustic)	Position (linear, angular) Velocity Acceleration Force Stress, pressure Strain Mass, density Moment, torque Flow velocity, rate of transport Shape, roughness, orientation Stiffness, compliance Viscosity Crystallinity, structural integrity Wave amplitude, phase, polarization, spectrum Wave velocity
Electrical	Charge, current Potential, potential difference Electric field (amplitude, phase, polarization, spectrum) Conductivity Permittivity
Magnetic	Magnetic field (amplitude, phase, polarization, spectrum) Magnetic flux Permeability
Chemical (includes biological)	Components (identities, concentrations, states) Biomass (identities, concentrations, states)
Radiation	Type Energy Intensity Emissivity Reflectivity Transmissivity Wave amplitude, phase, polarization, spectrum Wave velocity
Thermal	Temperature Flux Specific heat Thermal conductivity

Finally, there are a number of technical specifications of sensors that must be addressed in assessing the ability of a particular sensor/output combination to measure robustly the state of the process. These specifications relate to the operating characteristics of the sensors and are usually the basis for selecting a particular sensor from a specific vendor, eg [7]:

- ambient operating conditions;
- full-scale output;
- hysteresis;
- linearity;
- measuring range;
- offset;
- operating life;
- output format;
- overload characteristics;
- repeatability;
- resolution;
- selectivity;
- sensitivity;
- response speed (time constant);
- stability/drift.

It is impossible to detail the associated specifications for the six sensing technologies under discussion here. A number of references have done this for specific sensors for manufacturing applications, eg, Shiraishi [8–10] and Allocca and Stuart [2]. Others are referenced elsewhere in this volume or reviewed in [11].

1.2.3 Basic Sensor Types

1.2.3.1 Mechanical Sensors

Mechanical sensors are perhaps the largest and most diverse type of sensors because, as seen in Table 1.2-2, they have the largest set of potential measurands. Force, motion, vibration, torque, flow, pressure, etc., are basic elements of most manufacturing processes and of great interest to measure as an indication of process state or for control. Force is a push or pull on a body that results in motion/displacement or deformation. Force transducers, a basic mechanical sensor, are designed to measure the applied force relative to another part of the machine structure, tooling, or workpiece as a result of the behavior of the process. A number of mechanisms convert this applied force (or torque) into a signal, including piezoelectric crystals, strain gages, and potentiometers (as a linear variable differential transformer (LVDT)). Displacement, as in the motion of an axis of a machine, is measurable by mechanical sensors (again the LVDT or potentiometer) as well as by a host of other sensor types to be discussed. Accelerometer outputs, differentiated twice, can yield a measure of displacement of a mechanism. Shiraishi [9] relies on a number of mechanical sensing elements to measure the dimensions of a workpiece. Flow is commonly measured by 'flow meters', mechanical devices with rotameters (mechanical drag on a float in the fluid stream) as well as venturi meters (relying on differential pressure measurement, using another mechanical sensor) to determine the flow of fluids. An excellent review of other mechanical sensing (and transducing) devices is given in [2].

Mechanical sensors have seen the most advances owing to the developments in semiconductor fabrication technology. Piezo-resistive and capacitance-based devices, basic building blocks of silicon micro-sensors, are now routinely applied to pressure, acceleration, and flow measurements in machinery. Figure 1.2-2a shows the schematics of a capacitive sensor with applications in pressure sensing (the silicon diaphragm deflects under the pressure of the gas/fluid and modifies the capacitance between the diaphragm and another electrode in the device). Using a beam with a mass on the end as one plate of the capacitor and a second electrode (Figure 1.2-2b), an accelerometer is constructed and the oscillation of the mass/beam alters the capacitance in a measurable pattern allowing the determination of the acceleration. Figure 1.2-3 shows a TRW NovaSensor®, a miniature, piezoresistive chip batch fabricated and diced from silicon wafers. These sensor chips can be provided as basic original equipment manufacturer (OEM) sensor elements or can be integrated into a next-level packaging scheme. These devices are con-

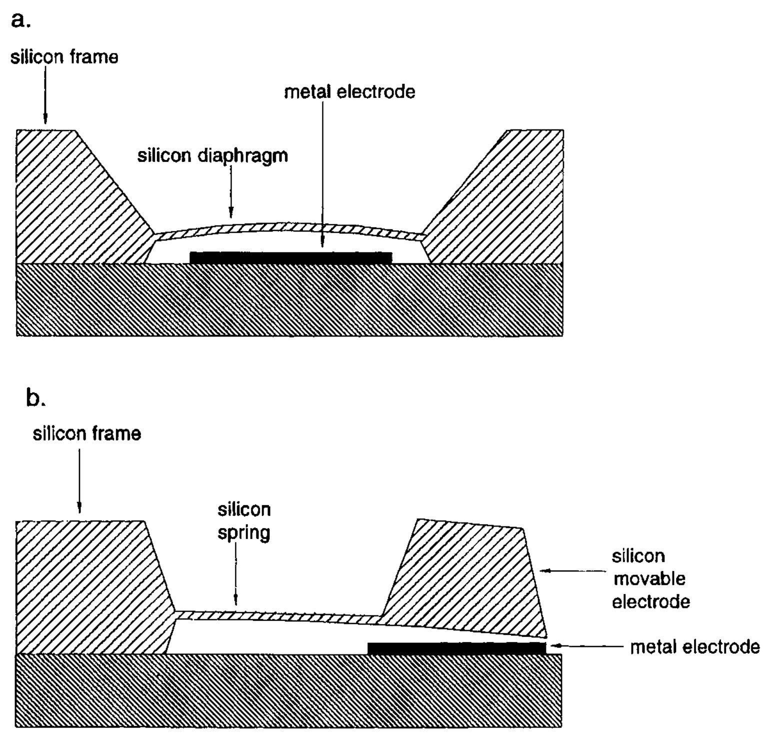


Fig. 1.2-2 Schematic of a capacitance sensor for (a) pressure and (b) acceleration

Fig. 1.2-3 Piezoresistive micro-machined pressure die. Courtesy of Lucas NovaSensor, 2000

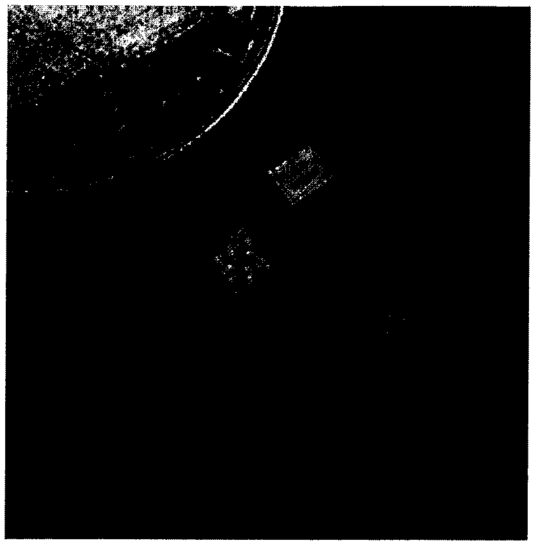
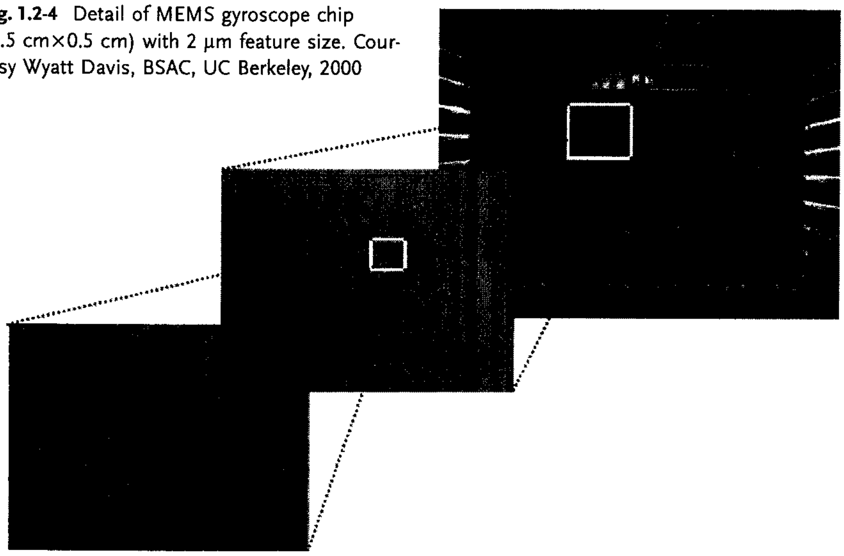


Fig. 1.2-4 Detail of MEMS gyroscope chip (0.5 cm×0.5 cm) with 2 μm feature size. Courtesy Wyatt Davis, BSAC, UC Berkeley, 2000



structed using conventional semiconductor fabrication technologies based on the semiconducting materials and miniaturization of very large scale integrated (VLSI) patterning techniques (see, for example, Sze [1] as an excellent reference on semiconductor sensors). The development of microelectromechanical sensing systems (so-called MEMS) techniques has opened a wide field of design and application of special micro-sensors (mechanical and others) for sophisticated sensing tasks. Figure 1.2-4 shows a MEMS gyroscope fabricated at UC Berkeley BSAC for use in positioning control of shop-floor robotic devices. In fact, most of the six basic sensor types can be accommodated by this technology. Accelerometers are built on these chips as already discussed. Whatever affects the frequency of oscillation of the silicon beam of the sensor can be considered a measurand. Coating the accelerometer beam with a material that absorbs certain chemical elements, hence changing the mass of the beam and its resonant frequency, changes this into a chemical sensor. Similar modifications yield other sensor types.

One particularly interesting type of micro-sensor for pressure applications, not based on the capacitance principles discussed above, is silicon-on-sapphire (SOS). This is specially applicable to pressure-sensing technology. Manufacturing an SOS transducer begins with a sapphire wafer on which silicon is epitaxially grown on the smooth, hard, glass-like surface of the sapphire. Since the crystal structure of the silicon film is similar to sapphire's, the SOS structure appears to be one crystal with a strong molecular bond between the two materials. The silicon is then etched into a Wheatstone bridge pattern using conventional photolithography techniques. Owing to its excellent chemical resistance and mechanical properties, the sapphire wafer itself may be used as the sensing diaphragm. An appropriate diaphragm profile is generated in the wafer to create the desired flexure of the diaphragm and to convey the proper levels of strain to the silicon Wheatstone bridge. The diaphragm may be epoxied or brazed to a sensor package. A more reliable method of utilizing the SOS technology involves placing an SOS wafer on a machined titanium diaphragm. In this configuration titanium becomes the primary load-bearing element and a thin (thickness under 0.01 in) SOS wafer is used as the sensing element. The SOS wafer is bonded to titanium using a process similar to brazing, performed under high mechanical pressure and temperature conditions in vacuum to ensure a solid, stable bond between the SOS wafer and the titanium diaphragm. The superb corrosion resistance of titanium allows compatibility with a wide range of chemicals that may attack epoxies, elastomers, and even certain stainless steels. The titanium diaphragm is machined using conventional machining techniques and the SOS wafer is produced using conventional semiconductor processing techniques. SOS-based pressure sensors with operating pressures ranging from 104 kPa to over 414 MPa are available.

Acoustic sensors have benefited from the developments in micro-sensor technology. Semiconductor acoustic sensors employ elastic waves at frequencies in the range from megahertz to low gigahertz to measure physical and chemical (including biological) quantities. There are a number of basic types of these sensors based upon the mode of flexure of an elastic membrane or bulk material in the sensor is employed. Early sensors of this type used vibrating piezoelectric crystal plates referred to as a quartz crystal microbalance (QCM). It is also called a thickness shear-mode sensor (TSM) after the mode of particle motion employed. Other modes of acoustic wave motion employed in these devices (with appropriate design) include surface acoustic wave (SAW) for waves travelling on the surface of a solid, and elastic flexural plate wave (FPW) for waves travelling in a thin membrane. The cantilever devices described earlier are also in this class.

1.2.3.2 Thermal Sensors

Thermal sensors generally function by transforming thermal energy (or the effects of thermal energy) into a corresponding electrical quantity that can be further processed or transmitted. Other techniques for sensing thermal energy (in the infrared range) are discussed under radiant sensors below. Typically, a non-thermal signal is first transduced into a heat flow, the heat flow is converted into a change in temperature/temperature difference, and, finally, this temperature difference is converted into an electrical signal using a temperature sensor. Microsensors employ thin membranes (floating membrane cantilever beam, for example). There is a large thermal resistance between the tip of the beam and the base of the beam where it is attached to the device rim. Heat dissipated at the tip of the beam will induce a temperature difference in the beam. Thermocouples (based on the thermoelectric Seebeck effect whereby a temperature difference at the junction of two metals creates an electrical voltage) or transistors are employed to sense the temperature difference in the device outputting an electrical signal proportional to the difference. Recent advances in thermal sensor application to the 'near surface zone' of materials for assessing structural damage (referred to as photo-thermal inspection) were reported by Goch et al. [12]. This review also covers other measurement techniques such as micromagnetic.

Thermal sensors are also employed in flow measurement following the well-known principle of cooling of hot objects by the flow of a fluid (boundary layer flow measurement anemometers). They can also be applied in thermal tracing and heat capacity measurements in fluids. All three application areas are suitable for silicon micro-sensor integration.

Thermal sensors have also found applicability traditionally in 'true-rms converters'. Root mean square (rms) converters are used to convert the effective value of an alternating current (AC) voltage or current to its equivalent direct current (DC) value. This is accomplished simply by converting the electrical signal into heat with the assistance of a resistor and measuring the temperature generated.

1.2.3.3 Electrical Sensors

Electrical sensors are intended to determine charge, current, potential, potential difference, electric field (amplitude, phase, polarization, spectrum), conductivity and permittivity and, as such, have some overlap with magnetic sensors. Power measurement, an important measure of the behavior of many manufacturing processes, is also included here. An example of the application of thermal sensors for true rms power measurement was included with the discussion on thermal sensors. The use of current sensors (perhaps employing principles of magnetic sensing technology) is commonplace in machine tool monitoring [11]. Electrical resistance measurement has also been widely employed in tool wear monitoring applications [8]. Most of the discussion on magnetic sensors below is applicable here in consideration of the mechanisms of operation of electrical sensors.

1.2.3.4 Magnetic Sensors

A magnetic sensor converts a magnetic field into an electrical signal. Magnetic sensors are applied directly as magnetometers (measuring magnetic fields) and data reading (as in heads for magnetic data storage devices). They are applied indirectly as a means for detecting nonmagnetic signals (eg, in contactless linear/ angular motion or velocity measurement) or as proximity sensors. Most magnetic sensors utilize the Lorenz force producing a current component perpendicular to the magnetic induction vector and original current direction (or a variation in the current proportional to a variation in these elements). There are also Hall effect sensors. The Hall effect is a voltage induced in a semiconductor material as it passes through a magnetic field. Magnetic sensors are useful in nondestructive inspection applications where they can be employed to detect cracks or other flaws in magnetic materials due to the perturbation of the magnetic flux lines by the anomaly. Semiconductor-based magnetic sensors include thin-film magnetic sensors (relying on the magnetoresistance of NiFe thin films), semiconductor magnetic sensors (Hall effect), optoelectronic magnetic sensors which use light as an intermediate signal carrier (based on Faraday rotation of the polarization plane of linearly polarized light due to the Lorenz force on bound electrons in insulators [1]) and superconductor magnetic sensors (a special class).

1.2.3.5 Radiant Sensors

Radiation sensors convert the incident radiant signal energy (measurand) into electrical output signals. The radiant signals are either electromagnetic, neutrons, fast neutrons, fast electrons, or heavy-charge particles [1]. The range of electromagnetic frequencies is immense, spanning from cosmic rays on the high end with frequencies in the 10^{23} Hz range to radio waves in the low tens of thousands of Hz. In manufacturing applications we are most familiar with infrared radiation (10^{11}–10^{14} Hz) as a basis for temperature measurement or flaw/problem detection. Silicon-on-insulator photodiodes and phototransistors based on transistor action are typical micro-sensor radiant devices [1] for use in these ranges.

1.2.3.6 Chemical Sensors

These sensors are becoming particularly more important in manufacturing process monitoring and control. It is important to measure the identities of gases and liquids, concentrations, and states, chemical sensors for worker safety (to insure no exposure to hazardous materials or gases), process control (to monitor, for example, the quality of fluids or gases used in production; this is especially critical in the semiconductor industry which relies on complex process 'recipes' for successful production), and process state (presence or absence of a material, eg, gas or fluid). Chemical sensors have been successfully produced as micro-sensors using semiconductor technologies primarily for the detection of gaseous species. Most of these devices rely on the interaction of chemical species at semiconductor surfaces (adsorption on a layer of material, for example) and then the change caused by the additional mass affecting the performance of the device. This was discussed under mechanical sensors where the change in mass altered the frequency of vibration of a silicon cantilever beam providing a means for measuring the presence or absence of the chemical and some indication of the concentration. Other chemical effects are also employed such as resistance change caused by the chemical presence, the semiconducting oxide powder- pressed pellet (so called Taguchi sensors) and the use of field effect transistors (FETs) as sensitive detectors for some gases and ions. Sze [1] gives a comprehensive review of chemical micro-sensors and the reader is referred to this for details of this complex sensing technology.

1.2.4 New Trends – Signal Processing and Decision Making

1.2.4.1 Background

Human monitoring of manufacturing processes can attribute its success to the ability of the human to distinguish, by nature of the physical senses and experience, the 'significant' information in what is observed from the meaningless. In general, humans are very capable as process monitors because of the high degree of development of sensory abilities, essentially noise-free data (unique memory triggers), parallel processing of information, and the knowledge acquired through training and experience. Limitations are seen when one of the basic human sensor specifications is violated; something happening too fast to see or out of range of hearing or visual sensitivity owing to frequency content. These limitations have always served as some of the justification for the use of sensors. Sensors, of course, are also limited in their ability to yield an output sensitive to an important input. Hence we need to consider the use of signal processing and along with that feature extraction. In most cases the utilization of any signal processing methodology has as its goal one or more of the following: the determination of a suitable 'process model from which the influence of certain process variables can be discerned; the generation of features from sensor data that can be used to determine process state; or the generation of data features so that the change in the performance of the process can be 'tracked. Figure 1.2-5 shows the path from process (and the source of the measurants) through the sensor, extraction of a control signal, and application to process control for both heuristic and quantitative methodologies.

An overview of signal processing and feature extraction is summarized in Rangwala [13] (Figure 1.2-6). The measurement vector extracted from the signal representation from the sensor (basic signal conditioning) is the 'feedstock' for the feature selection process (local conditioning) resulting in a feature vector. The characteristics of the feature vector include signal elements that are sensitive to the parameters of interest in the process. The 'decision-making' process follows. Based on a suitable 'learning' scheme which maps a teaching pattern (ie, process characteristics that we desire to recognize) on to the feature vector, a pattern association is generated. The 'pattern association' contains a matrix of associations between

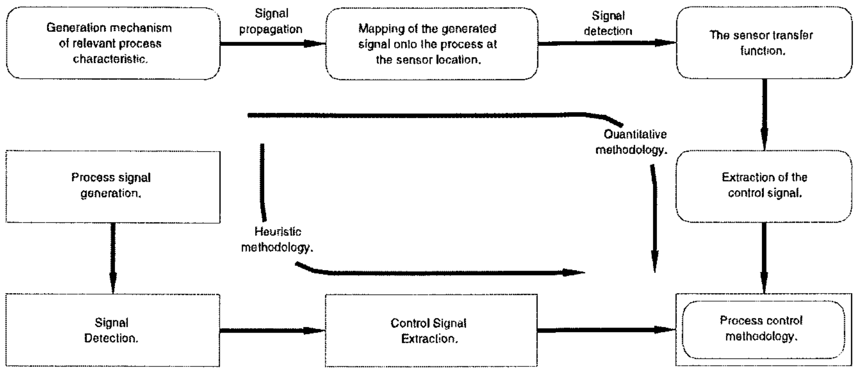


Fig. 1.2-5 Quantitative and heuristic paths for the development of in-process monitoring and control methodologies

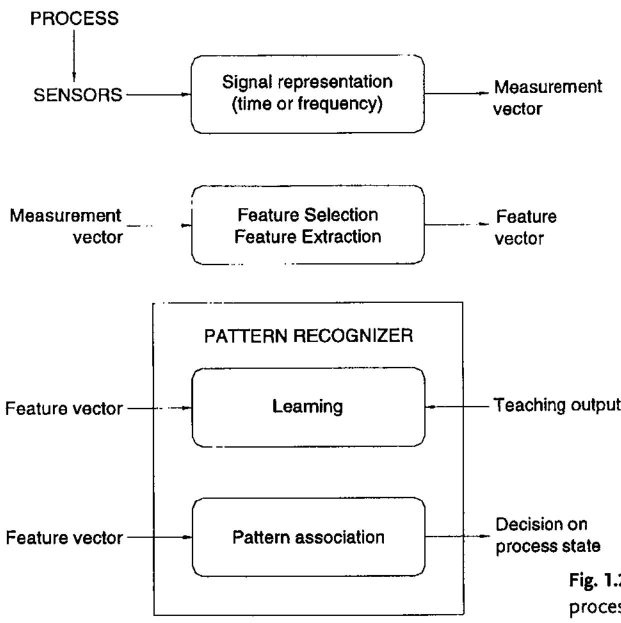


Fig. 1.2-6 An overview of signal processing and feature extraction

the desired characteristics and features of the sensor information. In application, the pattern association matrix operates on the feature vector and extracts correlation between features and characteristics – these are taken to be 'decisions' on the state of the process if the process characteristics are suitably structured (eg, tool worn, weld penetration incomplete, material flawed, etc.). In Figure 1.2-6, the measurement vector is the signal in the upper left corner. The feature vector in this case consists of the mean value shown in the upper right corner. Decision making, based on experience or 'training', sets the threshold at a level corresponding to excessive tool wear. When the feature element 'mean value' crosses the threshold a 'decision' is made that the tool is worn. The success of this strategy depends upon the degree to which the mean value of the sensor output actually represents the state (and progress) of tool wear.

1.2.4.2 Sensor Fusion

With a specific focus for the monitoring in mind, researchers have developed over the years a wide variety of sensors and sensing strategies, each attempting to predict or detect a specific phenomenon during the operation of the process and in the presence of noise and other environmental contaminants. A good number of these sensing techniques applicable to manufacturing have been reviewed in the early part of this chapter. Although able to accomplish the task for a narrow set of conditions, these specific techniques have almost uniformly failed to be reliable enough to work over the range of operating conditions and environments commonly available in manufacturing facilities. Therefore, researchers have begun to look at ways to collect the maximum amount of information about the state of a process from a number of different sensors (each of which is able to provide an output related to the phenomenon of interest although at varying reliability). The strategy of integrating the information from a variety of sensors with the expectation that this will 'increase the accuracy and ... resolve ambiguities in the knowledge about the environment' (Chiu et al. [14]) is called sensor fusion.

Sensor fusion is able to provide data for the decision-making process that has a low uncertainty owing to the inherent randomness or noise in the sensor signals, includes significant features covering a broader range of operating conditions, and accommodates changes in the operating characteristics of the individual sensors (due to calibration, drift, etc.) because of redundancy. In fact, perhaps the most advantageous aspect of sensor fusion is the richness of information available to the signal processing/feature extraction and decision-making methodology employed as part of the sensor system. Sensor fusion is best defined in terms of the 'intelligent' sensor as introduced in [15] since that sensor system is structured to utilize many of the same elements needed for sensor fusion.

The objective of sensor fusion is to increase the reliability of the information so that a decision on the state of the process is reached. This tends to make fusion techniques closely coupled with feature extraction methodologies and pattern recognition techniques. The problem here is to establish the relationship between the measured parameter and the process parameter. There are two principal ways to encode this relationship (Rangwala [13]):

- theoretical – the relationship between a phenomenon and the measured parameters of the process (say tool wear and the process); and
- empirical – experimental data is used to tune parameters of a proposed model.

As mentioned earlier, reliable theoretical models relating sensor output and process characteristics are often difficult to develop because of the complexity and variability of the process and the problems associated with incorporating large numbers of variables in the model. As a result, empirical methods which can use sensor data to tune unknown parameters of a proposed relation are very attractive. These types of approaches can be implemented by either (a) proposing a relationship between a particular process characteristic and sensor outputs and then using experimental data to tune unknown parameters of a model, or (b) associating patterns of sensor data with an appropriate decision on the process state without consideration of any model relating sensor data to the state. The second approach is generally referred to as pattern recognition and involves three critical stages (Ahmed and Rao [16]):

- sampling of input signal to acquire the measurement vector;
- feature selection and extraction;
- classification in the feature space to permit a decision on the process state.

The pattern recognition approach provides a framework for machine learning and knowledge synthesis in a manufacturing environment by observation of sensor data and with minimal human intervention. More important, such an approach allows for integration of information from multiple sources (such as different sensors) which is our principal interest here.

Sata et al. [17, 18] were among the first researchers to propose the application of pattern recognition techniques to machine process monitoring. They attempted to recognize chip breakage, formation of built-up edge and the presence of chatter in a turning operation using the features of the spectrum of the cutting force in the 0–150 Hz range. Dornfeld and Pan [19] used the event rate of the rms energy of an acoustic emission signal along with feed rate and cutting velocity in order to provide a decision on the chip formation produced during a turning operation. Emel and Kannatey-Asibu [20] used spectral features of the acoustic emission signal in order to classify fresh and worn cutting tools. Balakrishnan et al. [21] use a linear discriminant function technique to combine cutting force and acoustic emission information for cutting tool monitoring.

The manufacturing process may be monitored by a variety of sensors and, typically, the sensor output is a digitized time-domain waveform. The signal can then be either processed in the time domain (eg, extract the time series parameters of the signal) or in the frequency domain (power spectrum representation). The effect of this is to convert the original time-domain record into a measurement vector. In most cases, this mapping does not preserve information in the original signal. Usually, the dimension of the measurement vector is very high and it becomes necessary to reduce this dimension due to computational considerations. There are two prevalent approaches at this stage: select only those components of the measurement vector which maximize the signal-to-noise ratio or map the measurement vector into a lower dimensional space through a suitable transformation (feature extraction). The outcome of the feature selection/extraction stage is a lower dimensional feature vector. These features are used in pattern recognition techniques and as inputs to sensor fusion methodologies. This was illustrated in Figure 1.2-6.

1.2.5 Summary

The subject of sensors for manufacturing processes is well covered in other chapters of this book. The material in this chapter serves to acquaint the reader with the classification of sensor systems and some of the measurands that are associated with these sensors. How these sensor types and measurands map on to the various manufacturing processes will be the subject of the rest of the text. One important factor in the implementation of sensors in manufacturing is clearly the rapid growth of silicon micro-sensors based on MEMS technology. This technology already allows the integration of traditional and novel new sensing methodologies on to miniaturized platforms, providing in hardware the reality of multi-sensor systems. Further, since these sensors are easily integrated with the electronics for signal processing and data handling, on the same chip, sophisticated signal analysis including feature extraction and intelligent processing will be straightforward (and inexpensive). This bodes well for the vision of the intelligent factory with rapid feedback of vital information to all levels of the operation from machine control to process planning.

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