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● *Paper*

TOWARD AN INTELLIGENT MACHINE TOOL FOR FLEXIBLE MANUFACTURING

MARK L. NAGURKA* and PAUL J. ENGLERT†

*Department of Mechanical Engineering, Carnegie-Mellon University, Schenley Park, Pittsburgh, PA 15213, U.S.A. and †AT&T Bell Laboratories, Whippany, NJ 07981, U.S.A.

The need to manufacture accurate and inexpensive components in small batches has spurred the development of flexible manufacturing systems (FMSs). This paper reviews the basic components of FMSs and describes efforts currently underway at Carnegie-Mellon University to create an autonomous machine tool for the factory of the future. The machine tool would operate under computer control for part handling (manipulation), part fixturing, and metal cutting. This work argues for model-based engineering approaches integrated with expert systems that attempt to encapsulate the craftsmanship skills of human expert machinists.

INTRODUCTION

During the last decade, the United States and other Western industrial nations have experienced a significant lag in productivity. In these traditionally manufacturing-based economies, there has been a shift away from mass-production and toward the production of items in small batches, e.g. from 1 to 100 items. The prominence of batch manufacturing is evident in many industries, including the aerospace industries. Its importance is even being felt by industries with strong historical connections to mass-production such as the automotive industries. Pressure to offer more consumer choice has prompted smaller batches and rapid turn-around production of many items.

Batch manufacturing relies upon the skill of the human worker to achieve the flexibility required to get "a good first part right the first time". Yet, today there is a nationwide shortage of skilled craftsmen, including expert machinists, and projections based on apprenticeship appointments point to further dwindling numbers. To be a competitive manufacturing power, the United States must make automating the operations of batch manufacturing a high national priority.

In the past, industries have embraced hard automation, a key feature of mass production. In hard automation, there is emphasis on throughput (a time domain variable, i.e. number of items per time) and on accuracy, but not on flexibility. In contrast, the goal of flexible manufacturing is to offer flexibility without sacrificing accuracy, while hopefully maintaining throughput. Throughput, though, is not the principal goal, and industry today could be very competitive if its factories excelled in producing accurate parts with flexible manufacturing but could do so only in medium size lots.[2] In the factory of the future, machine tools will balance the requirements of throughput, accuracy, and flexibility.

In the Flexible Manufacturing Laboratory at Carnegie-Mellon University (Fig. 1) research is being conducted to create a factory floor machine tool that would offer flexibility and accuracy. This intelligent machine tool would operate unattended and would function as a robotic part-handling device, flexible fixture, and automated tooling system for batch machining of metal parts of medium size.

Flexible manufacturing systems

Flexible manufacturing systems (FMSs) or cells represent efficiently grouped machine tools for batch manufacturing. The early applications in the late 1960s consisted of only one or two hard-wired machines with simple conveyor systems. During the 1970s, computer control enabled the design of larger systems with different machines carrying out a variety of processes (e.g. machining, grinding, measuring). Today, FMSs typically consist of several machines coupled by sensor-based robots and controlled by an integrated computer system. Users of such systems realize that individual machine tools must be equipped with reliable and rugged sensors and the

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Fig. 1. The flexible manufacturing laboratory at Carnegie-Mellon.

host software must be responsive to unexpected problems.[7] Only then can larger autonomous systems be installed that will operate unattended for long periods. In the factory of the future, batch manufacturing will require some component of reflexive adaptation to a host of short-term minor disturbances. There will be a balance between 'proactive' and 'reactive' strategies to account for factors that work against any predetermined plan.

Over the last decade, many industries have realized the need of modern manufacturing to react quickly and economically to changing market demands. There has been widespread advertisement of major industries installing FMSs. Some of these systems have failed because of incompatibility of devices (machine tools, robots, etc. from different vendors). Some have failed for lack of appropriate software orchestrating the equipment. (Recently, promising strides in the area of governing information flow in manufacturing cells have been made at Carnegie-Mellon by the development of the Cell Management Language, CML.[1])

Successful systems seem to limit variability dramatically, i.e. they make the machining processes as deterministic as possible. For example, feed rates and machine tool speeds are set conservatively in an attempt to make the cutting process predictable; incoming parts are closely screened for anomalies so that the stock removal process may be more predictable; part material is constrained to a limited range of surface grades and prefabrication forms; schedules are carefully selected to provide a match between the parts in the queues and the desired running time; and part programs are painstakingly debugged during fully manned operations. In short, successful systems operate within constraints that limit flexibility. Furthermore, many of the implementations are efficient only for large batch sizes and for accuracies less than 0.005 in (which compares to accuracies attainable by human machinists on the order of 0.0002 in commonplace today).

To create a flexible, autonomous factory, human experience and manual dexterity must be understood and, in some way, duplicated. The advent of cheaper, factory-floor-compatible computers and the development of more adaptable robotic manipulators and more reliable sensors make this goal feasible.

Batch manufacturing and craftsmanship

In batch manufacturing, the skills of the human craftsman are needed to set up the machine tools, to guide them through the machining processes, and to inspect, gauge, and assemble the finished parts. These skills are especially crucial for the batch manufacture of components that have demanding sculptured surfaces and stringent accuracy requirements.

The craftsman brings vast experience and hand/eye coordination to a broad range of tasks (manufacturing, assembly, repair) in the factory. Many of these manufacturing skills involve intuition that has been developed through a wide array of experience over a long period of time, and is subtly displayed. For example, based on experience, an expert machinist will typically use one machine of many supposedly equivalent machines for a certain operation. One might say that, not unlike people, every machine has a personality which machinists can discern over time.

A considerable amount of craft knowledge must be "bottled" before computer-controlled mechanical systems will be able to take over jobs that currently only humans can perform. One branch of computer science research whose aim is to capture this knowledge is knowledge engineering. Much of the data collection necessary for the knowledge engineering of machinists has been carried out by researchers at Carnegie-Mellon via photographs, videotapes, and machine-in-process interviews with skilled machinists[6,7] (see Fig. 2). The general hypothesis of this work in protocol analysis is as follows. When skilled machinists set up and operate computer numerically controlled (CNC) machine tools, they depend upon craft knowledge and rules-of-thumb to get a good part right the first time. To create autonomous factories for small-batch production of high-accuracy components, it is imperative to learn about machinists' knowledge, document it, and then create software that can emulate craftsmen.

Long-term objective

The design and construction of an autonomous machine tool that will do the instinctual work of a craftsman is a monumental task. Although it will most likely not occur in the near future, there are two trends that are evolving (albeit slowly) that will hopefully converge. First, manufacturing is becoming more deterministic by designing for manufacturability, relying on better NC programming aids, and using more consistent work and tool materials. Second, machine tools are becoming smarter and more programmable and, although they are far from matching the master craftsman, they are starting to work within a more predictable manufacturing domain.

The development of integrated, intelligent, sensor-based machine tools is a long-term objective of current research efforts.

PART HANDLING

Part handling by robots is the first step in automated machining. Ideally, a robotic manipulator would identify and acquire a piece of stock, and then proceed to manipulate it into a desired position and orientation for subsequent fixturing and machining. To accomplish this goal, reconfigurable grippers with advanced sensing capabilities and control strategies are required. Despite impressive strides in research laboratories worldwide toward the development of actively controlled robotic hands, there has been minimal industrial endorsement and utilization of such devices.

Robotic arms, wrists, and hands

The first industrial robots were used primarily as stand-alone machines for painting, spot welding, or pick-and-place work in which parts were moved from

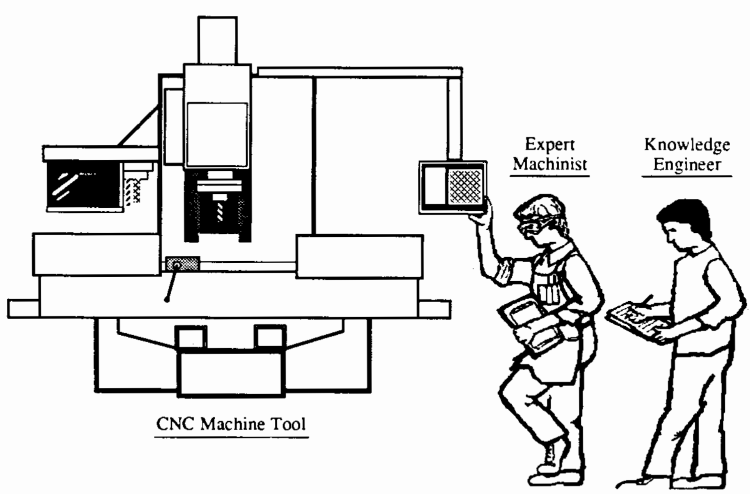

Fig. 2. Knowledge engineer observing machinist's planning actions at the machine tool.

one location to another without much attention to how they were picked up or put down. For pick-and-place work, simple beak-like grippers (such as parallel-jaw devices) were used and the ability of a robot to grasp and manipulate parts was at best equal to that of a person using fireplace tongs.

Since then, robots have been put to work in more challenging applications with fragile objects of complicated shape. Robots can perform tasks that place stringent demands on accuracy, such as assembling parts or fitting them into clamps and fixtures. Once a part has been picked up, it must be held securely and in such a way that the position and orientation remain known accurately. While an object is being manipulated during, say, an assembly task, forces arise between the object held by the robot and the mating parts. For assembly, the object should not slip and the gripper should be compliant enough to prevent contact forces from doing damage.

Some machine tool tasks can be performed by a robotic arm, primitive gripper, and a special compliant wrist, known as a remote center of compliance (RCC) wrist. Essentially, an RCC wrist consists of two plates separated at an angle by stiffness elements. One plate is fitted to the robotic arm and the other is connected to the gripper such that it can float with respect to the arm. The RCC is especially suitable for assembly tasks where a peg held by a gripper is inserted into a hole. By choosing an appropriate design (i.e. angle and stiffness), it is possible to project the center of compliance out to the tip of the peg in such a way that initial contact between the peg and a chamfered hole produces no tilting and consequently no jamming.[3]

The research community (at major universities such as M.I.T., Stanford, Utah, Pennsylvania, and elsewhere) is currently actively engaged in developing functional, dextrous robotic hands. This activity represents, in some sense, a natural evolution of robotic part handling in which the progression has been the development of simple pick-and-place arms to the development of more controllable arms with grippers mounted on RCC wrists. However, the increased dexterity and flexibility of such hands is obtained at an expense, i.e. they are more complex, difficult to control, and contain many delicate components, and from an industrial viewpoint are rather weak.

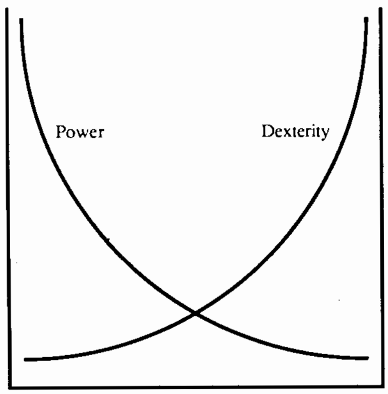

Fig. 3. Tradeoff plot of power vs. dexterity.

Figure 3 shows that there is an inherent trade-off between dexterity and the power that can be delivered in a manufacturing task by arms, wrists, and fingers.[8] Dexterous tasks require active fingers but at a loss of power, as might be measured by gripping force or interaction force. At the other extreme, heavy-duty pick-and-place tasks are likely to lack dexterity. In short, a robotic hand cannot possess both great power and dexterity, where dexterity is measured by the controllable degrees-of-freedom and the accuracy of placement. The same is true of human hands; we cannot finely manipulate large metal objects in our fingertips. Fingers are used for light, delicate manipulations. If we work with heavy objects we use our hands and forearms in cupping motions without finger motions, or use special-purpose tools.

Many manufacturing tasks, such as pick-and-place operations, can be performed using current industrial robotic arms without any kind of active wrists or active fingers (represented towards the left in Fig. 3). Some manufacturing tasks require local repositioning of a tool, and can be performed with robots equipped with RCC wrists. We are familiar with such tasks when holding a hammer or wrench. The fingers adopt a fairly passive grip around the object and then local repositioning is done at the wrist (corresponding to the middle of Fig. 3). Dexterity is thus increased, but experience shows that power is sacrificed. Finally, there are many delicate manufacturing tasks where actively controlled fingers are needed. One of the best examples is fine assembly, for instance, in threading a nut onto a bolt (with these tasks represented toward the right in Fig. 3).

Sensors

A major limitation of present day robots is their lack of reliable and rich sensory input. Position-sensing and force-sensing robots are slowly making their transition from research laboratories to industrial environments, but at present implementation is far from widespread. Today's vision systems are relatively primitive, although systems are available and in use with some robots.

For robotic hands, sensors at the joints can supply data regarding orientation of articulated fingers. Sensors at the fingerpads, or along the volar surface of the fingers can provide contact information, such as slip, stick-slip, vibration characteristics, and force. These sensors must have a high bandwidth response and be rugged enough to sustain applied loads, including impact-type loads. Linear variable differential transformers (LVDTs), rotary variable differential transformers (RVDTs), and a variety of position encoders can be used to measure displacement, accelerometers (inertial-mass and piezoelectric) can be used to measure acceleration, strain gages can be used to measure strain and hence stress, and thermocouples can be used to measure temperature. Data from these sensors generally require some signal processing and analog-to-digital conversion. Data from sensor arrays—such as pressure-sensitive arrays for fingerpads and palm, optical arrays, and actively stimulated piezoelectric devices—require considerable signal processing, usually accomplished by a dedicated microprocessor that communicates over serial or parallel lines with a higher level computer such as the robot controller. These advanced sensors are mostly confined to research laboratories, although some pressure-sensitive arrays are beginning to be marketed for industrial use.

Vision sensors can provide information for manipulation. Vision feedback can be used to detect obstacles and to ensure that parts have been grasped appropriately. Computer vision first appeared in university laboratories in the early 1960s, but it did not become sufficiently practical to be considered a serious tool in manufacturing until the late 1970s with the development of special purpose computers that could process binary pictures in reasonable times. In essence, these vision modules were the first CNC controllers for machine vision.

Individual sensor information, however, provides only partial information and thus an important thrust of research in active robotic hands is the integration of information from a number of sensors. The use of a number of sensors in parallel gives robustness to the control, but may tax available (and realistic) computer processing power.

PART WORKHOLDING

Precise part workholding is no less important than accurate part manipulation for the successful completion of part setup in FMSs. A workpiece must be properly positioned into a fixture, and subsequently rigidly clamped to achieve accurate machining results. Part manipulation and clamping are quite analogous. A representation of the part–machine tool–workholding device relationships as they correspond to machining is shown in Fig. 4.

A machine tool and a robotic arm are similar in the sense that both are physically the largest members (in manipulation and metal cutting tasks, respectively) and provide for gross motion capabilities. Briefly stated, a workholding device is any mechanism or structure that is used to maintain a fixed relation between the workpiece and the cutting tool. Wrists, hands, and fingers are comparable to workholding devices because they are the direct interface between the gross motion machines and the workpiece. Figure 5 lists some of the major attributes of the part–machine tool–workholding device triangle (of Fig. 4).

A fixture is a device that may be used to properly orient and rigidly clamp a rough stock or cast part for machining to close tolerances. In some instances, specialized fixtures are used that resemble human or robotic hands and fingers. Figure 6 shows a fixture[4] developed at Carnegie-Mellon that is used to clamp complex turbine blade shapes by the pneumatic actua-

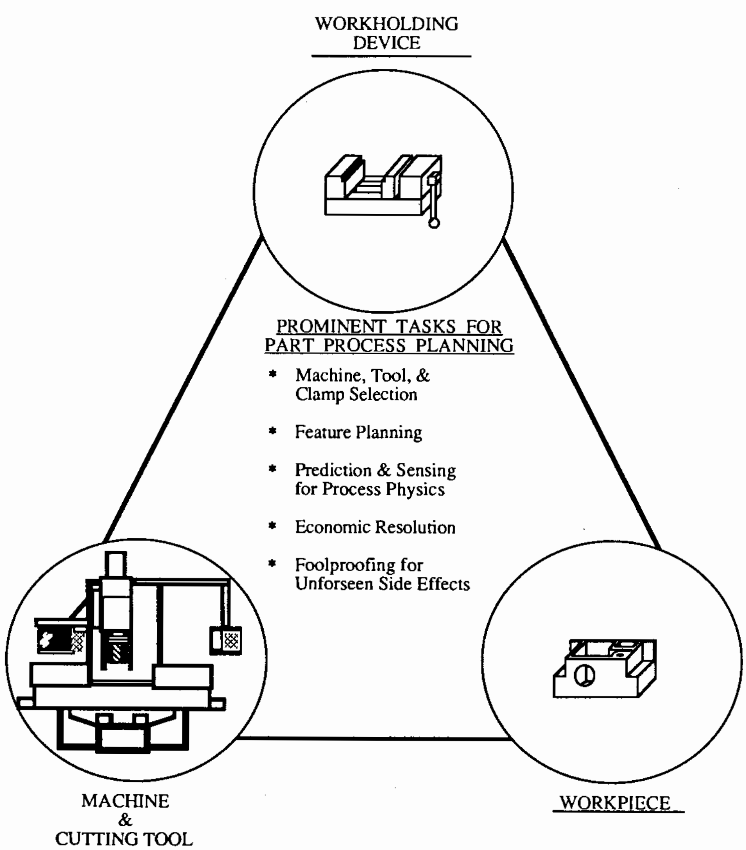

Fig. 4. Part–machine tool–workholding device triangle.

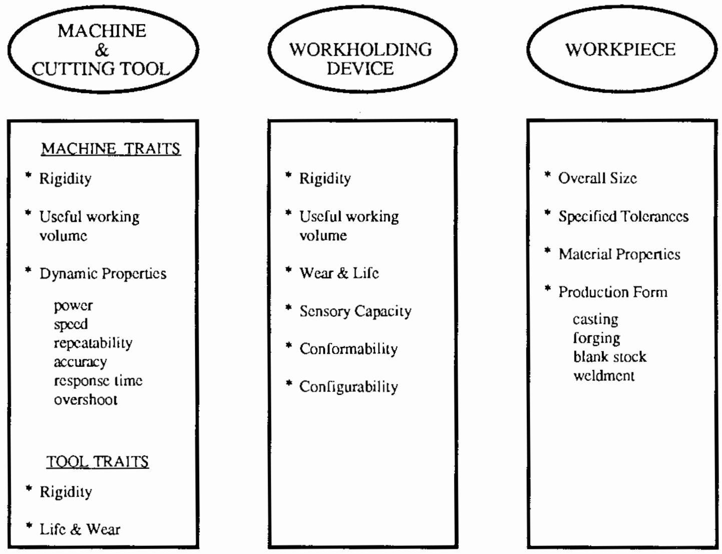

Fig. 5. Attributes of components of the part–machine tool–workholding device triangle.

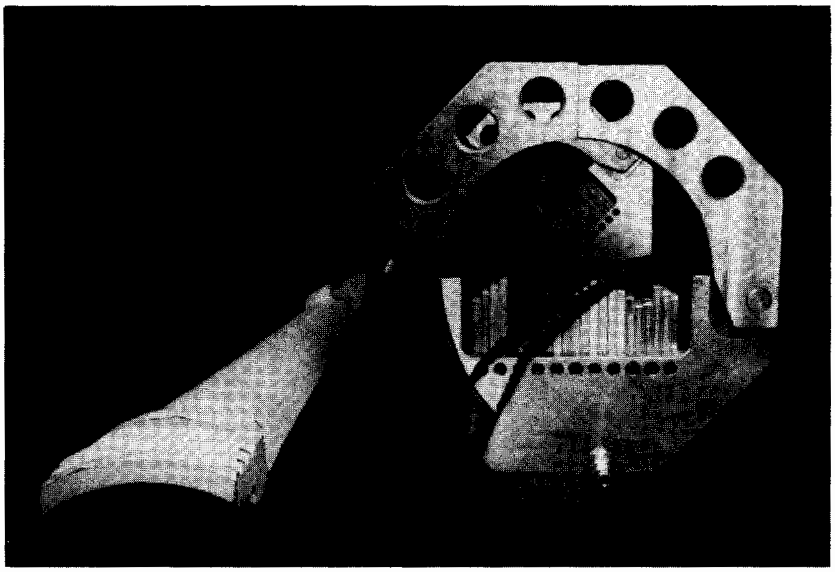

Fig. 6. Turbine blade fixture.[4]

tion of steel fingers to conform to the underside of the blade.

As in manipulation, sensing plays an important role in workholding. For example, a human machinist uses force feedback to determine the proper torque that should be applied to a vise to clamp a part. This feedback needs to be duplicated in automated clamping systems to obtain accurately machined parts. As an illustration of how sensors and clamps may be integrated, the system shown in Fig 7 has been developed. A hydraulic clamp is first remotely locked into a specialized fixture table by means of expandable split bushings. High pressure fluid routed to the swing clamp then causes it to pull down upon the part and build up force. Strain gages mounted on the clamping stud feed back calibrated force signals to a microprocessor. When the applied force equals the force preset by a user, the clamp's electrical control valve is closed off so that further pressure increases from the pump do not affect the force applied to the part. This clamping system is currently being integrated into a machining cell that includes a robot for part and clamp loading, a CNC machining center, and a vision-based gaging station (see Fig. 8).

PART METAL CUTTING

After the workpiece has been manipulated into a fixture and clamped, it is ready to be machined. As with manipulation and clamping, the metal-cutting process must be carefully monitored to ensure safety and accuracy. Machinists employ their senses and intuition to choose, typically conservatively, proper tool-cutting speeds and feed rates to account for the unpredictable nature of metal cutting. Cutting tools wear and sometimes break. Human craftsmen safely operate the machines, adjusting speeds and feed rates,

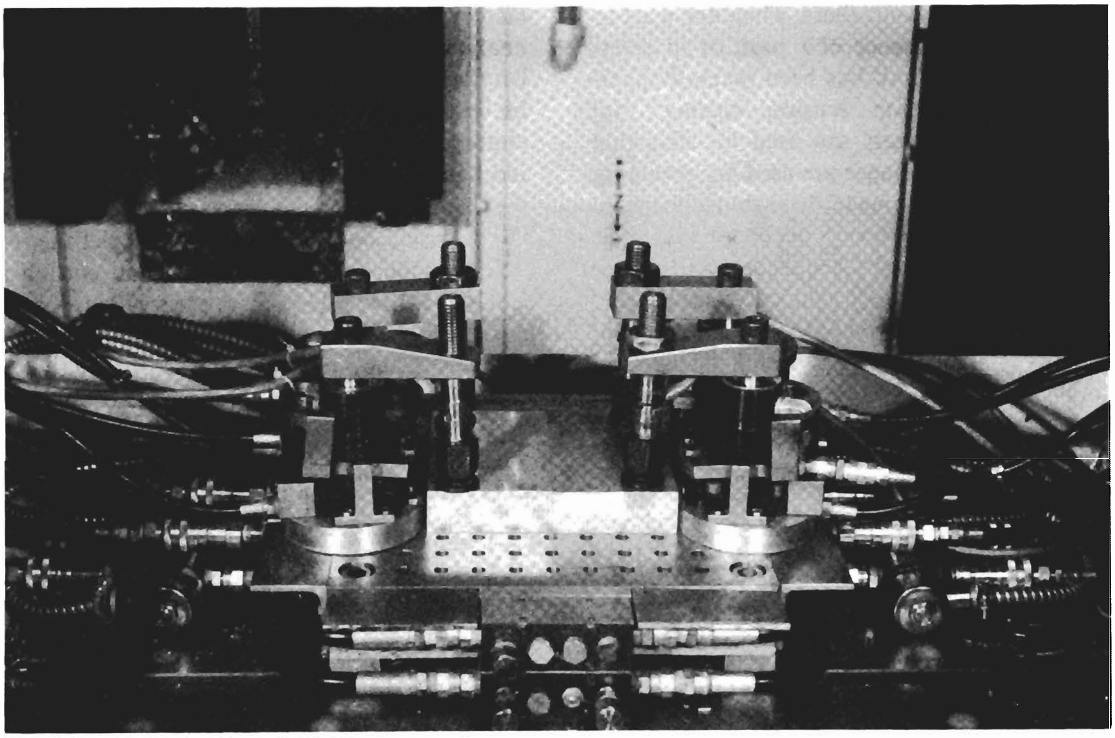

Fig. 7. Remotely securing clamping device.

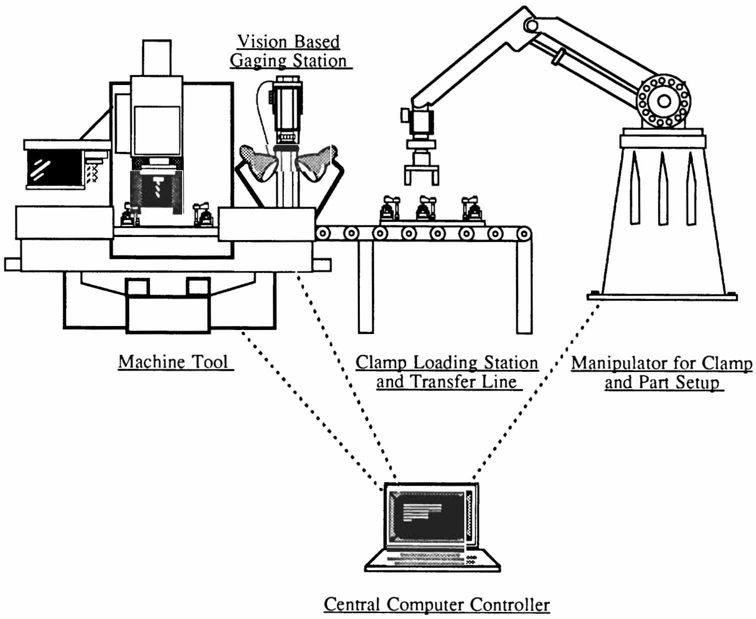

Fig. 8. FMS development at Carnegie-Mellon.[7]

to maximize tool life and thereby minimize tool changeover. In the process, machinists assess the potential life of a tool, detect any nuances in vibration and chip formation, and correctly cut metal per design specifications. Cutting metal is an art; the end product will be judged on the quality of the machining. However, in achieving the final product, a host of critical adjustments are made to ensure safety and economy (i.e. minimizing scrap and rework, and minimizing time).

To automate part metal cutting, human senses, judgements, planning, and actions must be imitated. A variety of sensors with a wide range of capabilities are needed to provide feedback during metal cutting. This sensor information must be integrated via some kind of central processor that will carry out the primitives of planning while satisfying task goals. Finally, the correct settings for machine tool speeds, feed rates, and other parameters must be made.

Most previous work on automating metal cutting has focused on acquiring sensor data. Binary sensors, including microswitches and optical and magnetic switches, are generally inexpensive, rugged and easy to interface with machine controllers. They are used to sense the presence or absence of a part, or to determine if a certain travel limit has been reached. Thermocouples are used for sensing cutting tool temperatures, accelerometers are used for detecting tool vibration, and strain gages are used for obtaining tool stresses and strains. Some of these transducers are fitted to the cutting tool and, with the use of a slip ring, feed back their signals to a microprocessor. Electrical and mechanical noise caused by the environment and the machine tool itself often make it difficult to obtain clear signals. Noncontact systems employing vision, acoustic, and infrared sensors are under development and complement information obtained from contact sensors.

Ultimately, the sensor data need to be integrated in a process known as "sensor fusion", in which signals are combined appropriately and inconsistent data are weeded out by using human information and knowledge embedded in a rule-based expert system. The expert system can also contain rules regarding planning, diagnosis, and action. These systems are under development at major research centers, but are far from being implemented. Hardware limitations exist because of sensors with finite resolution and computers with finite processing speeds. Software limitations exist because of inadequate languages for expert systems (i.e. today's interpretive languages are slow and not as portable as procedural languages) and incomplete understanding of human knowledge. As these limitations are surmounted, the goal of intelligent and automated metal part cutting will become realizable.

CONCLUSION

Some tasks involved in intelligent machining for the factory of the future may be approached by using analytical means, some may be approached by using heuristic-based reasoning techniques, and some may be best solved by a combination of the two solution strategies. Models based on the first principles of mechanics (kinematics, dynamics, solid mechanics), thermodynamics (heat transfer), and other engineering disciplines are being used to predict the results of different manipulation, fixturing and cutting process situations. In addition, interviews with expert machinists are exposing some of the thought processes associated with their planning and sensory activity during part setup and machining. These two pools of information need to be integrated into a coherent framework to create a favorable environment for intelligent, automated machining.

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