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Fuzzy Logic Control of Robotic Deburring Process Using Acoustic Emission Feedback

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Abstract

Burrs, created when metals deform plastically, are by-products of most machining processes. The increasing requirements of precision and reliability in manufacturing processes have led to the development of systems for automated deburring. In this paper the motivations and requirements for automated robotic deburring are discussed. Also, the feasibility of automating the deburring process using fuzzy logic controller is investigated. In implementing the fuzzy logic controller, particular attention is paid to the acoustic emission sensing for the characterization and feedback control of the burr removal process. The results of the experiments reveal the rule based control scheme based on fuzzy logics can be a good alternative to traditional control schemes.

1 Introduction

Burr formation is an unavoidable and undesirable by-product of most metal cutting or shearing operations due to the plastic deformation of metals. Deburring is typically done by human laborers. They move a motor-driven tool along the part, trying to establish a small, constant chamfer along the part edge. In the process, they use their senses of vision and touch, and their previous experience to ensure that the entire burr is removed. It may sometimes take several passes to get satisfactorily deburred edge.

Improving the quality and efficiency of deburring is of major concern to manufacturers. Deburring is labor intensive and can represent as much as 35 percent of the total component cost [6]. In addition, deburring is commonly a dirty, noisy and monotonous job with high personnel turnover rate [10]. These reasons have motivated the development of automated deburring systems. To allow for the required flexibility of today's manufacturing cell, these systems are being implemented using computer numerical control machines (CNC) or industrial robots.

Simple open loop deburring is not a feasible alternative due to the uncertainties in burr size and part demensions, and due to the limited accuracy of robots. Thus, monitoring of the deburring process with some sort of sensor is neccessary. If the sensor output can be realted to the chamfer size, one can obtain a deburred part with little variation in the size of the chamfer by implementing a controller using the sensor output as a feedback signal.

Force sensors have been used predominantly in closed loop deburring applications. In this study, however, the use of acoustic emission (AE) feedback for robotic deburring has been investigated, and the results are presented and discussed.

Modern control theory has proven to be very successful in areas where systems are well defined, but it has fallen short to cope with the practicalities of many industrial processes in spite of the development of a very large body of mathematical knowledge [13].

Complexities of processes, presence of non-linearities, variations in model parameters, poor quality of available measurements, and limited computer power are some of the reasons that account for the difficulties in implementing rigorous control algorithms in real industrial applications. Despite this, in many cases these systems are effectively controled by human operators by qualitative reasoning about the behavior of the process.

Zadeh [16] proposed the use of fuzzy algorithms based on fuzzy set theory as a means of incorporating the qualitative and approximate characteristics of human decision-making into automated controllers. Since then, fuzzy control has emerged as one of the most active and promissing areas for research in the application of fuzzy set theory and control in general. Current applications of fuzzy control include elevator control, water quality control, automatic train operation systems, automobile transmission control, and nuclear reactor control [9].

Fuzzy logic cntrol is a knowledge based control strategy that is suitable when it is impossible to formulate an analytical model of the process to be controlled, or when specification of a precise measure of performance is not neccessary. The fuzzy linguistic control can be applied to manufacturing processes such as deburring whose complexity exeeds the limitations of analytic modeling tools.

In this paper, the feasibility of implementing fuzzy logics controller using AE feedback for automation of deburring process is investigated.

2 Acoustic Emission Feedback

Acoustic emission is a recently developed methodology for fault diagnosis and location in nondestructive testing and process monitoring. It refers to the stress wave generated by a solid undergoing phase transitions, plastic deformation or fracture. These phenomena cause a dynamic variation of stress and strain fields in the medium which propagate as stress waves. These waves travel to the surface of the medium originating minute displacements detectable by a sensitive piezoelectric crystal that transforms the displacement or velocities into an electric signal which is then amplified and processed. Acoustic emission has been shown to be sensitive to different characteristics in manufacturing including chip formation, tool wear and fracture monitoring, and friction and contact phenomena for surfaces [2]. The power of the acoustic emission signal during machining is a function of the material properties, tool geometry and process parameters. The signal depends mostly on the material removal rate (MRR), sliding friction between chip and tool rake surface, and sliding friction between workpiece and tool flank surface [12]. For operations such as grinding, surface finishing and deburring, where the chip size is significantly smaller than the tool/workpiece contact area, the power of the AE signal depends mainly on the MRR. Kannatey-Asibu and Dornfeld [5] showed that the AE signal is linearly proportional to the MRR.

Cai and Dornfeld [3] first explored the potential use of AE for monitoring grinding. In this work, the sensitivity of the AE signal to wheel approach, contact and sparkout was determined. Masaki [12] evaluated the sensitivity of the AE signal to the different parameters involved in a chamfering operation in the presence of small burrs. His results showed that the AE-RMS energy signal is linearly proportional to the resulting chamfer on a workpiece, provided that the burrs' heights did not exceed the chamfer's size. He also determined that the AE signal is very sensitive to the initial contact between tool and workpiece. This can be very useful in controlling the tool engagement in deburring. Masaki's work, later supported by Hwu's [4], demonstrated the feasibility of using AE as a feedback signal for the control of the tool position relative to the workpiece during a deburring operation.

It has been determined that for metal cutting processes, the level of acoustic emission generation is a function of the rate of energy consumption. For the deburring process, since the chip size is small, the power of the AE signal, averaged over a time interval, is affected predominantly by the material removal rate (MRR):

$$\overline{AE - power} = a * MRR \tag{1}$$

The constant a depends on numerous parameters including tool condition, tool geometry, and material properties.

In the experiments by Masaki [11], a rigid rotary file was used to create a 45° chamfer on the workpiece. As long as the size of the burr is small compared to the chamfer size, the contact area is nearly equal to the area defined by the region 1 in Figure 1. This area, the area of the chamfer, is proportional to the square of the depth of cut. Therefore,

$$\overline{AE - power} = c * DOC^2 \quad (2)$$

The time average of the acoustic emission power is defined as the square of the root mean square energy of the AE signal:

$$\overline{AE - power} = \frac{1}{T}\int_T (AE - signal)^2 dt \quad (3)$$

or,

$$\overline{AE - power} = (RMS - AE)^2 \quad (4)$$

Equating equations (3) and (5) gives

$$RMS - AE = d * DOC \quad (5)$$

where $d = c^{1/2}$

Masaki showed that this realtionship to hold in fixed spindle deburring tests, and one of the goal of this investigation is to determine its validity when the tool is attatched to the end effector of a compliant robot arm.

3 Fuzzy Logic Controller

3.1 Fuzzy Sets

In this section we briefly review the basic features of fuzzy set theory and its ability to manipulate linguistic data.

The idea of fuzzy set, introduced by Zadeh [15] allows imprecise and qualitative information to be expressed in an exact way, and , as the name implies, it is a generalization of the ordinary notion of a set. Consider the statement:

temperature is *high*.

where temperature may take on values within the interval [100-200]. One may interpret this statement in the context of classical set theory by selecting a subset of this interval such as [135-165] an assigning the label *high* to it. This can be expressed in terms of a membership function, μ which can take values of either 0 or 1. If $\mu(T) = 0$, then the temperature T is not a member of the set, if $\mu(T) = 1$ then it is. Graphically, this might be represented by the rectangular function shown in Figure 1. However, this definition is missing the intuitive sense of the label *high*. The full meaning of *high* cannot be captured by this explication which requires sharp and clear definitions of set boundaries. An alternative interpretation using the notion of a fuzzy set is illustrated in Figure 1. Gradual, rather than abrupt loss of membership to a set is the most important assumption of the fuzzy set theory. The membership function of a set takes on values in the whole interval [0,1], in contrast to the binary valued classical set theory.

Fuzzy sets may be combined in a similar way to ordinary sets by means of the following definitions [14]: The union of two sets, $A + B$ is defined by:

$$\mu_{A+B}(x) = \max(\mu_A(x), \mu_B(x)) \quad (6)$$

The intersection $A * B$ is defined by:

$$\mu_{A*B}(x) = \min(\mu_A(x), \mu_B(x)) \quad (7)$$

Negation $\bar{A}$, is defined by:

$$\mu_{\bar{A}} = (1 - \mu_A(x)) \quad (8)$$

3.2 Approximate Reasoning

Consider the statement:

$$If\ X\ is\ A\ then\ Y\ is\ B \quad (9)$$

where A and B are subsets of U and V, respectively. Given the fact that X is A', we may infer using classical logic that Y is B', if and only if A' is a subset of A, in which case B' is B, otherwise nothing can be inferred. However, if we interpret the rule using fuzzy set theory, A' does not need to be a subset of A. The extent to which A' is a subset of A, determines the extent of truth of the premise of the rule. The result of this inference, B', is shown in Figure 2.

Formally, B' is defined using the compositional rule of inference [14]:

$$B' = A' \circ R \quad (10)$$

or

$$\mu_{B'}(v) = \max_u(\min(\mu_{A'}(u), \mu_R(u, v))) \quad (11)$$

where $\mu_R(u, v)$ is defined by:

$$\mu_R(u, v) = \min(\mu_A(u), \mu_B(v)) \quad (12)$$

and R is a fuzzy relation, a fuzzy subset of $U \times V$, and denotes the mathematical formulation of the given rule using fuzzy set theory [15].

In the case where several rules must be used:

$$If\ X\ is\ A_i\ then\ Y\ is\ B_i,\ i = 1, ..., n. \quad (13)$$

where A and B are fuzzy subsets of U and V, respectively, the rules are described by a fuzzy relation R as follows:

$$R = \bigcup_i R_i \quad (14)$$

$$\mu_R(u, v) = \max_i \mu_{R_i}(u, v) \quad (15)$$

An example of fuzzy inference based on two rules is shown in Figure 2.

3.3 Structure of a Fuzzy Logic Controller.

The basic configuration of a fuzzy logic control system (FLC) is shown in Figure 3. The system consists of four principal components: a fuzzification interface, a knowledge base, a decision-making logic or inference engine and a defuzzification interface [9].

In general the output of the process is not fuzzy, because its value is singularly determined through some measurement. For the purpose of the fuzzy inference, crisps values must be converted into fuzzy variables using a fuzzification interface.

The knowledge base is composed of two components, a data base and a fuzzy control rule base. The data base provides the definitions which are used to specify linguistic control rules and fuzzy data manipulation in a fuzzy logic controller. These definitions are subjective in nature, and are based on experience and engineering judgement.

The rule base characterizes the control goals and control policy of the domain experts through a set of linguistic control rules. The expert knowledge is usually of the form:

if (set of conditions are satisfied)
then (a set of consequences can be inferred)

The antecedents and the consequences are associated with fuzzy concepts presented in linguistic terms using fuzzy sets to describe the magnitude of the control variables. Typically, the control variables used in the implementation of a fuzzy controller are the process error (difference between set-point and output), change in error, and input. The fuzzy sets have linguistic meaning such as NB: negative big, NM: negative medium, NS: negative small, ZE: zero, PS: positive big, PM: positive medium, and PS: positive small. Example of fuzzy control rules is [8]:

$$If\ e\ is\ NS\ and\ ce\ is\ Z,\ then\ \delta u\ is\ NS \quad (16)$$

where:
$e = r - y\ (error)$
$r = setpoint$
$y = output$
$ce = change\ in\ error\ (e_k - e_{k-1})$
$\delta u = change\ in\ input\ (u_k - u_{k-1})$
NS, Z : *linguistic fuzzy sets*

The decision-making logic, sometimes referred as inference engine, is the kernel of the fuzzy logic controller. It has the capability of simulating human decision making based on fuzzy concepts and inferring fuzzy control actions using fuzzy implication and the rules of fuzzy inference described in the previous section.

Defuzzification is necessary in order to apply a crisp control action to the process. The result of fuzzy inference however, is in general a fuzzy subset. A number of approaches for defuzzification have been proposed [8] such as mean of max and centroid of area.

4 Experimental Setup

The experimental setup used in this investigation is shown in Figure 4. A Fanuc S108 five-axis robot was used to hold a die grinder at a 45° angle in order to achieve the chamfer shape desired. Workpieces made from 0.5 inch by 1 inch (12.7 mm by 25.4 mm) 6061-T6 aluminum bar stock were mounted on a rotary table which allowed a simple way of changing the orientation of the workpiece. An acoustic emission sensor attached to the workpiece holder picked up the AE generated during deburring. The tool holder was designed to allow attachment of a JR3 force torque transducer between the wrist and the tool. The serial and parallel connections allowed communication between the robot controller and the host computer, an IBM PC-AT.

Through the serial port, the computer was made to send to the robot sets of joint angles for positioning of the deburring tool as desired. One of the requirements of this research was the ability to stop the robot when the workpiece edge was detected. In order to provide this capability, a relay circuit was inserted in parallel with the existing start and hold switches on the controller panel. These were activated by pulsing bits on a parallel port of the computer.

One limitation of the robot which had to be considered was that it had only five, not six, degrees of freedom. For this reason, not all points in the robot's workspace can be reached with the orientation axes as desired. Craig [1] states that with a five degree of freedom robot, the pointing axis of the tool attached to the end effector must lie in the vertical plane of the robot arm. In order to create a 45° chamfer and at least have the point of tool/workpiece contact in the plane of the arm, a complicated tool holder would have been necessary. Instead, a short software algorithm was written which projects the Cartesian coordinates of the contact point onto the plane of the arm. The coordinates of the projection are used to calculate the proper joint angles. This allowed a much simpler tool holder to be used.

The deburring tool used in these experiments was a electric die grinder (Makita) with a spindle speed of 25,000 rpm. The bit used was a carbide-tipped rotary file with a quarter-inch diameter.

A diagram of the acoustic emission signal processing is shown in Figure 5. The output of the AE sensor is amplified by a preamplifier (40 dB) and an amplifier (39 dB). The amplified signal is then filtered by an RMS meter with a 25 ms time constant. The RMS meter was made in the lab and is based on the Analog Devices 637JD RMS chip. The output of the RMS meter is connected to a stripchart recorder and to one of the A/D channels of the DACA board attached to the computer.

The AE-RMS voltage tends to have fairly high frequency components. It is desired to remove these components since they are caused by surface variations on the workpiece and are not related to the depth of cut. A first order digital filter was employed for this task. A weighting parameter is used to create a "fading memory." A running total of the sensor readings was kept:

$$sum(k) = y(k) + weight * sum(k-1) \tag{17}$$

where y(k) is the sensor output at sampling interval k and *weight* is the weighting parameter mentioned above. The weight is also summed in a similar manner:

$$sum\_of\_weight(k) = 1 + weight * sum\_of\_weight(k-1) \tag{18}$$

Finally, the digital filter output $s(k)$ is found as follows:

$$s(k) = \frac{sum(k)}{sum\_of\_weight(k)} \tag{19}$$

It was found that a weight of 0.9 followed the general trends of the AE-RMS signal very well, but eliminated the high frequency components.

A fuzzy logic controller used in this study calculates the changes in control input (feed in the direction perpendicular to the tool movement), δu, based on the error (difference between set-point and output) in RMS-AE, e, and the change of the error, ce. It was implemented with the following 25 rules:

- **Rule 1-4.** If just started, begin to apply control:
  - if e is SP and ce is SP then δu is SP.
  - if e is LP and ce is LP then δu is LP.
  - if e is LN and ce is LN then δu is LN.
  - if e is SN and ce is SN then δu is SN.
- **Rule 5-8.** If error is not changing, keep input proportionally high
  - if e is SP and ce is Z then δu is SP.
  - if e is LP and ce is Z then δu is LP.
  - if e is LN and ce is Z then δu is LN.
  - if e is SN and ce is Z then δu is SN.
- **Rule 9-12.** If going in right direction, keep the control same:
  - if e is SP and ce is SP then δu is Z.
  - if e is LP and ce is SP then δu is Z.
  - if e is LN and ce is SN then δu is Z.
  - if e is SN and ce is SN then δu is Z.
- **Rule 13-16.** If getting worse, speed up a bit:
  - if e is SP and ce is LP then δu is LP.
  - if e is LP and ce is SP then δu is LP.
  - if e is LN and ce is LN then δu is LN.
  - if e is SN and ce is SN then δu is LN.
- **Rule 17-20.** If moving too fast, slow down a little bit:
  - if e is SP and ce is LN then δu is SN.
  - if e is LP and ce is LN then δu is SN.
  - if e is LN and ce is LP then δu is SP.
  - if e is SN and ce is LP then δu is SP.
- **Rule 21.** If reached steady state, keep the control same:
  - if e is Z and ce is Z then δu is Z.
- **Rule 22-23.** If error is small but changing slightly, wait and see:
  - if e is Z and ce is SP then δu is Z.
  - if e is Z and ce is SN then δu is Z.
- **Rule 24-25.** If error is small but changing significantly, take action:
  - if e is Z and ce is LP then δu is SP.
  - if e is Z and ce is LN then δu is SN.

where fuzzy sets, LP(Large Positive), SP(Small Positive), Z (Zero), LN(Large Negative), SN(Small Negative), were defined based on normalized values of e, ce and u, respectively.

5 Experimental Results

To verify the sensitivity of the AE signal to the tool-workpiece contact and the relationship between the RMS-AE and the resulting depth of cut, and to test the performance of the fuzzy logic controller, two series of deburring experiments were conducted.

As originally demonstrated by Masaki [11], acoustic emission is very sensitive to initial contact between a tool and a workpiece. A typical AE spike due to initial contact is shown in Figure 6. This knowledge was used to develop an edge detection routine which would stop the robot when the part edge is contacted. The point of the first contact between the tool and the workpiece was established by advancing the deburring tool which is attatched to the robot manipulator toward the workpiece until an AE spike is detected. This method, compared to visual observation, was proved to be more accurate and reliable in determining the point of the first contact. The acoustic emission signal was sampled at 2 ms while the robot was moved toward the workpiece. The speed of the robot during edge finding was 3.94 in/min. When a spike in RMS-AE is detected the robot was designed to stop. This edge-finding routine was found to work very well. Using the sampling and feed rates given above, the robot motion stopped when the depth of cut was about 0.028 inches. For other tests, the sampling rate was increased from 2 ms to 1 ms, and the feed rate was slowed from 3.94 in/min to 1.97 in/min. With sampling in effect quadrupled, the robot stopped at a depth of around 0.021 inches.

Then, the robot manipulator was advanced further to the desired depth of engagement, and the deburring action was started by a start pulse upon user's command at the feed speed of 0.5 in/min. The acoustic emission signal was read at a 3 ms sampling rate. At the feed speed used, this corresponded to about one sample every 0.0015 in. When the deburring tool is moved along the edge of the workpiece the depth of engagement was regulated by the fuzzy logic controller using the RMS-AE feedback.

After cut was made, the depth of cut was measured using a microscope. In observing the workpieces after deburring, the chamfered surface had a fairly smooth surface with no secondary burrs. Therefore, the speed was not so fast as to initiate chatter. The depth of cut was measured every 0.05 inches along the workpiece.

Figures 7 and 8 show representative plots of AE-RMS voltage and depth of cut versus deburring distance in a constant reference input case and in a linearly increasing reference input case, respectively.

In the first set of experiments, the reference input for RMS AE was a constant (2 volts) so that the depth of cut is regulated at a constant (about 0.017 in). According to the Figure 7, the RMS-AE level is kept close to the desired value by the fuzzy logic controller. Also, the depth of cut is well regulated to a constant due to the linear relationship between the RMS-AE and the depth of cut as shown in Figure 7. It is evident that the AE output is closely related to the depth. The general trends of the two plots match very well.

Figure 8 shows AE-RMS plotted against depth of cut. From this graph, the expected linear relationship is apparent. The RMS-AE level increases linearly proportional to the depth of cut with relatively little scatter. A linear regression computed through the origin indicated a slope of 0.195 volts per mil and a correlation factor of 0.93. The combined data from several other tests gave a slope of 0.183 volts per mil with a correlation factor of 0.85. This indicates that further testing and evaluation need to be done in order to reduce the amount of scatter.

In the experiment, the AE-RMS voltage did not increase substantially for depths of cut above 0.050 inches. This is most likely due to the fact that the assumption of small chip size is no longer valid and that changes in contact characteristics have occurred.

Also, while most of the plots of AE-RMS versus depth of cut had a nearly constant slope for the entire distance, some had a higher slope at the very beginning of the cut which quite suddenly decreased. This is most likely due to the fact that the workpiece did not have sharp corners. Instead, they were somewhat rounded. Thus, at small amounts of engagement, the chamfer size increased dramatically as the tool moved deeper into the workpiece.

In second series of experiments, the reference input for RMS-AE was linearly increased, so that the initial RMS AE is 1 volt, and the final RMS-AE at the point 2 in. away form the initial contact point is 4 volts. A typical AE-RMS plot in this series of experiments are shown in Figure 9(a). In the figure the RMS-AE level follows the linearly increasing reference input with more fluctuations than in the constant reference input case. Figure 9(b) shows the resulting depth of cut profile as obtained by measuring the depth of cut at 40 points along the chamfer. Again, an exellent correlation between the RMS-AE and the chamfer size profile is observed.

6 Conclusions

Several conclusions can be drawn from the results of the experiments conducted in this study. The first is that the AE-RMS signal provides an excellent means of detecting contact between a tool and workpiece. The sudden rise in acoustic emission is easily detected by the controller computer. The speed at which the robot decelerates is the presiding factor affecting the resultant depth of engagement.

Another conclusion is that AE-RMS is proportional to the depth of cut in robotic deburring. The additional compliance of the robot arm had no noticeable effect on the linear relationship. As discussed above, the AE-RMS voltage appeared to level off once the depth of cut reached 0.050 inches. This, however, should not be a major problem since the chamfer created by deburring operations is usually desired to be below this size.

A third conclusion that AE-RMS can be used for controlling depth of cut in robotic deburring due to the good linear relationship between the RMS-AE and the depth of cut.

Fourth conclusion is that a fuzzy logic controller for robotic deburring that takes advantage of the positive characteristics of AE sensor can be implemented successfully. Unlike traditional logic systems, fuzzy logic is much closer in spirit to human thinking and natural language. The fuzzy logic controller (FLC) methodology provides a means of converting a linguistic control strategy, based on expert knowledge, into an automatic control scheme. This approach seems particularly appropriate to deburring, a process that can be successfully controlled by a skill human without the knowledge of its underlying dynamics.

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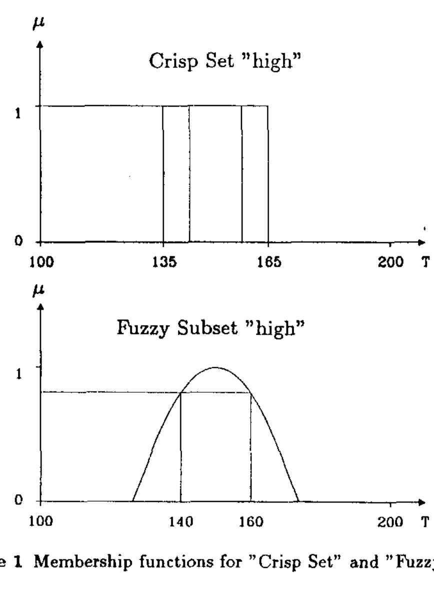


Figure 1 Membership functions for "Crisp Set" and "Fuzzy Set".

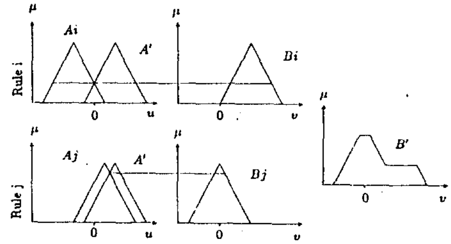


Figure 2 An example of fuzzy inference based on 2 rules.

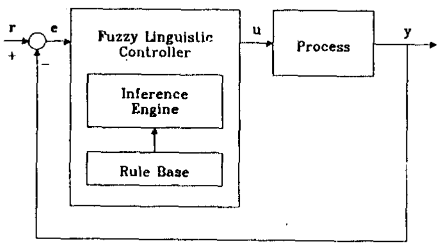


Figure 3 Typical architecture for a fuzzy logic controller.

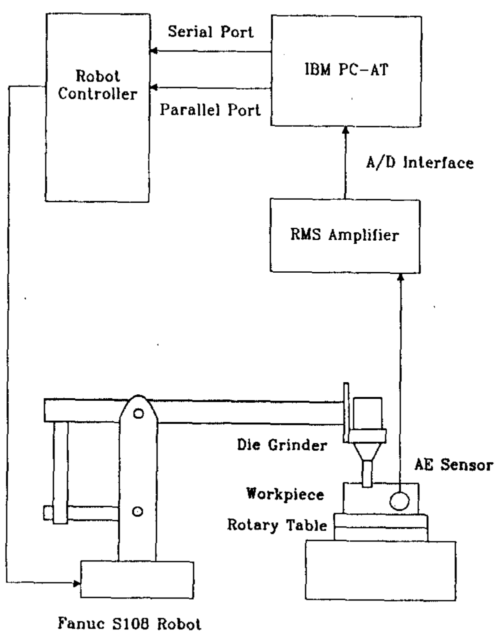


Figure 4 Robotic deburring setup.

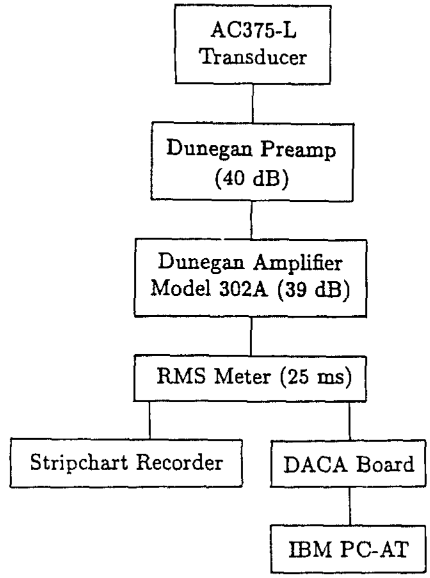


Figure 5 Acoustic emission signal processing.

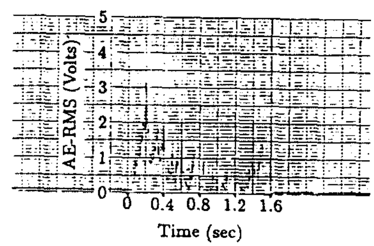
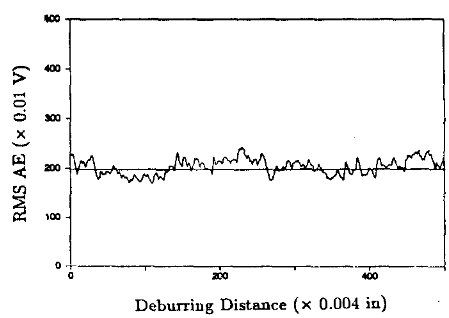
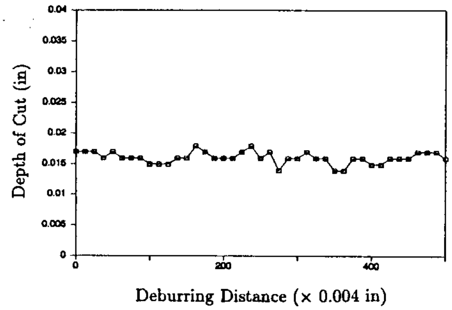


Figure 6 AE spike resulting from initial contact.

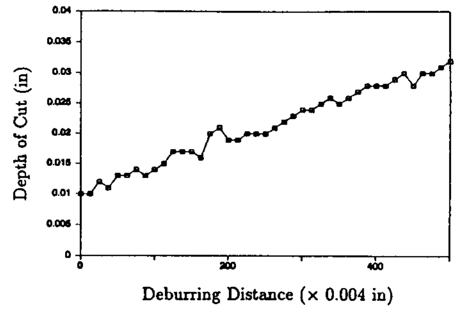


(a)



(b)

Figure 7 AE-RMS vs. deburring distance (a), and depth of cut vs. deburring distance (b), when the reference input was constant



(b)

Figure 9 AE-RMS vs. deburring distance (a), and depth of cut vs. deburring distance (b), when the reference input was linearly increased.

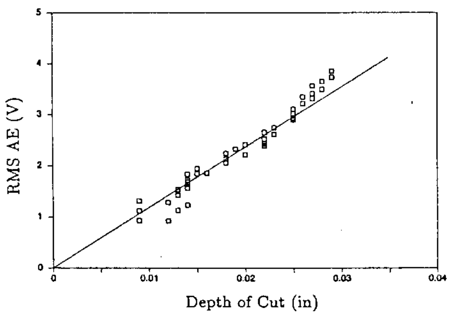
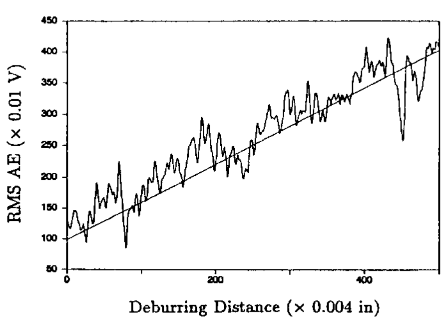


Figure 8 Correlation between AE-RMS and depth of cut.



(a)