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A human-assisted knowledge extraction method for machining operations

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Abstract

This paper deals with a human-assisted knowledge extraction method to extract "if…then…" rules from a small set of machining data. The presented method utilizes both probabilistic reasoning and fuzzy logical reasoning to benefit from the machining data and from the judgment and preference of a machinist. Using the extracted rules, one can determine the values of operational parameters (feed, cutting velocity, etc.) to ensure the desired machining performance (keep surface roughness within the stipulated range (e.g., moderate)). Applying the presented method in a real-life machining knowledge extraction situation and comparing it with the inductive learning based knowledge extraction method (i.e., ID3), the usefulness of the method is demonstrated. As the concept of manufacturing automation is shifting toward "how to support humans by computers", the presented method provides some valuable hints to the developers of futuristic computer integrated manufacturing systems.

Keywords: Computer integrated manufacturing; Machining data; Knowledge extraction; Human intelligence; Fuzzy logic; Probabilistic reasoning

1. Introduction

Machining of materials (turning, milling, drilling, etc.) is an empirical science. The decision-making activities in machining operations depend on the numerical data acquired from various machining experiments. The acquired machining data is not directly used in the decision-making activities. It is required to find structures (i.e., knowledge) in a given set of data to make it more useful for making decisions. Most of the times the extracted knowledge is represented by algebraic expressions (empirical equations) or by logical expressions (a trained neural network, "if…then…" rules, decision trees) [9,12,17–19,22,24,26,27,30,31]. The knowledge represented by a set of "if…then…" statements (or rules) is preferable because it can easily integrate different subsystems of computerized manufacturing systems, as illustrated in Fig. 1. As seen from Fig. 1, a piece of knowledge "if V/f ratio is high then Ra is high" extracted from a given set of experimental data is used to make some operational decisions (e.g., in determining the proper NC codes (S and F codes) ensuring the desired performance (roughness), in determining the control limits of a control chart for process control, in exchanging the experimental results among the experts in the field for validation and domain knowledge refinement, and alike).

In order to automate the knowledge extraction process such artificially intelligent computing methods as inductive learning, artificial neural networks, and alike are often recommended. See Li and Elbestawi [16], Ochiai et al. [21], Baradie [9], Pham and Pham [22], Monostori [18], and the references therein for more details. Even though such methods are used to automate the knowledge extraction process, a great deal of human assistance (knowledge extractor's judgment, preference, intuition, overall familiarity to the problem, and alike) is required for getting good results. Particularly, a knowledge extractor him/herself makes some method-specific decisions that ensure the

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Notations

CV	control variable
PM	performance measure
AC	acceptable range of CV defined by a trapezoidal fuzzy number (a, b, c, d)
RE	recommended range of PM defined by a trapezoidal fuzzy number (h, g, f, e)
$U_{()}$	universe of discourse of "()", a segment of $\Re$
$DoB_{()}$	degree of belief (or membership function) of "()" in the scale [0, 1]
$AC_{()}$, $RE_{()}$	alpha-cuts of AC, RE at alpha-level "()"
Supp(·)	support of ".", which is the largest alpha-cut of "."
$E(\cdot)$	expected or average value of "." based on the centroid method
max(·)	maximum of "."
min(·)	minimum of "."
Pr	a value of probability in the scale [0, 1]
Pr(·)	probability of "."
Pr(.|.)	probability of "." given "."
Pr(.|¬.)	probability of "." given not "."
LL(j)	jth linguistic likelihood (a fuzzy number in the universe of discourse [0, 1])
LLL	likely-predominant linguistic likelihood (E(LLL) > 0.5)
ULL	unlikely-predominant linguistic likelihood (E(ULL) < 0.5)
(pm_i,cv_i)	ith data point, pm_i is a numerical value of PM and cv_i is a numerical value of CV
V	cutting velocity (m/min)
r	nose radius of a cutting tool (mm)
f	feed rate (mm/rev)
Ra	arithmetic mean of surface roughness profile (micro-meter)
nd	number of data points
nl	number of linguistic likelihoods

successful application of a preferred method. For instance, to extract knowledge using an artificial neural network or using neurofuzzy computing, the network topology, learning algorithm, etc., have to be selected by the individual who applies the method; improper selection does not produce the expected result [10]. Similarly, to extract knowledge using inductive learning (i.e., ID3) [23], the demarcation lines between the positive and negative examples for each attribute are sensitive decisions taken by the individual who applies the method [21]. Therefore, on

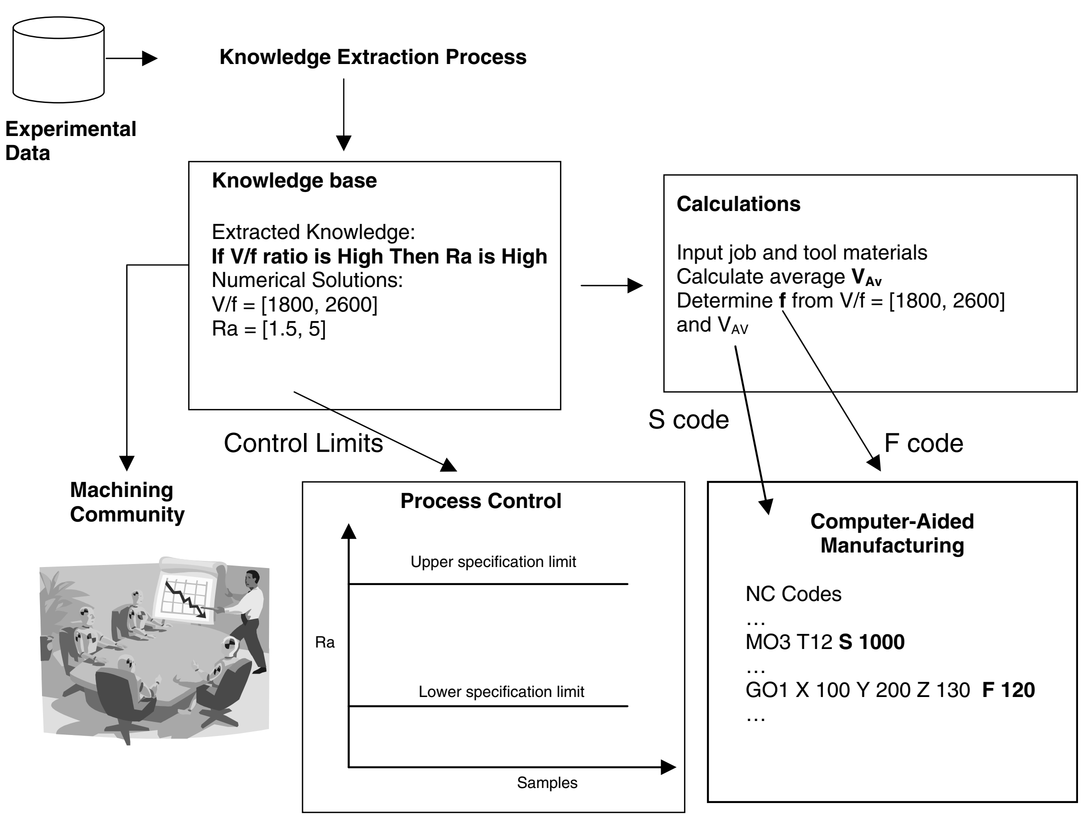

Fig. 1. Knowledge-based machining operation.