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AUTOMATIC TOOL FAILURE MONITORING IN THREAD TAPPING

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Abstract: *This paper presents a study of various methods suitable for automatic tool failure monitoring in thread tapping. To facilitate a specific diagnosis scheme for the tapping process the tow steps were taken: pattern recognition and fuzzy system. They should be evaluated based on success rate, sensivity and robustness. For example, in pattern recognition, large variance of a process conditions, and hence, is ineffective. In fuzzy systems, a small fuzzy degree indicates inaccuracy. From a tapping test the five tapping conditions were obtained: normal, tap wear, misalignment, hole oversize and hole undersize.*

Key words: *tapping process, automated monitoring, pattern recognition, fuzzy systems.*

1. INTRODUCTION

Internal thread tapping is one of the major machining operations performed in the manufacturing industry.

Along with the fast development of computer, monitoring and diagnosis techniques for machining processes, such as turning, drilling, have became available, but not for the tapping process.

Tapping processes differ due to the variety of the tapes and holes. The process is a discontinuous type with very short intervals. The internal thread cutting tap is one of the most fragile cutting tools. In the tapping process exist large uncertainties. The tapping failures are three components: tap configuration, hole quality and machine tool performance.

2. FAILURE MODES IN THE TAPPING PROCESS

Major causes of top breakage and poor thread quality are tap wear, hole size error (both oversize and undersize) misalignment and poor lubrication.

Most machine tools are employed, either singly or in groups, within manufacturing cells which again are either arrange as single cells or grouped into complex manufacturing system. The ultimate aim of any monitoring system is to ensure the continuous reliable production of components of acceptable quality, while maintaining the integrity and well-being of the production machinery. The machine tool monitoring system must be equipped with:

- sensor and detectors,
- data processing means,
- access to appropriate actuators,
- suitable displays, alarms, etc.

so as to ensure as far as possible that the machine can be maintained continuously in good working order. Any definite or apparent malfunction will be corrected on-line wherever possible, and a record of the symptoms and the corrective action should be displayed and recorded for reference.

The essential aim of any supervision system is:

- to monitor the performance of the activity, operation or process under consideration,
- to ensure that the performance is satisfactory, i.e. that all the specified targets are being achieved,
- to identify immediately when any change in performance occurs, whether dangerous, potentially dangerous or of no consequence,
- to process all received signals,
- to carry out whatever corrective actions may have been programmed, both promptly and effectively.

This implies that a malfunction by one machine tool is likely to influence other machines in the cell, and also that any supervision system should be designed with the requirements of the total cell in mind, as opposed to considering each machine tool in isolation as would have been appropriate only two decades ago.

A further target of the manufacturing cell, and for that matter the individual stand-alone machine tool, must be a regime of total protective safety including fail-safe operation should a malfunction occur. In the event of failure, protection should be afforded in priority to:

- the human operator (if applicable),
- the machinery/cell itself,
- the component or workpiece.

Since the machine tool is being used to manufacture a workpiece – the ultimate saleable item – utilizing appropriate manufacturing processes to achieve this, it is clear that supervision of the performance of a machine tool may be carried out by monitoring:

- the workpiece,
- the process,
- the machine tool itself.

The justification for monitoring the workpiece is firstly that there is little point in ensuring that the process and the machine tool are operating correctly under control if they are producing unsatisfactory workpiece *e.g.* with surface finish outside tolerance, and secondly that in many instances the first evidence of unsatisfactory operation may be revealed by a change in the process itself, *e.g.* the formation of a "built-up edge" in a metal-cutting process.

The automatic supervision of a range of different manufacturing processes has been discussed elsewhere; nevertheless, any discussion of the automatic supervision of machine tools must also touch on process and component supervision if it is to be comprehensive and thorough.

The automatic supervision of a machine tool (accepting here that the item being monitored may be the machine tool itself, the process or the component) may conveniently be sub-divided into:

- fault detection
- fault identification
- fault correction.

To these three actions must also be added:

- fault prediction

which, especially in an age which is becoming increasing quality conscious and in which major advances are being made in pattern recognition techniques expert system and artificial intelligence, is likely to prove of major importance in the future.

To detect a fault requires one or more sensors. In the days of manually-operated machine tools, sensing was performed by those of the human operator, principally sight, hearing, touch and smell.

A further, and very important, factor to be considered in any investigation of sensors is how they should be incorporated into the machine: should they be mounted in contact with the machine or remotely. The advantages to be derived from directly mounting sensors onto the machine tool itself are obvious: monitoring is carried out directly, and signals are least likely to be affected by interference from adjacent machines. This very proximity of sensors introduces a potentially serious problem: the sensors themselves can interfere with, or cause significant alterations to the process itself. This interference can include mechanical obstructions or (more likely) serious limitation to the working envelope of the machine, change in friction and inertia of moving elements, and alterations to the performance of electronic circuitry.

It has already been made clear that the priority of preserving the workpiece itself falls below the importance of protecting the lives and limbs of the human operators (if any) or of saving the machine itself in the event of a sensor failure. Nevertheless, the prime purpose of a manufacturing cell is to produce "good" components, i.e. components within tolerance which do not require any rework, as rapidly and as cheaply as possible. There is therefore, a prima facie case for monitoring appropriate parameters of the workpiece to ensure that the manufacturing cell is producing satisfactory components.

In the case of the automatic supervision of an unmanned manufacturing cell, a strong case can be made for 100 per cent in-process inspection, with feedback directly to the machine itself to provide in-process quality control at the point of manufacture. By this means not only will any deviation of the process which results in change of monitored workpice parameters be sensed and corrected (within the range of correction available to the machine system) but a signal can also be provided to indicate that this correction is being made. If direct online quality control is not possible, then immediate post-process inspection with feedback to the machine tool is a strong alternative strategy.

Failure modes Fig. 1 can be classified to the tap breakage and poor thread quality.

Tap breakage may by cause by overload (both torsion and bending), material fatigue, inadequate heat treatment, etc.

Thread quality is described by two specifications: size and surface finishing. The quality failure mode considered here are thread oversize, thread undersize, burr on entry or exit and the inner diameter oversize.

3. METHODS USED FOR THREAD TAPPING

Automated operation of machine tools has been demanding the development and implementation of tool failure monitoring in all kinds of machining operations. A field survey has shown that more than 60 % of the applications of the tool failure sensor have been reported in hole making operation including the drilling, gun drilling and thread tapping among all spectra of machining operations.

The schematic experimental setup is shown in Fig. 2. The sensor signals (torque and thrust force) were measured from a dynamometer mounted under the workpiece.

The monitoring methods discussed in this paper include pattern recognition and fuzzy systems.

In general, pattern recognition methods can be divided into two groups: statistical method (also called nondeterministic pattern classification methods).

Statistical pattern recognition methods are based on the Baycs estimation [1].

The distribution – free pattern recognition methods are based on the similarity between a simple *x* and the pattern that describe the process conditions. From a geometrical

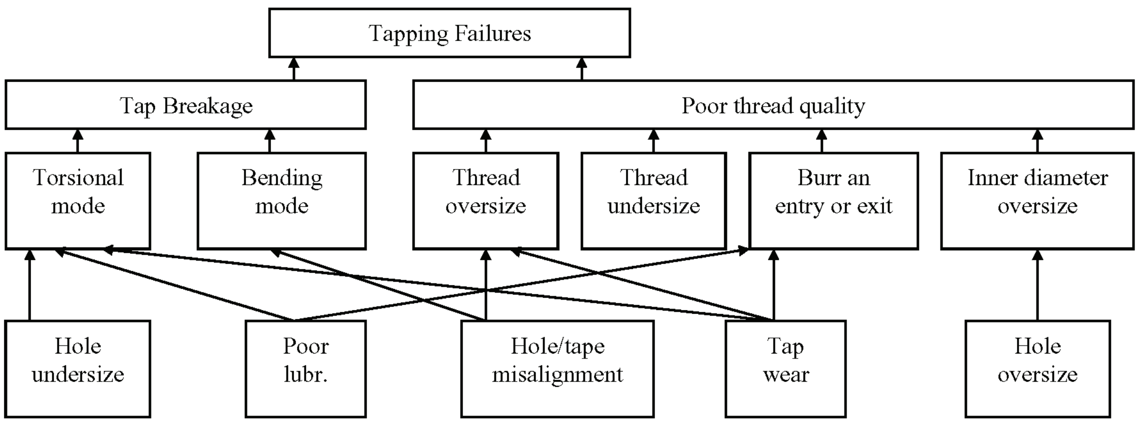

Fig. 1. Failure mode and causes in tapping process.

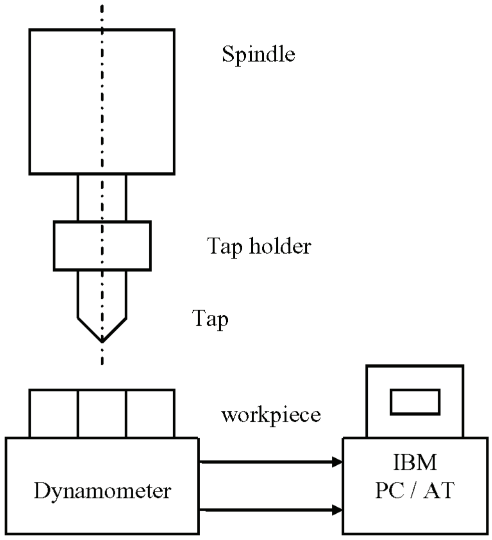

Fig. 2. Schematic experimental setup for tapping process condition monitoring.

point of view, the monitoring indices span an m – dimensional space s. In the space, each process condition h_j, is characterized by a pattern vector $p_j = \left[p_{j1}, p_{j2}, ..., p_{jn} \right]$. The similarity between the sample and a pattern can be measured by the distance in then used as the criterion for classifying the sample. There are a number of ways to define patterns and distances. Some used methods include the Mahalanobis algorithm, the linear discriminate algorithm and the Fisher's algorithm.

In the Fisher's algorithm, the distance is defined as:

$$q_j(x) = \beta_j^t x, \qquad (1)$$

where β_j is determined by maximizing:

$$J = \sum_{j=1}^{n} \beta_j^t \sum_j \beta_j. \qquad (2)$$

The architecture of the fuzzy-nets in process (FNIP) system for tool – breakage monitoring is schematically shown in Fig. 3. It has two components:

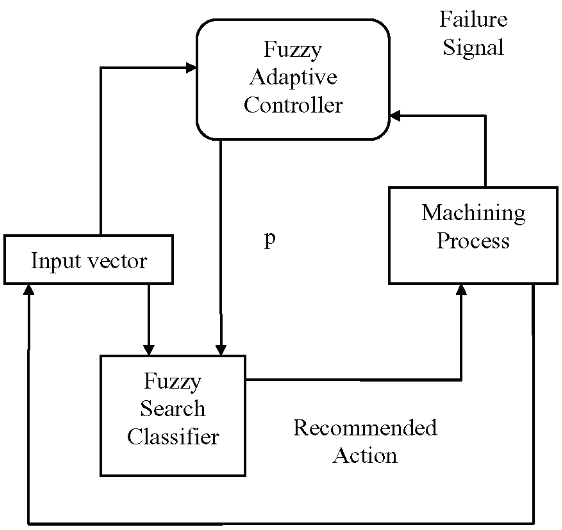

Fig. 3. The architecture of the FNIP system.

- the fuzzy search classifier (FSC) which maps a state vector into a recommended action using fuzzy pattern recognition;
- the fuzzy adaptive controller (FAC) which maps a state vector and a failure signal into a scalar grade that indicates state integrity. The FAC also produces the output active value, p, to upgrade FSC mapping according to the variation of the input state.

The encoding state is feedback into FNIP, along with the failure signal. Learning is accomplished by fine tuning the parameter is the fuzzy-nets systems (FSC and FAC). Consequently the parameters describing the fuzzy membership function in the FSC are changed and the FAC the weights (the fuzzy active value) are adjusted. By using this adaptive function, the FNIP system can realize the change of the machining condition and upgrade the classifier for proper functioning.

Fuzzy system methods and pattern recognition methods are all based on same sort of weighting of the monitoring indices. For example, in the fuzzy linear equation method, monitoring induces are equally weighted in evenly distributed subintervals. Also, monitoring indices in pattern recognition methods are weighted according to discriminate functions.

For the tapping process is Table 1 are shown the possible indices which are relevant for the monitoring and diagnosis purpose. The considered modes should be verified and ranked according to the relevancy to the tapping process.

Information gain of an index to a process is the amount of information carried by index about the process. The information gain of index y to a diagnoses process with pattern space Ω can be estimated by:

$$G_\Omega(y) = -\sum_{i=1}^{N_c} \frac{N_i^c}{N} \log_2 \frac{N_i^c}{N} + \sum_{j=1}^{N_c} \sum_{i=1}^{N_c} \frac{n_{ij}}{N_j^R} \log_2 \frac{n_{ij}}{N_j^R}. \qquad (3)$$

where $\Omega = \{c_i, i = 1, \ldots, N_c\}$ is the class space with c_i representing the i th class and N_c the total number of classes.

Table 1

Definition of monitoring indices

Index y_k; k =	Physical Quantities
1	Maximum of tapping torque T
2	Mean of tapping torque
3	Standard deviation of tapping torque
4	Mean of retraction torque
5	Standard deviation of retraction torque
6	Mean of tapping thrust force F_z
7	Covariance of thrust force in tapping
8	Correlation of thrust force
9	Correlation of thrust force in retraction
10	Mean of lateral force F_x
11	Covariance of lateral force
12	Mean of force circle in tapping F_y
13	Mean of lateral force in retraction
14	Mean of force circle in retraction

In order to evaluate the potential indices for the diagnoses of the tapping process as listed in Table 1 the machining conditions of tapping are divided in normal tapping tap-hole misalignment, tap wear, tap undersize, tap oversize as defined in Table 2. The notes of tap wear were created by grinding and measured under a microscope. Misalignment is the eccentricity between the tap center and the hole center. Tap undersize and tap oversize were produced by drilling holes using different drills.

Different indices will introduce different information gains to the process. The estimation of the information gain is made for each index consecutively. The information gain of index *y* to the process depends on the selection of the partition $R = \left\{R_{j,\, i=1,\ldots,\, N_c}\right\}$. Let $B_j = \left[b_1, \ldots, b_{N_c+1}\right]^{\mathrm{T}}$ denote a boundary vector associated with the partition *R* such that $R_j \supset$ all $y,\ b_j < y \le b_{j+1}$, $j = 1, \ldots, N_c$.

In this case, the optional boundary vector b_j, $j = 1, \ldots, 14$ was estimated for each of the indices and a boundary matrix $B = \left[B_1, \ldots, B_{14}\right]$ was obtained. Based on the optional partition defined by the optimal boundary matrix *B*, the information gain of all the indices regarding each of the 4 class were calculated. The total information gain of each index was also calculated using equation (3) and the results are shown in Table 3.

Table 2

Definition of tapping process conditions

Class	Process condition	Description
C1	Normal	
C2	Slight wear tap	0.25 mm less in diameter
C3	Medium wear tap	0.5 mm less in diameter
C4	Sever wear tap	1 mm less in diameter
C5	Slight misalignment	0.15 mm eccentricity
C6	Severe misalignment	0.25 mm eccentricity
C7	Slight undersize	
C8	Severe undersize	
C9	Slight oversize	
C10	Severe oversize	

Table 3

Results of index evaluation

Index/Class	1	2	3	4	5	6	7
C1	1.12	1.33	1.32	0.40	1.40	1.62	0.58
C3	2.32	2.32	2.32	0.44	0.69	2.02	0.86
C8	1.88	1.90	2.32	0.02	0.91	0.86	0.10
C10	1.50	1.67	2.32	0.99	0.48	1.30	0.26
Total gain	6.82	7.22	8.28	1.85	3.48	5.80	1.80
Index/Class	**8**	**9**	**10**	**11**	**12**	**13**	**14**
C1	0.84	0.90	1.37	0.67	1.06	1.27	0.40
C3	0.48	0.13	2.17	0.69	1.27	1.06	0.06
C8	0.14	0.07	0.70	0.59	0.46	0.93	0.16
C10	0.16	0.12	1.58	0.52	1.35	0.94	0.60
Total gain	1.62	1.22	5.82	2.47	4.14	4.20	1.76

The following conclusions result from this evaluation of indices:

- The cutting torque contains the most information about the topping process, which is confirmed by the high information gains of the first three indices.
- Indices 7, 8, 9 and 11 are the least relevant to the topping process and should be dropped from the index list

10. CONCLUSION

The monitoring scheme consists of sensing, signal processing and decision making.

Monitoring indices should represent the characteristics of the process conditions without being affected by process working conditions.

A practical index evolution procedure for the diagnosis of the tapping process has been developed based on the information measure of each index to the process. This index evaluation procedure can also be extended to another cutting process.

REFERENCES

[1] Pham, D. T., Pham, P. T. N. (1988). *Expert System in Mechanical and Manufacturing Engineering*, International Journal of Advanced Manufacturing Engineering, Vol. 3, No. 3, p. 3–21.

[2] Wang, M., Zhu, J. Y., Zhang, Y. Z. (1985). *Fuzzy Pattern Recognition of the Metal Cutting States*, Annals of the CIRP, Vol. 34, No. 1.

[3] Li, P. G., Wu, S. M. (1988). *Monitoring Drill Wear States Using a Fuzzy Pattern Recognition Technique*, ASME Journal of Engineering for Industry, Vol. 110, No. 6, p. 297–300.

[4] Liu, N. S., Lee, B. Y., Tarng, Y. S. (1996). *Monitoring of drill fracture from the current measurement of a the faze induction motor of paper*, International Journal Machine Tools Manufacturing, vol. 36, no. 6, pp. 729–738.

[5] Subramanian, K., Cook, N. H. (1977). *Sensing of Drill Wear and Prediction of Drill Life*, ASME Journal of Engineering for Industry, vol. 99, pp. 295–301.

[6] Dorin, Al. (1987). *Controlul automal al uzurii sculelor aschietoare in sistemele tehnologice flexibile*, Construcţia de maşini, no. 1, pp. 17–24.

[7] Dorin, Al. (1987). *Metode indirecte de diagnoza a uzurii sculelor aschietoare*, Construcţia de maşini, no. 1, pp. 24–31.

[8] Sata, T., Hirakoka, H., Miki, M., Takata, S. (1987). *Functions required for advanced flexible manufacturing systems*, Robotics & Computer Integrated Manufacturing, vol. 3, no. 4, pp. 417–421.

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