Technical Paper

Assessment of micro turning machine stiffness response and material characteristics by fuzzy rule based pattern matching of cutting force plots

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A B S T R A C T

In micro-nano systems technology (MNST), application of mechanical based machining operations such as micro turning, micro milling, micro EDM have shown promising trends to produce micro parts in batch scale. In order to ensure reproducibility better understanding on micro cutting process dynamics and sensitivity of machine stiffness and material characteristics becomes critical. In this paper, a methodology has been developed to assess machine stiffness and material dependent characteristics and demonstrated for micro turning operations conducted on DT-110 micro machining center. In this method, authors incorporate pattern matching algorithm to compare run data image of cutting force plots with that of reference plot. The reference plots of cutting forces v/s time were drawn from simulation run data computed from the micro turning process models. The run data plots of cutting force v/s time were drawn from the processed signal data obtained from the dynamometer during machining operation. The plots were fragmented into patterns and Euclidean distance computed between pair patterns of reference and measured cutting forces v/s time plot image represents the changes happened in machining conditions. This has been used to perform backward calculation to assess the machine stiffness response and material characteristic constants variations over machining time. In order to perform these comparative pattern error adjustments between reference and measured cutting force plots a fuzzy rule based algorithm has been developed.

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1. Introduction

The growing interest in applications of micro–nano scale devices in many applications has diversified the market demand toward batch production of multi material micro parts. Therefore, innovative integration and development of knowledge base for scaling up of production by precision manufacturing technologies to ensure effective industrial utilization has become the primary focused area of micro-nano scale manufacturing research. The successful adaptation of material removal processes such as milling and turning that uses cutting tools having geometrically defined cutting edges, have shown significant potential for producing accurate simple holes to a complex 3D features.

Micro metal cutting research sees the creative results in understanding process physics, and modeling. In the view of the issues associated with tool breakage, and instability of micro machine tools dynamics, process control is getting much importance. Tool breakage, instability and machine chattering occur due to improper machine stiffness and material constants. These parameters are not fixed but vary with operation and aging. This paper presents a systematic methodology for assessing the machine stiffness and material constants during run time of machine using image pattern matching approach. This work is an essential element of intelligent controllers being developed for micro factory test bed by the authors. The proposed fuzzy rule base driven comparative pattern error adjustment algorithm is generic, and it can be adapted to several micro machining process. In this paper, authors demonstrate the assessment of machine stiffness and material constants to use in micro turning operations. In order to establish the better context to this multidisciplinary study a brief overview of micro turning process and methodologies of pattern matching of reference and measured images are reviewed next, before discussing the proposed algorithm, its implementation and evaluation.

2. Micro turning process modeling: an overview

Micro turning is the precision machining process, used to produce cylindrical shaped micro parts varying from few hundred microns to 1 mm in diameter. In this process, normally single point
tool (diamond tip brazed on to miniaturized HSS tool shank) is fed against the rotating work piece. The elastic deflection of micro-scale work piece by induced cutting and feed forces becomes the primary concern for process control. This elastic deflection changes the process kinematics; hence prediction of real feed rate and real depth of cut, which are important parameters in preserving surface integrity of machined work piece, becomes approximate. This prediction becomes further unrealistic, because of a complex dynamics contributing to changes in machine stiffness, changes in tool positioning and orientation. Therefore, dynamic representation of micro-turning process conditions is the current demand. Many researchers including Hwang et al. [1], Aris and Cheng [2], Luo et al. [3] and Budak and Ozulu [4] have investigated on dynamic modeling and simulation of surface generation for conventional macro scale turning process conditions. They have investigated a single or multiple aspects of dynamic machine tool structural response, cutting process variables, tool geometry and dynamic cutting force modeling. Some of these dynamic modeling approaches have been adapted for other micro machining processes such as micro-drilling by Gong and Ehmann [5], micro-milling by Piotrowska-Kurczewski and Jost [6] and micro scale grinding by Park and Liang [7].

For micro turning operations, recently, Piotrowska et al. [8] have developed a mathematical model to predict real feed rate, real cutting depth, as well as cutting and feed forces. In this work deflection of tool has been considered. The derivation of the model and further discussion is available in the reference. The final equation sets derived in the paper are as in Eqs. (1)–(7).

\[
d_{p}(t) = v_{f}(t) \\
\delta_{x}(t) = v_{f} - v_{f}^{0}(t) \\
\delta_{y}(t) = \frac{c_{y}}{c_{x}} \left[ (v_{f} - v_{f}^{0}(t))(r - \int_{0}^{t} v_{f}^{r}(\tau)d\tau) - \delta_{x}(t)v_{f}^{r}(t) \right] \\
a_{p}^{0}(t) = -\frac{1}{h} \left[ \delta_{x}(t)(v_{f} - v_{f}^{0}(t)) + \delta_{x}(t)\frac{c_{y}}{c_{x}} [(v_{f} - v_{f}^{0}(t))(r - \int_{0}^{t} v_{f}^{r}(\tau)d\tau)) \right] + c_{y}A_{r}(t) \\
v_{f}^{r}(t) = \frac{v_{f} - v_{f}^{0}(t)(1 + c_{d}a_{p}^{0}(t))}{c_{a}d_{p}^{0}(t)} \\
\]

where \(c_{x}\) and \(c_{y}\) are given by Eqs. (6) and (7)

\[
c_{x} = \frac{c_{r}b_{x}}{K_{ex}} \\
c_{y} = \frac{c_{r}2\pi}{K_{ey}} \tag{7}
\]

These differential equations are solved with the following initial conditions: \(\delta_{x}(0)=0, \delta_{y}(0)=0, a_{p}^{0}(0) = a_{p}, \ v_{f}^{r}(0) = 0, \ d^{0}(0) = 0. \)

**Nomenclature**

- \(v_{f}\) feed velocity
- \(a_{p}\) depth of cut
- \(l_{h}\) length of tool holder
- \(K_{ex}\) machine stiffness in X-direction
- \(K_{ey}\) machine stiffness in Y-direction
- \(\delta_{x}\) deflection of tool tip in X-direction
- \(\delta_{y}\) deflection of tool tip in Y-direction
- \(r\) radius of work piece
- \(b_{x}\) width of tool in X–Y plane
- \(A_{r}\) frictional area during machining process
- \(d\) displacement of turning tool on work piece surface
- \(C_{f}, C_{r}, C_{s}\) material related constants affecting the machining dynamics

Note: Symbols bearing superscript ‘a’ denotes its dependence on machining time. For example \(a_{p}^{0}(t)\) denotes instantaneous depth of cut varying with time.

In the above study, the authors solved these non-linear differential equations by taking two stage input information. The work piece properties, tool specifications and the process parameters of the turning process are used in MATLAB calculations. For numerical calculations nominal system parameters for machine stiffness and material constants have been used at three different values.

However in practice, metal cutting mechanics in micro turning changes with time. This is owing to the elastic deflection of tiny work piece, wear of cutting edge having minimum nose radius. This dynamic change in cutting mechanisms also depends on work-tool combinations, operation cycle, position and orientation of tool and tool holder, and also because of aging effects. Thus assessment of these changes is critical, demanding dynamic process control of micro turning. On the other hand, selection of appropriate instrumentation to monitor this process dynamically is difficult. Because, change in cutting forces resulting from these cutting dynamics is in few fraction of Newton-force and appreciating the deflection of micro parts becomes difficult till the damage is significant. Often this situation leads to breakage work piece and/or tool cutting edge. Further, Kistler dynamometer used widely for micro cutting force measurements are capable of acquiring the force signals in micro-Newtons resolutions at higher frequency. Therefore, in this work, authors have integrated simple image pattern matching techniques, wherein the cutting forces v/s time plots drawn from the run data (acquired from the dynamometer) is being constantly compared with the model (reference) plots which are drawn based on the solutions obtained from the micro turning models proposed by Piotrowska et al. [8]. The methodologies and results on its implementation into practical micro turning experiments have been discussed in later part of this paper. In order to appreciate and for the better understanding, pattern matching techniques and their applications are reviewed next.

### 3. Previous work on pattern matching methods

Pattern matching algorithms deal with adjustment of image patterns. One of the patterns is essentially theoretical obtained using a model, whereas the other pattern is obtained using a sensor from real time operation of a system known as observed pattern. The job of the algorithm is to match the theoretical and observed patterns as cited in Trochim [9]. The theoretical pattern is governed by a known relationship or more specifically a mathematical equation. Further the equation bears some constant and variable parameters. The observed pattern can also be described using a mathematical equation. In real time operation of a system, generally it becomes impossible to evaluate the exact mathematical relationship for the observed pattern. Pattern matching algorithm allows the user to match the two mentioned patterns. In this process the exact mathematical relationship along with the constants and variables present in the relationship gets evaluated at exact match of the patterns.

In matching patterns between two images, the issue lies with registering of transformation (i.e. rotation, scaling and translational) parameters. It is usually impossible to determine the transformation that maps an arbitrary point coordinates of first image to the corresponding coordinates of the point in the second image, unless they are spare set of points and are unique from their neighbors as in Goshtasby et al. [10]. In image processing...
In literature, there are several approaches including template matching proposed by Wagner and Galiana [11], pre-assumption of certain points in the regions by Chen et al. [12], and clustering as in Trochim [9], etc. have been developed. Therefore, in order to match two patterns initially the algorithm must search for distinct features in both the pattern to be matched. The selection of feature is user dependent but must be distinct, interpretable and stable as in Forstner [13].

In our application of micro turning, variation of cutting forces (cut force and feed force) with machining time are plotted. These plots are typically X-Y scatter plots, in which the independent variable i.e. time is used for X-axis and cut/feed forces induced during metal cutting are dependent variables plotted along Y-axis. Therefore, in our work the image has been fragmented into distinctive patterns such as different slopes (rising and falling segment slope), points corresponding to convexity, starting and end points. These patterns from measured plots and reference plots are compared in pair and the error between them are computed in terms of Euclidean distance. Next a rule base alters the constant parameters present in the mathematical relationship of theoretic pattern. By doing so the algorithm finds an exact match between the theoretical and observed patterns and provides the correct values of these constant parameters as its output on match of these patterns. As the entire methodology consists of pattern matching between measured and reference plots of cutting forces v/s time (computation of Euclidean distance) and reverse calculation of machine stiffness response and material constants using mathematical model together, hence is called as ‘Comparative pattern error adjustment’ algorithm. This would in turn facilitate process control engineers to re-adjust the machining conditions such that metal cutting dynamics could be maintained over entire machining period. This methodology and its implementation algorithm are explained next in detail.

4. Methodology

The proposed algorithm comparative pattern error adjustment of force v/s time plots of measured (using dynamometer) run data and reference (using mathematical model computation) data is illustrated in Fig. 1. This methodology involves the following four steps.

1. The initial step is to solve the above micro turning process model to draw the reference plots of cutting forces v/s time and feed forces v/s time. In order to do this computation machine stiffness and material related constants are assumed based on similar cases.
2. Use of dynamometer to acquire both cutting and feed force run data while micro turning of specific tool-material combinations at desired process conditions is under way, and plotting the similar machining forces v/s time graphs.
3. A tree clustering algorithm to fragment the plots into clearly distinctive patterns. This deals with comparing the patterns such as minima, maxima and slopes of plot images and computes the pattern matching error based on Euclidean distance for all pairs of image patterns.
4. Optimization of step size for increment or decrement of the constants to be determined to abridge the dissimilarities between the respective geometric patterns of plot images using fuzzy logic based error adaptive increment or decrement algorithm.

Fig. 2 shows the flowchart of the methodology implemented in MATLAB software and tested by practical experiments conducted on DT-110 micro machining center using Kistler-9256C dynamometer.

4.1. Forces v/s time plots from Simulink based model

The mathematical models for micro-turning process proposed by Piotrowska et al. [8] (Eqs. (1)–(7)) were implemented in Simulink as shown in Fig. 2. The initial set of machine stiffness and materials constants chosen were $K_n = K_r = 0.5 \text{ N/um}$, $C_j = 6.8 \times 10^3$, $C_s = 250$, and $C_t = 8.5$. The common frictional area $(A_f)$ was modeled as step function as generalized in reference paper. In order to test the proposed methodology, authors determined these values through iterations, such that the force models represent similarity with the published literature. However, one can standardize some of these constants based on similar cases using appropriate techniques such as Case Based Reasoning (CBR), which is beyond the scope of this paper. The tool related parameters such as length of tool holder $(h_t = 28.5 \text{ mm})$; width of the tool $(b_t = 0.094 \text{ mm})$ and work piece radius/size $(r = 3 \text{ mm})$ are used in concordance with the experimental setup. Fig. 3 shows the plots drawn for cutting and feed forces as function of time plotted from the computation results generated for different sets of machine stiffness and material constants.

4.2. Integration of experimental force v/s time data

The experiment was conducted on DT-110 micro machining center of MikroTools, Singapore. For micro turning experiment, work was mounted into the spindle rotating about Z-axes. A single point polycrystalline diamond insert mounted on HSS tool shank (Model: TCMX 18.50), manufactured by Sumitomo Carbide, Japan was mounted horizontally in X–Y plane. In order to facilitate the force measurements, the tool post was mounted on Kistler Dynamometer (Model: 9256C). The dynamometer, which is of five-channel type, acquires the cutting forces along three axes $(F_x, F_y, \text{ and } F_z)$ and moments along two axes $(M_x, \text{ and } M_y)$ as its output. However, tool mounting was such that micro turning experiments were conducted on micro X–Y plane and material is removed from the bottom face of work piece as illustrated schematically along with the images of the setup in Fig. 4.

The values of cut and feed forces were found using Eqs. (9) and (10).

\[
F_c = F_x + \frac{M_z}{a} \tag{9}
\]

\[
F_f = - \left( F_y + \frac{M_x}{t} \right) \tag{10}
\]
4.3. Rule based approach for image patterns comparison

A rule-based algorithm has been proposed for comparative adjustment of minima, maxima and slope patterns of time dependent machining force graphs, plotted by experimental and theoretical data sets. The initial process involves fragmentation of force v/s time plots using tree clustering algorithm. Subsequently, comparative adjustment of set of patterns either to their nearest value or threshold values is performed using rule based algorithm.

4.3.1. Fragmentation of images into different patterns

In this work both the machining force graphs (i.e. cutting force v/s time and feed force v/s time plots) were fragmented into smaller sections with termed patterns and features namely first minima, second minima, first maxima, second maxima, slope of rise segment, slope of constant segment and slope of fall segment as shown in Fig. 5. The fragmentation was done based on tree clustering algorithm proposed by Gonzalez et al. [14]. From the simulation iterations, the effects of machine stiffness and material constants on cutting force and feed force in micro plane turning have been investigated and summarized in Table 1.

4.3.2. Comparative adjustment of set of patterns using the rule base

The rule based algorithm adopted for this micro turning process performs comparative adjustment of set of patterns from force v/s time graphs plotted from the data set computed from Simulink based model and the experimental force data set. The input data for the algorithm include

1. Cut force v/s time and feed force v/s time graph from machine (experimental) data.

Fig. 2. Flowchart of the algorithm for determination of machine and model constants.
2. Initially values for machine stiffness and material dependent constants $K_{ex}$, $K_{ey}$, $C_r$, $C_f$ and $C_t$.
3. Radius of tool ($R_e$).
4. Length of tool holder ($h_l$).
5. Radius (size) of work piece ($r$).
6. Depth of cut ($a_p$).
7. Feed velocity ($f_f$).
8. Thr_Delay, Thr_Maxima and Thr_Max as threshold values of acceptable value of difference in the position of hot points (set of recognized patterns) in the graphs.

The outputs from this algorithm include the computed data set of $K_{ex}$, $C_r$, $C_f$ and $C_t$ at convergence of graphs. The efficiency of this rule based algorithm depends on selection of patterns (hot points) on the graph, measure of distances (similarities), dimension and resolution of distances, etc. In this work considering the nature of graphs obtained for cutting and feed forces, the following recognizable patterns have been chosen as hot points to perform comparative pattern adjustments.

1. $MAX$ is the 2-Dimensional Array in which each row stores a coordinate of maxima point for the cut force $v/s$ time graph. Column 1 of MAX has data of $X$-coordinate of points and Column 2 of MAX has data of $Y$-coordinate of points.
2. $MAXF$ is the 2-Dimensional Array in which each row stores a coordinate of maxima point for the feed force $v/s$ time graph. Column 1 of MAX has data of $X$-coordinate of points and Column 2 of MAX has data of $Y$-coordinate of points.
3. $MIN$ is the 2-Dimensional Array in which each row stores a coordinate of minima point for the cut force $v/s$ time graph. Column 1 of MIN has data of $X$-coordinate of points and Column 2 of MIN has data of $Y$-coordinate of points.

**Table 1**

<table>
<thead>
<tr>
<th>Sl. no</th>
<th>Increase in parameter</th>
<th>Effect on cut force</th>
<th>Effect on feed force</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$C_f$</td>
<td>Negligible effect</td>
<td>First and second maxima increase</td>
</tr>
<tr>
<td>2</td>
<td>$K_{ex}$ and $K_{ey}$</td>
<td>First maxima increases, left shift (lesser time delay), slope of rise segment increases, length of constant segment increase</td>
<td>Left shift in first maxima</td>
</tr>
<tr>
<td>3</td>
<td>$C_r$</td>
<td>First and second maxima increases, second minima increases</td>
<td>Negligible effect</td>
</tr>
<tr>
<td>4</td>
<td>$C_f$</td>
<td>First and second maxima increase, slope of fall segment decreases, minute change in second minima</td>
<td>Negligible effect</td>
</tr>
</tbody>
</table>
(4) $E_{Maxima}$ (error in maxima for cut force graph) is calculated by subtracting the $Y$-coordinates of maxima points of the cutting force v/s time graph obtained from model from the $Y$-coordinates of maxima points of cutting force v/s time graph obtained from experimental data.

(5) $E_{Minima}$ (error in minima for cut force graph) is calculated by subtracting the $Y$-coordinates of minima points of the cutting force v/s time graph obtained from model from the $Y$-coordinates of minima points of cutting force v/s time graph obtained from experimental data.

(6) $E_{Delay}$ (error in delay) is calculated by subtracting the $X$-coordinate of first maxima points of the cutting force v/s time graph obtained from model from the $X$-coordinates of first maxima points of cutting force v/s time graph obtained from experimental data.

(7) $E_{Len Seg}$ (error in length of segment) is calculated by subtracting the length of segments of the cutting force v/s time graph obtained from model from the length of segments of cut force v/s time graph obtained from experimental data.

(8) $E_{Slope}$ (error in slope) is calculated by subtracting the slope of segments of the cutting force v/s time graph obtained from model from the slope of segments of cutting force v/s time graph obtained from experimental data.

(9) $E_{Maxima f}$ (error in maxima for feed force graph) is calculated by subtracting the $Y$-coordinates of maxima points of the feed force v/s time graph obtained from model from the $Y$-coordinates of maxima points of feed force v/s time graph obtained from experimental data.

(10) $E_{Delay f}$ (error in delay for feed force graph) is calculated by subtracting the $X$-coordinate of first maxima points of the feed force v/s time graph obtained from model from the $X$-coordinate of first maxima points of feed force v/s time graph obtained from experimental data.

In order to perform comparative adjustments at respective patterns, for example to compute the errors in item no. 4–10, many distance-measuring techniques have been used in previous image processing and pattern recognition literature. These
include Euclidean distance, squared Euclidean distance, city-block (Manhattan) distance, Chebychev distance, power distance, and percentage disagreement. Selection of right method of measure is application dependent. As the application of pattern comparison for machining force graph by rule based algorithm combined with tree cluster approach has been attempted first time in this paper, authors have adopted Euclidean distance measurement method. This is because: it is the geometric distance in the multidimensional space, usually computed from raw data, and not from standardized data. In this method the distance between any two patterns is not affected by addition of new patterns to the analysis as long as the scale among the pattern dimensions remains same. It is computed as the following equation.

$$\text{Distance}(x, y) = \left( \sum_{i} (x_i - y_i)^2 \right)^{1/2} \quad (11)$$

Fig. 5 illustrates the typical pattern comparative adjustment performed between experimental curve and its corresponding theoretically computed curves. For every, Euclidean distance measured between two graphs, a set of if-then-else rules as shown in flowchart (Fig. 2) have been designed that serves as criteria for matching. In order to appreciate the design of this algorithm, one of the conditions used in this algorithm is explained next.

In second decision box of the flowchart states that, if error in first maxima is negative (i.e. the first maxima of the graph obtained from the experiment has lesser amplitude than the graph obtained from model by assumed values of constants then it is clear from Table 1 that a decrement of $K_{ex}$ is required). If $K_{ex}$ is decreased the graph obtained from our model will fall in amplitude and will match the graph obtained from experiment. This is one of the conditions for decrement of $K_{ex}$. Now in each recursive step of model run for matching, the increment or decrement step for $K_{ex}$ and other constants need to be determined. For example, in the flowchart we have used $K_{ex} = K_{ex} - K_{ex, \text{step}}$ i.e. by what shall we decrement $K_{ex}$ value. If the step size is very small the number of recursions will be very large resulting computationally intensive analysis. On the contrary, coarse step size may not compute accurate machine stiffness values. In order compute optimized step size a fuzzy logic based error adaptive algorithm has been integrated. This will help to determine optimal values of increment or decrement of the constants in every recursion, considering stochastic nature of micro-turning process, where machine stiffness and material conditions vary non-linearly.

### 4.4. Fuzzy based error adaptive algorithm

The Mamdani based fuzzy algorithm as in Jin [15] has been implemented to determine optimized step size for machine stiffness and material constants values for adaptive comparison of patterns of machining force models curve (for example $K_{ex, \text{step}}$ size as discussed above). The fuzzy system has been initially trained based on the computational outputs obtained from the above-discussed models implemented in Simulink. As discussed earlier, the initial set for the constants were selected based on prior experience or datasheet published by cutting tool manufacturers or combination of both as discussed in Section 4.1. The Simulink model has been processed by varying the values of the constants ($K_{ex}$, $C_e$, $C_f$ and $C_i$), and subsequently determining the range (maximum and minimum limit values) by analyzing the drastic changes in pattern of forces vs time curves. In this work, the operating range for the constants has further divided into 11 parts as shown in Table 2 to create the membership functions. Dividing the entire range into parts refer to dividing the data points into clusters. The clustering was done based on city block distance method as reported in Jahnkhani et al. [16]. Such triangular fuzzy functions for each of the constants ($K_{ex}$, $C_e$, $C_f$, $C_i$), for the image patterns (maxima, minima, slopes) and also for their changes are generated. In Fig. 6, the typical triangular fuzzy functions generated by iterative $K_{ex, \text{step}}$ values are shown.

The next step involves error optimization using these triangular fuzzy functions and rule base to determine minimum step size for the machine stiffness and material constant variables such that on pattern comparative adjustment for the Euclidean distance measured between model and experimental curve as discussed in Section 4.3.2 is minimum. For this purpose, fuzzy rule base has been designed as discussed in Leondes [17] for each constants ($K_{ex}$, $C_e$, $C_f$ and $C_i$) and for image patterns (maxima, minima, slopes). The fuzzy algorithm during run requires the present value of $K_{ex}$ and the present error in Maxima, Minima and Slope as input. These inputs then pass through the previously trained model to provide $K_{ex, \text{step}}$ (required value of step for increment or decrement in $K_{ex}$) as output. Fig. 7 shows the typical fuzzy rule base and the flowchart used to compute optimized $K_{ex, \text{step}}$ size to have better pattern comparative adjustment between the model and experimental curves. For other constants ($C_e$, $C_f$ and $C_i$) similar methodology has been implemented.

### 4.5. Implementation and validation

The overall methodology to compute machine stiffness and material constants dynamically during micro-turning operations as discussed in Section 4 has been implemented on MATLAB. The entire methodology has been tested by conducting micro turning experiments. The details on experimental setup and data acquisition have been discussed in Section 4.2. Initially micro-turning forces were calculated using Simulink model, assuming the initial values for stiffness and material constants. The experiments were conducted at two levels as shown in Table 3, with a dynamometer to record cut force and feed forces generated in micro plane turning. The pattern recognition algorithm was processed to identify appropriate patterns (maxima, minima, slope, etc.) to perform pattern comparative adjustment between the theoretical and experimental curves.

The plots obtained from experiment and the matched plots from model are shown in Fig. 8. The algorithm yields the corresponding values of constants resulting in match. These values are presented in Table 4.

### 5. Discussions

The significance of the methodology can be understood by the following interpretations and examples.

- The cutting force in Fig. 8(a) is nearly 8.5 N and the assessed stiffness is 6.3 N/μm as in Table 4. The deflection defined as the ratio

### Table 3

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Data set 1</th>
<th>Data set 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Feed velocity</td>
<td>7 mm/min</td>
<td>3 mm/min</td>
</tr>
<tr>
<td>2. RPM</td>
<td>2500 rpm</td>
<td>4500 rpm</td>
</tr>
<tr>
<td>3. Depth of cut</td>
<td>25 μm</td>
<td>70 μm</td>
</tr>
</tbody>
</table>
Fig. 6. Typical triangular fuzzy functions generated by monitoring the changes in image patterns for variable constants.

Fig. 7. Fuzzy rule base and algorithm to determine minimum step size for improved pattern comparative adjustment.
of applied force and stiffness is 1.34 μm. The depth of cut is 25 μm as in Table 3. Thus the error in machining pertaining to deflection due to stiffness is 5.36% of the required value of depth of cut. This error may be negligible in macro scale machining processes but becomes significant at micro scale. Thus the accuracy of the micro machining process is limited by the stiffness of combined tool and tool holder. During machining if the assessed values of stiffness are too low, this indicates that the tool and/or work holder are not rigid enough to get the desired accuracy.

- Increase in material related constant $C_t$ signifies an increase in cut force during the machining process (Fig. 3(III)). Higher values of cut force leads to tool shear (effect due to force coplanar with the tool) and hence breakage.
- Small increment in value of $C_f$ infers very large increment in cut force. Further with increase in value of $C_f$ the cut force increases abruptly at the beginning of cutting process (Fig. 3(V)). Such impulsive force leads to breakage of the tool.

- Increment in value of $C_f$ signifies the fact that the feed force has increased (Fig. 3(VIII)). Increased feed force leads to bending of tool tip (Fig. 4) and hence tool tip deformation.

6. Conclusion

It is very well appreciated that in micro turning process, because of operational and physical differences (size effects), there is a poor understanding with respect to influence of response of micro machine structure stiffness and elastic deflection of tiny tool and work pieces that makes ensuring reproducibility in micro cutting a daunting task. In this paper a generic methodology to assess dynamically the machine stiffness and material related constants by comparative adjustment of pattern errors of cut and feed forces over time has been developed. The proposed rule based approach to perform comparative pattern adjustment of force v/s time plots is independent of material, tool, and geometry being cut; irrespective of the processing conditions, cutting forces are measured dynamically using dynamometer and match the respective patterns with the theoretical curve to assess the machine stiffness and material constants. In process control, these changes in $K_{ex}$, $K_{ey}$, $C_t$, $C_f$ and $C_t$ constant values, would play a decisive role, as they reflect the change in micro cutting dynamics. The methodology has been tested for micro turning operations over DT-110 micro machining center. This pattern error adjustment based algorithm has a

<table>
<thead>
<tr>
<th>Constants</th>
<th>$K_u = K_v = K$</th>
<th>$C_t$</th>
<th>$C_f$</th>
<th>$C_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data set 1</td>
<td>6.328 N/μm</td>
<td>239.45</td>
<td>8.02</td>
<td>6.7863 × 10^4</td>
</tr>
<tr>
<td>Data set 2</td>
<td>6.392 N/μm</td>
<td>248.62</td>
<td>8.21</td>
<td>6.81 × 10^4</td>
</tr>
</tbody>
</table>
potential to use for other micro cutting operations, provided the basic process models and clear definition of material stiffness and material dependent constants are available.

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References