Building the knowledge base of a production system from the raw data of a multi-sensor system

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Abstract

The knowledge base of the rule-based systems, or production systems, is built from the experience of human experts using well-known techniques and highly developed tools of knowledge engineering. Although this is not a simple task in itself, the difficulties dramatically increase when it is intended to synthesize the inference rules directly from signals obtained from sensors on complex applications. Specific problems concerning knowledge acquisition and representation must be solved. This paper introduces an automatic method to build the knowledge base of a production system from the raw data of a multi-sensor system, using a machine-learning procedure and abstracting the numerical data for symbolic knowledge representation. The method is demonstrated for two applications for monitoring the tool condition in machining processes.

1. Introduction

Recent developments on sensors have notably improved monitoring and control systems. Nowadays, 'smart' sensors exist whose performance goes beyond the basic transduction function and some devices now feature environmental compensation, communication and the ability to self diagnose [1]. Sensors provide more and more complete and accurate data. However, this information cannot always be easily used. Traditional techniques for identification and control cannot be applied in many cases because reliable mathematical models to represent conveniently the dynamics of the process are not available. Contrary to this problem, expert operators can be found controlling complicated processes (Fig. 1). Applications that entail skill, experience, intelligence and the perception capability of human beings cannot be automized using conventional techniques. Such complex situations are closer to the perception–action paradigm rather than to that of monitoring–control. The alternative approach to these problems is based on the development of artificial intelligence, as, for instance, is found in expert systems.

2. Problems arising

Expert systems have been used for some problems concerning monitoring and control of processes [2] and real time [3–5]. In these cases, the existence of sensors gives rise to important differences within the pioneering applications of the expert systems. Firstly, when the system is running, data must be gathered directly from sensors instead of from the operator. Secondly, these numerical data must be somehow integrated into the symbolic processing module. Until now, the use of expert systems has presented serious difficulties for this kind of application, because they were not initially designed for this purpose [3].

Knowledge acquisition also presents difficulties even before the system is ready for running. Some of them are related to the complexity of the considered domain. It is customary to build the knowledge base of an expert system by codifying the experience of experts. While the procedure is well founded, it consumes excessive time [6, 7]. Tools for helping in the acquisition of knowledge are being developed to improve this [8, 9].

In extremely complex applications neither adequate mathematical models exist nor is it feasible to generate the knowledge base debriefing experts. This happens, for example, in the real-time estimation of the tool condition in machining processes. The enormous number of variables involved in the process, some of them absolutely unobservable and uncontrollable, makes the knowledge of even the best machinists too incomplete and vague. Although if it were possible to represent the knowledge of these experts, it would be necessary to have a sensor system imitating the human senses, because that knowledge would be expressed in terms

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of the feelings as they are perceived by the operators

Synthesizing inference rules directly from sensor signals would avoid these inconveniences However, it cannot be done experimentally until we become expert interpreters of the signals This would be a very arduous task because of the underlying complexity On the one hand, the variability inherent in the process gives rise to major inaccuracies and uncertainties in the observations and on the other, multi-sensor information is so rich, but at the same time so complex [10], that it is not easily interpreted

A method for resolving these difficulties is proposed in this communication

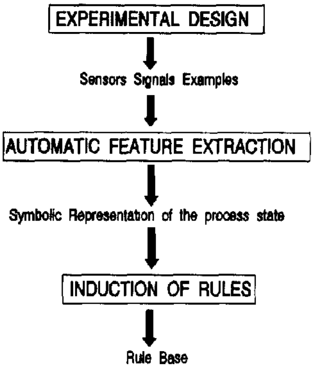

Fig 2 Components and operation of the proposed method

3. Method

The need for knowledge-based systems on complex applications of processes monitoring and control has been presented It has also been shown that many difficulties then arise These are overcome here by acquiring knowledge directly from the signals of sensors by means of a machine-learning procedure and abstracting the numerical data to represent the knowledge in symbolic form, (see Fig 1)

An important aspect, not mentioned until now, is the repercussion of replacing experts' knowledge by machine learning To ensure the good quality of the knowledge represented by the system, the experience to be learned must be very carefully planned Obviously, this is impossible without a thorough knowledge of the application

In this paper, a method for automatically generating the knowledge base of a production system is introduced, see Fig 2 This has the following features

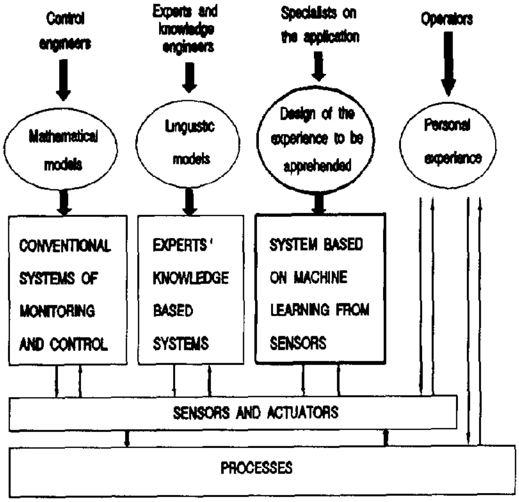

Fig 1 Different approaches for monitoring and control

(1) the experience to be perceived and learnt is planned according to experimental design techniques,

(2) the knowledge is based on signal information from sensors, either homogeneous or heterogeneous,

(3) an automatic procedure of feature extraction is used for abstracting the raw numerical data and getting a symbolic representation of the state of the monitored process,

(4) a machine-learning procedure is used to discover production rules by induction from the examples,

(5) both computation levels, numeric and symbolic, are efficiently integrated,

(6) explicative models can be built in parallel, making the most of the experimental design, and making it possible to implement second generation expert systems, which use reasoning based on heuristic rules as well as based on a deep model [11];

(7) the experimental design also enables the estimation of the confidence levels of the rules on an objective probabilistic base, rather than by the subjectivity of the experts' beliefs

The method is made up with three procedures design of experiments, automatic feature extraction and induction of rules Next, a short description of the general framework, the procedures and its role is presented

Production systems

Production systems, or rule-based systems, constitute a very common schema for representing knowledge in the context of artificial intelligence They include the rule-based expert systems and have been particularly useful in making deductions by stringing together IF–THEN statements [7] A production system is composed of a base of rules, a context (the known facts) and an interpreter of rules The base of rules consists of a set of IF a given situation exists, THEN an action must be taken, in which the knowledge about a certain domain is encoded Both the base of rules and the context form the knowledge base of the system

Experimental design

Experimental design techniques are thought to collect samples efficiently when variability is present. They allow the lowering of the number of experiments needed, reduce the experimental error and give validity to the results. In the absence of experts that provide knowledge, the system must learn by itself from an experience truly representative of the explored domain. Experimental design is used here to grant it.

Automatic feature extraction

The aim of this stage is to extract features from the raw signals, to establish states or categories relevant to the system objective, thus enabling symbolic representation of the knowledge. It uses an automatic procedure developed by our team [12].

Induction of rules

Induction is a way of reasoning in which an apparently chaotic collection of cases is used just to discover their underlying structure. The ID3 algorithm [6] is employed here to acquire knowledge and construct decision trees from the examples collected from the experiments. Each example belongs to one of the distinguishing categories and has associated categorical values of the extracted features. Rules are obtained by direct reading of the tree.

4. Applications

This method was used to build a part of the knowledge base of TEMOS (Tool Expert Monitoring System), an expert system implemented by a European consortium under the BRITE programme. The objective of this system is the in-process monitoring of the tool condition in machining processes using multiple sensors. This is a current problem [13] which has been attacked with different techniques for many years [14]. Here it is considered as a problem of classification of tool states, expressible in the form of IF–THEN rules which can be adequately treated by the method proposed here. Its application is demonstrated in the following two examples.

Milling

The method was used in this case to synthesize rules to distinguish between three tool states.

(i) low wear $\equiv$ 0.0 mm < average width of the flank wear $\leqslant$ 0.2 mm

(ii) medium wear $\equiv$ 0.4 mm < average width of the flank wear $\leqslant$ 0.6 mm

(iii) high wear $\equiv$ 0.8 mm < average width of the flank wear $\leqslant$ 1.0 mm

Signals from sensors were collected according to a factorial design, in which tool wear state was considered the main factor. Table 1 shows the cutting conditions employed. Two piezoelectric sensors, B&K 4384 and PAC S9208, were used for measuring respectively vibration and acoustic emission and the electric current was directly measured. The signals, time series of fixed length, were digitized using a Nicolet system 500. Tool wear was recorded by means of a video camera Sony CCD monochrome AVC-D5/D5CE and a video cassette recorder. Wear was computed by image processing. More details can be found in ref. 15 about the use of experimental design to take samples in these kind of experiments.

The feature extraction procedure was applied over the raw data to obtain independent features that effectively discriminate between the three states. Two of them were the mean of the electric current and the variance of the vibration. The best were selected and the range of each feature was divided into five levels

very low $\equiv$ (minimum, $\mu - 3\sigma/4$)
low $\equiv$ ($\mu - 3\sigma/4$, $\mu - \sigma/4$)
medium $\equiv$ ($\mu - \sigma/4$, $\mu + \sigma/4$)
high $\equiv$ ($\mu + \sigma/4$, $\mu + 3\sigma/4$)
very high $\equiv$ ($\mu + 3\sigma/4$, maximum)

using the mean μ and the standard deviation σ of its own distribution.

Finally, the examples were presented to the induction procedure, using categorical values for features and tool states. One rule was derived from every branch of the constructed decision tree. A second independent collection of examples was then used to test the rules, estimating its confidence level by the success rate. Two conditions were imposed on the rules to be included in the knowledge base: to have a confidence level greater than a threshold and to be representative, i.e., the rule must be constructed from a significant number of examples. The following rules enlighten the form adopted by the milling rule base.

IF (f_1 is very low) THEN (tool wear is low)

IF (f_1 is medium and f_3 is low) THEN (tool wear is medium)

TABLE 1 Cutting conditions on milling

Machine tool	LAGUN FBF 1600
Cooling liquid	None
Workpiece material grade	AISI 4340
Tool	SECODEX SR 220 13-0050-12 Ø50 4 inserts
Insert	SEKN 1203 AFN P10
Cutting operation	Surfacing (roughing face milling)
Cutting speed (m/min)	175
Feed (mm/tooth)	0.1
Axial depth of cut (mm)	2
Radial depth of cut (mm)	35.3

TABLE 2 Cutting conditions on drilling

Machine tool	LAGUN FBF 1600
Cooling liquid	Metalina C
Workpiece material grade	F-1282
Workpiece hardness (HB)	304
Tool	DIN 338
Tool diameter (mm)	5
Tool material	HSS-M2
Cutting speed (m/min)	15
Feed (mm/revolution)	0 1
Depth of cut (mm)	20

IF (f_1 is very high and f_3 is low) THEN (tool wear is medium)

IF (f_1 is very high and f_3 is high) THEN (tool wear is high)

where f_n represents the nth selected feature

Drilling

A similar experiment was conducted on drilling In this case, the following tool states were considered

tool resharpening,

linear wear stage,

wear curve corner,

critical stage

Also, a factorial design was chosen Table 2 shows the cutting conditions employed Several piezoelectric sensors were used for the measurements thrust and torque, Kistler 9271B, acoustic emission, PAC S9208, and vibration, Endevco KE66

Some features showed good performance in discriminating tool states, for example, maximum of the sliding mean of the thrust force, and the mean divided by standard deviation of the Cepstrum of the thrust force The range of each feature was divided on five levels, as in milling

Drilling rule base is composed of such rules as

IF (f_5 is medium and f_4 is very low and f_2 is high) THEN (tool is on the linear wear stage)

IF (f_5 is very high and f_4 is high) THEN (tool is on the critical stage)

where f_n represents the *n*th selected feature

In both applications the control operation is carried out immediately, combining previous inference rules with others such as

IF (tool wear is not high) THEN (acquire data from sensors again) ELSE (change the tool)

The result is a continuous in-process monitoring of the tool state and control of the process

5. Conclusions

The need has been presented for knowledge-based systems for monitoring and controlling complex processes and it has been shown that problems then arise in acquiring and representing the knowledge These difficulties have been overcome by introducing in this paper a method that automatically generates the knowledge base of a rule-based system using raw data from sensors

The method is composed of three efficiently integrated procedures By means of the first one the experience to be perceived and learnt is planned according to an experimental design This guarantees that the said experience is absolutely representative of the process The second one, an automatic procedure of feature extraction, is used for making abstractions of the raw numerical data and for getting a symbolic representation of the existing knowledge about the state of the process Finally, the ID3 machine learning procedure is used to discover production rules by induction from examples

The introduction of the experimental design gives rise to other benefits Firstly, confidence levels of the rules are estimated on an objective probabilistic base, rather than by the subjectivity of the experts' beliefs Secondly, it enables the building of explicative models in parallel, giving the possibility to implement second generation expert systems Finally, it has been shown how the method was used to produce inference rules for the TEMOS expert system, developed for the in-process monitoring of tool conditions in machining processes using multiple sensors It is important to note that, strictly speaking, the rules are only valid for those specific experimental conditions which generate them

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