Fuzzy cutting force modelling in micro-milling using subtractive clustering for learning evaluation

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Abstract: Cutting forces prediction is very important for cutting tool’s design and process planning. This paper presents a fuzzy cutting force modelling method using subtractive clustering for learning evaluation. In this method, subtractive clustering, combined with the least-square algorithm, identifies the fuzzy prediction model directly from the information obtained from the sensors. In the micro-milling experimental case study, two fuzzy models learned through different evaluation strategies are tested. The modelling results are compared and discussed.

Key words: fuzzy logic, cutting force, subtractive clustering.

1. INTRODUCTION

Today, the demand of miniaturization in electronics, medical, telecommunication, aerospace, automotive and defense industries is increasing. Meantime, highly wear resistant materials are heat treated before micro-cutting to achieve a reasonable surface finish. Development of the micromilling process for micro-mould manufacturing is driven due to its capability of machining 3D free-form micro-structures of those high-tech products [El Gomayel and Bregger, 1988]. Reliable prediction of cutting forces in micromilling is essential for the design of cutting tools, as well as planning machining operations for maximum productivity and quality [Pérez and al., 2007].

Due to the difficulty in understanding the exact physics of micromilling process, the information obtained during machining process is not complete and precise. It is difficult to establish theoretical and analytical approaches or mechanistic model by using this kind of information. Some research has been done for predicting the micromilling forces with the needed precision. For example, analytical cutting force model [Bao and Tansel, 2000], model based on the elastic contact between the tool and the workpiece [Friedrich and Kulkarni, 2004], mechanistic model [Uriarte et al., 2008], Taylor-based model [Demir, 2008], ploughing force model [Malekian et al., 2009].

Fuzzy logic (FL) [Zadeh, 1965] provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. The aim of this paper is presenting a fuzzy approach method for modelling
cutting forces in micromilling using subtractive clustering method for learning evaluation. In this approach, the subtractive clustering is used to partition the input space and extract a set of fuzzy rules, and then least-square algorithm is used to find the optimal membership functions (MFs) and consequent parameters of the rule base.

This paper has four sections. In Section 1, recent achievements on cutting force modelling is introduced. Fuzzy identification algorithm using subtractive clustering method for learning evaluation is presented in Section 2. A micromilling case study is presented in Section 3. In the experiment, two sets of data are used for learning and testing the fuzzy model, and a comparison of the results is made from different evaluation strategies. Concluding remarks follow in Section 4.

2. FUZZY IDENTIFICATION ALGORITHM USING SUBTRACTIVE CLUSTERING METHOD FOR LEARNING EVALUATION

Takagi-Sugeno-Kang (TSK) fuzzy logic modelling [Takagi and Sugeno, 1985, Sugeno and Kang, 1988] was proposed in an effort to develop a systematic approach to generating fuzzy rules from a given input-output data set. This model consists of rules with fuzzy antecedents and mathematical function in the consequent part. The antecedents divide the input space into a set of fuzzy regions, while consequents describe behaviour of system in those regions. TSK fuzzy modelling is a very powerful tool for function approximation due to its capability to explain nonlinear relation using a relatively low number of simple rules. In fact, TSK fuzzy model is a general non-linear approximator that can approximate every continuous mapping, and on the other hand it is a piecewise linear model that is relatively easy to interpret [Johansen and Foss, 1995] and whose linear sub-models can be exploited for control and fault detection [Füssel, 1997].

A generalized type-1 TSK model can be described by fuzzy IF-THEN rules which represent input-output relations of a system. For a multi-input-single-output (MISO) first-order type-1 TSK model, its kth rule can be expressed as:

\[
\text{IF } x_1 \text{ is } Q_{1k} \text{ and } x_2 \text{ is } Q_{2k} \text{ and } \ldots \text{ and } x_n \text{ is } Q_{nk},
\]

\[
\text{THEN } Z \text{ is } w^i = p_0^i + p_1^ix_1 + p_2^ix_2 + \ldots + p_n^ix_n \tag{1}
\]

where \(x_1, x_2, \ldots, x_n\) and \(Z\) are linguistic variables; \(Q_{1k}, Q_{2k}, \ldots, Q_{nk}\) are the fuzzy sets on universe of discourses \(U, V, \ldots, W\), and \(p_0^i, p_1^i, \ldots, p_n^i\) are regression parameters.

The fuzzy TSK model can be manually constructed based on knowledge about the target process or using data-driven techniques. Identification of the system using clustering involves formation of clusters in the data space and translation of these clusters into TSK rules such that the model obtained is close to the system to be identified.

2.1. Chiu’s method

The aim of Chiu’s subtractive clustering identification algorithm [Chiu, 1994] is to estimate both the number and initial location of cluster centers and extract the TSK
fuzzy rules from input/output data. Subtractive clustering operates by finding the optimal data point to define a cluster centre based on the density of surrounding data points. This method is fast, and designed for high dimension problems with a moderate number of data points. This is because its computation grows linearly with the dimension and as the square of the number of data points. A brief description of Chiu’s subtractive clustering method is as follows:

Consider a group of data points \( \{ x_1', x_2', \ldots, x_n' \} \) for a specific class. The M dimensional feature space is normalized so that all data are bounded by a unit hypercube.

Then calculate potential \( P_i \) for each point as follows:

\[
P_i = \sum_{j=1}^{n} e^{-\alpha \| x_i' - x_j \|^2}
\]

with \( \alpha = 4/r_a^2 \) and \( r_a \) is the hypersphere cluster radius. Data points outside \( r_a \) have little influence on the potential. \( \| \) denotes the Euclidean distance. Thus, the measure of potential for a data point is a function of the distance to all other data points. A data point with many neighboring data points will have a high potential value. After the potential of every data point is computed, suppose \( k = 1 \) where \( k \) is a cluster counter. The data point with the maximum potential \( P_i' \) with \( P_i' = P_i \) is selected as the first cluster center \( x_1' = x_i' \). Then the potential of each data point \( x' \) is revised using the formula

\[
P_i = P_i - P_i' e^{-\beta \| x_i' - x_c \|^2}
\]

with \( \beta = 4/r_b^2 \) and \( r_b \) is the hypersphere penalty radius. Thus, an amount representing the potential of each data point is subtracted as a function of its distance from \( x_1' \).

More generally, when the \( k \)th cluster center \( x_k' \) has been identified, the potential of all data is revised using the formula:

\[
P_i = P_i - P_i' e^{-\beta \| x_i' - x_c \|^2}
\]

When the potential of all data points has been revised using (4), the data point \( x' \) with the highest remaining potential is chosen as the next cluster center. The process of acquiring a new cluster center and revising potentials uses the following criteria:

- **if** \( P_i > \epsilon P_i' \) (\( \epsilon \) is the accept ratio)
  - Accept \( x' \) as the next cluster center, cluster counter \( k = k + 1 \), and continue.
- **else if** \( P_i < \epsilon P_i' \) (\( \epsilon \) is the reject ratio)
  - Reject \( x' \) and end the clustering process.
- **else**
  - Let \( d_{\text{min}} \) = shortest of the distances between \( x' \) and all previously found cluster centers.
  - **if** \( d_{\text{min}} + \frac{P_i}{P_i'} \geq 1 \)
    - Let \( x' \) as the next cluster center, cluster counter \( k = k + 1 \), and continue.
  - **else**
    - Reject \( x' \) and end the clustering process.
Accept $x'$ as the next cluster center. Cluster counter $k = k + 1$, and continue.

else

Reject $x'$ and set $p_i = 0$.

Select $x'$ with the next highest potential as the new candidate cluster center and retest.

end if

end if

end if

The number of clusters obtained is the number of rules in the TSK FLS. A Gaussian MF of the $v$th variable can be expressed:

$$Q_v = \exp \left[ -\frac{1}{2} \left( \frac{x_v - x_v^{k*}}{\sigma} \right)^2 \right]$$

where $x_v^{k*}$ is the mean of the $v$th input feature in the $k$th rule for $v \in [0, n]$. The standard deviation of Gaussian MF $\sigma$ is given as

$$\sigma = \sqrt{\frac{1}{2\alpha}}$$

2.2. Extended subtractive clustering method

In this paper, extended subtractive clustering method [Demirli et al., 2003] is used for learning evaluation for clusters to identify the number of rules. $r_a$ is confined to the range $[0.15; 1.0]$ with a step size of 0.15. $\varepsilon$ and $\varepsilon'$ are both considered in the range $[0; 1.0]$ with a step size of 0.1. The squash factor $\eta = r_b / r_a$ is in the range $[0.05; 2]$ with a step size of 0.05. A least-square estimation algorithm is used to identify the parameters of consequent equation. As the diagram shown in Figure 1, subtractive clustering, combined with least-square estimation, accomplish the integration of multi-sensor information to identify a fuzzy model. The detailed description can be found in [Ren et al., 2008].

3. CASE STUDY

3.1. Experimental setup

The experiment was performed on a high precision milling machine KERN Evo, equipped with a 50,000 rpm electrospindle and an HSK 25 tool holder [Jemielniak and Arrazola, 2008, Jemielniak et al., 2008]. Figure 2 shows the experimental setup. A laser system was used to measure the tool’s length. The workpiece was a cold-work tool steel X155CrVMo12-1, 50HRC clamped on a three-axis Kistler 9256C1 mini-dynamometer side-by-side with Kistler 8152B221 AE sensor. Signals from those sensors were acquired at a sampling frequency of 50 kHz. Two-flute uncoated micro-grain WC ball
end mills with 400 μm radii and 30° helix angle were used for a side-milling operation performed on a 45° tilted workpiece surface 20x20 mm² in subsequent cuts with cutting parameters: rotational speed \( n = 36,210 \) rpm, cutting speed \( v_c = 68 \) m/min, feed \( f_z = 0.016 \) mm/tooth, depth of cut \( a_p = 0.05 \) mm, width of cut \( a_e = 0.05 \) mm. Thus one cut lasted little more than one second, and the surface was machined in 400 cuts. The total wear in the flank wear \( V_{BMAX_{Bmax}} = 0.11 \) mm, was used as the tool life criterion. The test was regularly interrupted to measure the wear in an optic stereo microscope.

### 3.2. Cutting force measurement

Simple tap tests were performed to evaluate the natural frequencies of the dynamometer with the workpiece and AE sensor attached. Spectral analysis of the obtained cutting force signals showed that apart from the main mode 5080 Hz frequency, much lower frequency modes also exist in the x and y directions. Figure 3 is an example of cutting force signals on the z direction registered during tests. The cutting force signals are supposed to change periodically, based on the tool load, so the dominant frequency
should be equal to the tooth passing frequency in the case of the absence of tool runout, or spindle speed if the runout is significant. In z direction, the signal dominates 4828 Hz component — the fourth harmonic of the tool passing frequency, closest to the natural frequency of the dynamometer (5080 Hz). It means that the dominant frequency is high. It is obvious that the cutting force measurements, as they are, cannot be used for modelling of forces by conventional method.

![Figure 3 Raw cutting force $F_z$ signals registered during tests](image)

3.3. Evaluation strategy
Due to the difficulty in understanding the exact physics of micromilling process, the information obtained during machining process is not complete and precise. It is difficult to establish theoretical and analytical approach or mechanistic model by using this kind information. But fuzzy logic modelling provides the possibility to filter the noise and modelling the system by using this kind information.

The vector of main cutting force can be obtained as:

$$\vec{F} = \vec{F}_x + \vec{F}_y + \vec{F}_z,$$

and the norm of the main cutting force can be calculated from:

$$\|\vec{F}\| = \sqrt{F_x^2 + F_y^2 + F_z^2}$$

In this paper, the values of cutting forces for data processing are the effective values of the force signals (called RMS amplitudes of cutting force). Fuzzy approach using subtractive clustering method for learning evaluation is used to filter and model the cutting force along two different evaluation strategies as shown in Figure 4. The first strategy is shown in the Figure 4(a). First the norm value of cutting force $F$ is calculated from the cutting force components $F_x, F_y, F_z$ measured by sensors, then the cutting force $\hat{F}$ is estimated with the fuzzy model. The second strategy is shown in the
Figure 4(b). The cutting force components $F_x, F_y, F_z$ are modelled as $\tilde{F}_x, \tilde{F}_y, \tilde{F}_z$ by fuzzy models, then the cutting force $\tilde{F}$ is computed with eq.(3).

$$ F = \sqrt{F_x^2 + F_y^2 + F_z^2} $$

Figure 4 Fuzzy evaluation strategies

Root-mean-square-error (RMSE) of estimation is computed by as:

$$ RMSE = \sqrt{\frac{1}{N} \sum (\tilde{A} - A)^2} $$

where $\tilde{A}$ is the estimated result, $A$ is the calculated results and $N$ is number of data samples.

3.4. Data processing

In this experiment, there are two sets of data registered. The first set, shown in Figure 5(a), is used for fuzzy learning, and the second set, shown in Figure 5(b), is for testing.

Figure 5 Cutting forces measurements (RMS amplitude)

In order to choose the better fuzzy learning strategy, two fuzzy systems are learned from the first set of data. Figure 6(a) shows the results $(\tilde{F}, \tilde{F})$ from the two different
fuzzy evaluation strategies, and the calculated value \( F \) from eq. (4). Figure 6(b) shows the testing results from the two different fuzzy evaluations.

![Graph showing learning results](image1)

**Figure 6(a) Learning results**

![Graph showing testing results](image2)

**Figure 6(b) Testing results**

Table 1 lists the differences between the results from learning and testing on data sets. Figure 7 shows the differences between the two learning results of Figure 6(a). The RMSE for the first strategy is 59.3 and for the second one is 43.8. Comparing the results from the two strategies, the second one is better.

**Table I. Difference between the results from the two fuzzy evaluation strategies**

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<thead>
<tr>
<th>Difference from learning (N)</th>
<th>Difference from testing (N)</th>
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<td>minimum</td>
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4. CONCLUSION

This paper presented a fuzzy approach method for filtering and modelling cutting forces in micromilling using subtractive clustering method for learning evaluation. In this approach, the subtractive clustering is utilized to partition the input space and extract a set of fuzzy rules, while the least-square algorithm is used to find the optimal membership functions and consequent parameters of the rule base. In the experimental case study, two different evaluation strategies are used for learning and testing. The second strategy (modelling the three components of cutting force separately) is better than the first strategy (modelling only the norm of the cutting force separately) and the results are satisfactory.

REFERENCES


