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Tool wear assessment based on type-2 fuzzy uncertainty estimation on acoustic emission

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ABSTRACT

In modern manufacturing industry, developing automated tool condition monitoring system become more and more import in order to transform manufacturing systems from manually operated production machines to highly automated machining centres. This paper presents a nouvelle cutting tool wear assessment in high precision turning process using type-2 fuzzy uncertainty estimation on acoustic Emission. Without understanding the exact physics of the machining process, type-2 fuzzy logic system identifies acoustic emission signal during the process and its interval set of output assesses the uncertainty information in the signal. The experimental study shows that the development trend of uncertainty in acoustic emission signal corresponds to that of cutting tool wear. The estimation of uncertainties can be used for proving the conformance with specifications for products or auto-controlling of machine system, which has great meaning for continuously improvement in product quality, reliability and manufacturing efficiency in machining industry.

1. Introduction

Because the information obtained during machining process is vague, incomplete or imprecise, conventional methods need a large number of cutting experiments and additional assumptions in many circumstances for effective uncertainty handling. These requirements reduce the reliability of the models and increase the money and time consuming. Artificial intelligence methods have played an important role in modern tool condition monitoring (TCM) to observe the relation between tool wear and acoustic emission (AE) signal such as neural networks [1,2], fuzzy system [3–5] and fuzzy neural network [6–10]. The increased use of artificial intelligence within TCM has enabled the development of more robust and comprehensive strategies.

Fuzzy logic has been originally proposed by Zadeh in his famous paper “Fuzzy Sets” in 1965 [11]. Fuzzy logic provides a simple way to obtain a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information [12]. Takagi-Sugeno-Kang (TSK) fuzzy logic system (FLS) [13,14] was proposed in an effort to develop a systematic approach to generate fuzzy rules from a given input-output data set. This model consists of rules with fuzzy antecedents and a mathematical function in the consequent part. The antecedents divide the input space into a set of fuzzy regions, while consequents describe behaviour of the system in those regions. TSK FLS has a powerful capability of explaining complex relations among variables using rule consequents which are functions of the input variables.

Based on Zadeh’s conception of type-2 fuzzy sets and extension principle [15], practical algorithms for conjunction, disjunction and complementation operations of type-2 fuzzy sets were obtained by extending previous studies [16]. By using the discrete probability theory, embedded interval valued type-2 fuzzy sets was introduced and it made type-2 fuzzy sets easy to understand and explain [17–21]. A general formula was developed for the extended composition of type-2 relations which is considered as an extension of the type-1 composition [22]. Based on this formula, a complete type-2 fuzzy logic theory with the handling of uncertainties was established [23]. The characterization in the definition of type-2 fuzzy sets uses the notion that type-1 fuzzy sets can be thought of as a first order approximation to uncertainty and, therefore, type-2 fuzzy sets provides a second order approximation. First order type-2 TSK FLS and its structures were presented in 1999 [24]. High order type-2 TSK FLS can be found in [25,26]. Because of its larger number of design parameters for each rule, it was believed that type-2 FLS

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have the potential to be used in control [27] and other areas where a type-1 model may be unable to perform well [28,29] Recent Industrial applications of type-2 fuzzy sets and systems are reviewed in [30]. Application of type-2 fuzzy logic in TCM can be found in [31–33].

The aim of this paper is to present an innovative cutting tool wear assessment in high precision hard turning process using type-2 fuzzy uncertainty estimation on acoustic Emission. Type-2 TSK fuzzy approach is not only model the high complex non-linear physical machining processes, but also estimate the ambiguities and uncertainties associated with AE. In this paper, type-2 TSK fuzzy modelling filter the raw AE signal directly from the AE sensor during turning process. Its interval set of output assesses the information of uncertainty in AE, which is of great value to investigate the complicated tool wear condition during machining process.

This paper is divided into four sections. In Section 1, a brief review of previous studies on intelligent TCM and FLS is given. The description of the fundamentals and learning algorithm of TSK fuzzy approach is in Section 2. A high precision hard turning process experimental case study is in Section 3. Type-2 TSK fuzzy approach is used to filter the raw AE signal directly from the AE sensor and identify the uncertainty interval of AE. The sufficient information from AE uncertainty scheme is used to investigate tool condition so as to enhance the reliability of tool wear. The experimental results show the effectiveness and advantages of type-2 TSK fuzzy modelling. Section 4 is the conclusion and future research direction.

2. Type-2 TSK fuzzy uncertainty modelling

2.1. Type-2 fuzzy logic system

A generalized kth rule in a first-order type-2 TSK fuzzy MISO system can be expressed as

IF x_1 is $\tilde{Q}_{1k}$ and x_2 is $\tilde{Q}_{2k}$ and ... and x_n is $\tilde{Q}_{nk}$,

THEN Z is $\tilde{w}^k = \tilde{p}_0^k + \tilde{p}_1^k x_1 + \tilde{p}_2^k x_2 + \cdots + \tilde{p}_n^k x_n$ where $\tilde{Q}_{1k}, \tilde{Q}_{2k}, \ldots, \tilde{Q}_{nk}$ are type-2 fuzzy sets on universe of discourses. $\tilde{w}^k$ is the output from the kth IF–THEN rule in a total of m rules FLS, $\tilde{p}_0^k, \tilde{p}_1^k, \ldots, \tilde{p}_n^k$ are consequent parameters. Detailed type-2 fuzzy sets and interval type-2 FLS background material can be found in [34].

To obtain a type-2 fuzzy system directly from its type-1 counterpart, type-1 fuzzy membership functions (MFs) are considered as principal MFs of type-2 MFs. A width a_j^k of x_{jk}^* is extended to both directions of cluster centre x_{jk}^* as shown in Fig. 1. By so, cluster centre is expanded from a certain point to a fuzzy number:

$$\tilde{x}_{jk}^* = [x_{jk}^*(1 - a_j^k), x_{jk}^*(1 + a_j^k)] \quad (1)$$

where a_j^k is spread percentage of cluster centre x_{jk}^* as shown in Fig. 1. The cluster centre x_{jk}^* becomes a constant width interval valued fuzzy set $\tilde{x}_{jk}^*$.

Consequent parameter $\tilde{p}_j^k$ is obtained by extending the consequent parameter p_j^k from its type-1 counterpart using the following expression:

$$\tilde{p}_j^k = [p_j^k - s_j^k, p_j^k + s_j^k], \quad (2)$$

where $j \in [0, n]$. s_j^k denotes the spread of fuzzy numbers $\tilde{p}_j^k$, and $s_j^k = b_j^k \times p_j^k$, b_j^k is spread percentage of consequent parameter.

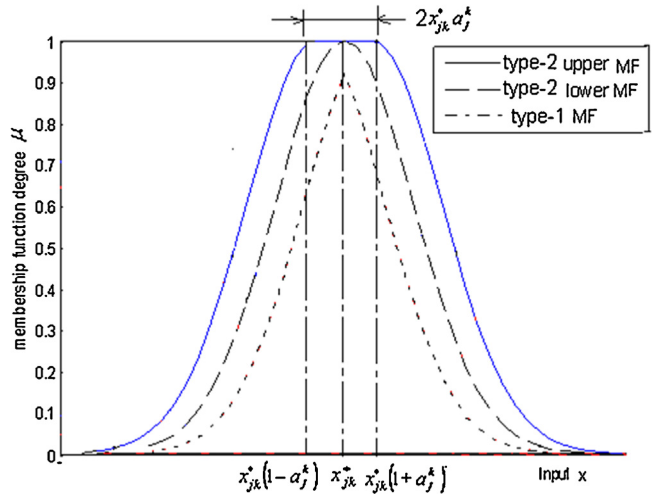

Fig. 1. Spread of cluster centre.

Hence, the premise MF is a type-2 fuzzy set, i.e.,

$$\tilde{Q}_{jk} = \exp\left[-\frac{1}{2}\left(\frac{x_j - x_{jk}^*(1 \pm a_j^k)}{\sigma_j^k}\right)^2\right] \quad (3)$$

where σ_j^k is the standard deviation of Gaussian MF.

Type-2 FLSs are very useful in circumstances in which it is difficult to determine an exact membership function for a fuzzy set. They can be used to handle rule uncertainties and even measurement uncertainties. To date, type-2 FL moves in progressive ways where type-1 FL is eventually replaced or supplemented by type-2 FL [35].

2.2. Type-2 TSK system inference engine

Consequent parameters are obtained by expanding consequent parameters p_j^k in its type-1 counterpart to fuzzy numbers.

$$\tilde{p}_j^k = p_j^k(1 \pm b_j^k) \quad (4)$$

where b_j^k is the spread percentage of fuzzy numbers $\tilde{p}_j^k$.

For the most general structure of type-2 TSK FLS, antecedents are type-2 fuzzy sets and consequents are type-1 fuzzy sets. Membership grades are interval sets, i.e.,

$$\mu_v^k = [\underline{\mu}_v^k, \overline{\mu}_v^k] \quad (5)$$

where $\underline{\mu}_v^k$ and $\overline{\mu}_v^k$ are the lower value and upper value of the vth input variable in the kth rule.

The explicit dependence of the total firing interval for kth rule can be computed as:

$$\underline{f}^k = \underline{\mu}_1^k(x_1) \cap \underline{\mu}_2^k(x_2) \cap \cdots \cap \underline{\mu}_n^k(x_n) \quad (6)$$

$$\overline{f}^k = \overline{\mu}_1^k(x_1) \cap \overline{\mu}_2^k(x_2) \cap \cdots \cap \overline{\mu}_n^k(x_n) \quad (7)$$

where variable $\underline{f}^k$ and $\overline{f}_k$ denote lower value and upper value of fire strength. The symbol $\cap$ is a conjunction operator, which is a T-norm. It can be either MIN operator $\wedge$ or product operator *.

The interval value of the consequent of the kth rule w^k is $w^k = [w_l^k, w_r^k]$, where

$$w_l{}^k = \sum_{j=1}^{n} c_j^k x_j + c_0^k - \sum_{j=1}^{n} s_j^k |x_j| - s_0^k \quad (8)$$