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An Application Case Study on Multi-sensor Data fusion System for Intelligent Process Monitoring

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Abstract

Multi-sensor data fusion is a technology to enable combining information from several sources in order to form a unified picture. Focusing on the indirect method, an attempt was made to build up a multi-sensor data fusion system to monitor the condition of grinding wheels with force signals and the acoustic emission (AE) signals. An artificial immune algorithm based multi-signals processing method was presented in this paper. The intelligent monitoring system is capable of incremental supervised learning of grinding conditions and quickly pattern recognition, and can continually improve the monitoring precision. The application case indicates that the accuracy of condition identification is about 87%, and able to meet the industrial need on the whole.

Keyword : Multi-sensor Data Fusion, Negative-Selection Algorithm, Artificial immune, Process Monitoring, Grinding ;

1. Introduction

Facing increasing demands on manufacturing productivity quality control based on detection after the manufacturing process is no longer adequate. The pressure of costs is increasingly forcing the exploitation of the full potential of manufacturing processes. Grinding is known as one of the most important and complicated machining (or material removal) process for high precision parts, mostly due to the fact that a grinding operation is performed by a grinding wheel which is composed of many tiny, irregular shaped, and randomly positioned and oriented abrasives (also called grits) bonded by some medium. Up to now it is still challenging to apply in-loop quality control in grinding using in-process measurement techniques [1-3]. Indirect methods in condition monitoring rely on some sensory signals such as forces, power, vibration, and acoustic emission (AE). Among them, AE is generally thought to be the most sensitive signal because it has a key advantage over other types of signals [4]: its frequency range is far beyond that of noises can be easily filtered. The AE technique has also been used for various purposes of detection, such as of wheel wear/burn/collision, grinding gap elimination, dressing verification, etc. However, a successful grinding wheel condition monitoring depends to a great extent on reliable and robust sensors used for this purpose [5,6]. In the absence of human operators, the sensors must have the ability to recognize process abnormalities and initiate corrective action. There are various signals which correlate to the condition of the process and they are the subject of different sensing and processing techniques. Each of these signals is able to provide a feature related to the phenomenon of interest although at varying reliability. So to collect the maximum amount of information about the state of a process from a number of different sensors is the best solution. To introduce such an idea to practice an intelligent sensing system embodying strategies for sensor fusion should be implemented [7].

In our study, an intelligent monitoring system with multiple sensors data fusion is proposed within grinding process and the performance of it is experimentally evaluated.

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This system includes the measurements of acoustic emission and grinding forces, and a novel multi-signals processing method---artificial immune algorithms based data fusion model. The basic concept, model architecture and experiments are discussed in detail.

2. Multi-sensor data fusion based process monitoring model

The advanced equipment and sensor technologies have recently provided more and more immediate data to reveal the grinding condition. However, such data have not been effectively analyzed and put to use in practice due to their enormous volume and the lack of efficient analysis methods. If we can establish a mechanism to analyze these real-time data, the process condition can be then observed and evaluated in a more timely fashion. The process of combining the provided information from multiple sensors is called sensor fusion, and can overcome a number of problems ranging from noise to incipient sensor failure. Even in the absence of these issues, one can increase the system's accuracy and the reliability using sensor fusion. Especially for high performance operational system such as: rotorcraft, airplanes, space shuttles and process control systems [8]. The grinding and wheel preparation processes may be characterized by numerous parameters including forces, power, temperature, wheel wear, surface roughness, etc. Monitoring of these and other parameters requires multiple sensors. Force and acoustic emission (AE) sensors could be selected for a 'smart' wheel because of their ability to monitor many diverse aspects of the grinding process. Another important factor was the possibility of using the same small and inexpensive piezoceramic chips to measure both force and AE.

In our study, a multi-sensor data fusion model (DFM) is built up for condition monitoring and parameter optimization within grinding process, shown as fig.1. The proposed multi-sensor monitoring system was composed of several modules. First, the two sensor signals (i.e. Force signal and AE signal) were respectively pre-processed and filtered in order to remove disturbances, and to compensate the transfer function of the sensors. Then, statistical parameters were calculated from each signal by using wavelet decomposition, and hence the process features from online data were obtained. The artificial immune algorithm (AIA) is applied in order to combine information from several sources, which include expert knowledge, historical data and online process features, to evaluate the condition of grinding wheel. The mapping the immune system negative selection mechanism to the monitoring process is shown as table1.

The construction of the monitoring system is based on the availability of normal process data and would formally incorporate the definition of a shape space U, an appropriate affinity measure, as well as a self set S with elements of length L, followed by generation of a set R of detectors, such that each fails to match any element in S, i.e. $U = S \cup R$ and $S \cap R = \phi$.

Table 1. Mapping of AIA based monitoring system for grinding process

Immune system	Monitoring process
Self	Normal operating conditions such as grinding depth of cut, wheel speed, workpiece speed.
Non-self(antigen)	Abnormal operating conditions
Antibody	Detector and matching condition
Inactivation	Abnormal signal and normal operation for the system

Main functions of DFM are summarized below.

(1) Grinding parameters predicting. The system can realize the prediction of grinding parameters in different machining by evolution and incremental supervised learning of grinding parameters. The artificial immune algorithm in the intelligent system is use as a self-organizing tool to model the process of learning and enhancing grinding conditions. It implements a supervised learning mechanism capable of recognition categories in response to arbitrary sequences of input patterns.

(2) Optimizing for the inspection and suggestion of input grinding parameters. If the features of some sensors were not in the normal range, grinding parameter would be refused. Rational parameters would be given by the optimization system.

(3) Processing of machining is monitored in real time. Data of sensors are sampled and compared to the standard or normal conditions stored in the historical database. The state of the machining is controlled and alarms were given in abnormal state, Normal machining and parameter optimization was ensured.

(4) If better processing can be realized and the machine is in normal state all the time, new operation parameters will be added to the corresponding database. The constantly evolving system of parameters is generated by the improvement of the operation parameter. Not only the faults avoiding but also the efficiency or quality of machining are considered with the running of monitoring and optimizing modules.

The system also includes the other functions, such as, mass data analysis, data sampling, saving, featuring, predicting, trend analysis, graphical display and auto alarming etc.

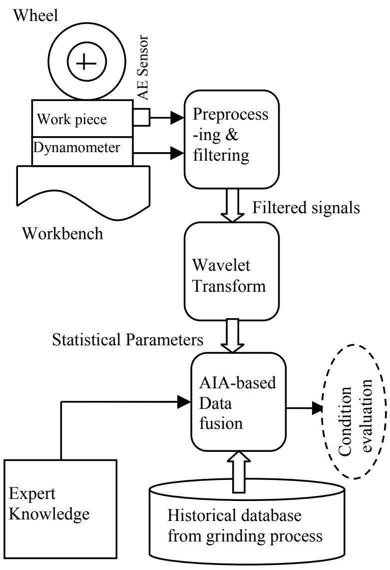

Fig.1. Data fusion-based process monitoring model.

3. Artifical immune negative selection

Artificial immune systems can be defined as abstract computational systems inspired by theoretical immunology and observed immune functions, principles, and models, applied to solve problems [9,10]. In the operation of an immune system, the antibody eliminates the antigen, and the lymphocyte produces the antibody through the clonal proliferation. A B-lymphocyte can make only one antibody that is placed on the outer surface of the lymphocyte to act as a receptor. T-lymphocytes can regulate the control mechanisms of antibody productions. To detect and eliminate the nonself materials that originate from inside or outside, an immune system must possess the functions of distinguishing self and nonself materials (antigens). Although various sets of antibodies can be observed in a system; but an antibody can only specifically recognize an antigen. Once the corresponding antibody has bound an antigen, the receptor of lymphocytes receives triggering signals. Such triggering signals help activate the clonal proliferation and large clone of plasma cells are formed.

In recent years, artificial immune system attracted wide attention in many applications such as: feature extraction, pattern recognition, learning skills, system control and fault detection. Fosset [11] first proposed a negative selection mechanism in 1994, which depends on the immune system ability to recognize unknown foreign antigens as a non-self body's cells from those of the bodys own cells. The main principles of hybrid system is normal/abnormal identification of the system behavior which is similar to the immune system self/non-self classifications for the body cells.

The mechanism of negative selection can be described as follows. The thymus is protected by a blood barrier capable of efficiently excluding non-self antigens from the thymus environment. Thus, the elements found within the thymus are representative of self instead of non-self. In turn, T-cells containing receptors capable of recognizing these (self) antigens are eliminated from the repertoire of T-cells and all T-cells that leave the thymus to circulate throughout the body are tolerant to self in that they do not detect self-antigens. The basic computation procedures of the artificial immune algorithms (AIAs) are described as follows:

Step1. Randomly generate an initial population of antibodies.

Step2. Evaluate the corresponding affinity value for each individual.

Step3. Choose the best k individual with highest affinity values and then clone these k antibodies.

Step4. The set of the clones in previous step will suffer the genetic operation process, i.e., crossover and mutation.

Step5. Update the memory set. The process includes replacement and elimination.

- Firstly, calculate the new affinity values of these new individuals (antibodies). Select those individuals who are superior to the individuals in the memory set, and then the superior individuals replace the inferior individuals in the memory set.
- Secondly, antibodies will be eliminated while their structures are too similar so that the individuals in the memory set are able to keep the diversity.

Step6. Check the stopping criterion, if not stop then go to Step 2. Otherwise go to next step.

Step7. Stop. The optimal or near optimal solution(s) can be provided from the memory set.

Because of the soul of diversity in the AIAs, the quality of solutions in the feasible space can be better guaranteed and obtained. So, a suppression process (diversity embodiment) is needed and shown on the Step5 in the proposed IAs procedure. The diversity in each pair of antibody i (Abi) and antibody j (Abj) can be evaluated by calculating their affinity (fij) by following way:

$$f_{ij} = \left\| Ab_i - Ab_j \right\| \quad (1)$$

The Negative Selection Algorithm (NSA) provides a model of the self/non-self discrimination capability learned in the thymus of biological immune system. This algorithm has been proposed with application focused on the problem of anomaly detection, such as computer and network intrusion detection, image inspection and segmentation, and hardware fault tolerance [9]. It can be summarized as follows:

step1. n candidate detectors are generated.

step2. Each candidate detector, C_i, i = 1,2, . . . ,n, is compared to a set of protected elements, PE.

step3. If a match occurs between C_i and PE, the detector is discarded.

step4. Otherwise (if a match does not occur), C_i is stored in the detector set D.

NSA produces a set of detectors capable to recognize non-self patterns, so can be utilized to the grinding tool condition detecting.

4. Experiments study

The experiments were performed on the surface grinder (M7130D/H) using a wheel (WA60L5V) to grind 45 Steel. In these experiments, the grinding process was monitoring with multiple sensors including three-component dynamometer (YDH-9702) and AE sensor (CAE-150). The three-component dynamometer is mounted on the work table, and the specimen was held on the top of the dynamometer by the fixture. The AE sensor is located on the side of the workpiece. During the grinding the process, the force signals are sampled at 100Hz while the AE signals are 1MHz. The specimen has dimensions of 160x120x50mm3. The steps of grinding procedure are shown as follows:

- True and dress the wheel.
- Grind a block of steel to stabilize the wheel.

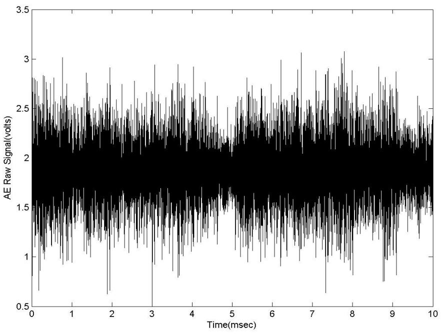

Fig. 2. Time series data from AE sensor

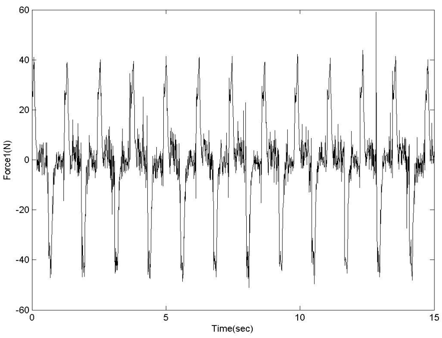

Fig. 3. Time series data from force sensor (tangent direction)

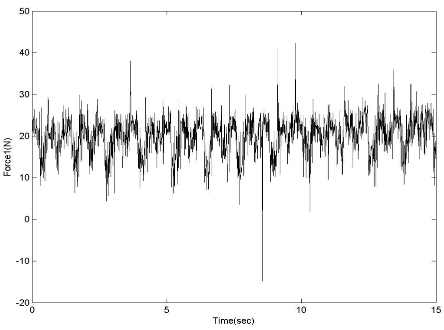

Fig. 4. Time series data from force sensor (normal direction)

- Obtain the ambient signal to check the range of environmental noise.
- Grind the specimen using different grinding parameters

Time series data are sampled form sensors, shown as fig.2~fig.4. For continuous online monitoring, nongrinding signals are removed from the monitoring data. According to signals sampled, either in the time domain or in the frequency domain, more signal processing methods are provided to feature extracting for the following monitoring.

Here, twelve features are selected, which are grinding depth of cut, wheel speed, workpiece speed, mean value of AE----x, standard deviation of AE----s^2, root mean square of AE----d, maximum value of forces----max. The twelve selected features were used to train a NSA model for classification. It is well known that Fourier transform is a useful tool for transforming a time domain signal from the time domain to the frequency domain. However, wavelet transforms are more powerful than the Fourier transform due to the following properties [7]: Some wavelet transforms have compact support, thus are able to capture local time-dependent properties of data, whereas Fourier transforms can only capture global properties. The wavelet transforms method for AE signals can also be used for features extraction.

The grinding experiment procedure is shown as follows:

(1) Simulation of operating patterns and data acquisition. There are twelve patterns of different grinding conditions in this experiment, and each pattern gathers the data of multi-groups. The data of each group is a sample.

(2) Extracting features of each operating pattern. The data of each group is transformed and twelve feature values of sensors are extracted and united with the grinding conditions as the description of this example.

(3) Standardization of the operating patterns. Get mean value of each pattern as the standard value.

(4) Data Coding. Code 12 feature values and standardize them.

(5) Generating set of monitoring detectors. Use each standard value of the pattern to train the system and generate the detectors set.

(6) Make experiments of system monitoring based on detectors set.

Table 2. Experimental parameters in grinding process

Pns	Wheel speed (r/min)	workpiece speed (mm/s)	grinding depth (μm)
…	…	…	…
2	1440	350	10
3	1440	400	20
4	1440	400	5
5	1440	300	15
…	…	…	…

Note : Pns=Patterns

Four of twelve grindings modes of 45 Steel grinded by wheel (WA60L5V) are shown as Table 2. Table 2 shows the mean values of study samples. Table 3 shows the training data after being normalized. Table 4 is the partial testing data with

Table 3. Samples patterns2~5

Pns	AE sensor			Tangent Force (N)			Normal Force (N)		
	x	s^2	d	x	s^2	max	x	s^2	max
2	4.736	0.278	4.744	14.02	7.125	24.9	7.99	6.616	18.6
3	5.074	0.394	5.089	14.39	22.09	70.2	49.89	15.78	92
4	5.296	0.792	5.355	6.32	5.955	17.2	8.405	5.05	1.1
5	7.471	0.52	7.489	14.27	9.697	28.8	21.54	5.63	31.4

Table 4. System tests data (normalization, are partial)

TP	AE sensor			Tangent Force(N)			Normal Force(N)			EP
	x	s2	d	x	s2	max	x	s2	max	
2	43	20	46	25	10	2	6	44	44	2
3	51	33	50	27	72	58	54	93	98	3
5	87	44	89	27	23	16	22	28	42	3
5	85	43	87	26	23	16	25	14	28	5
2	48	25	44	26	9	8	18	17	10	2
3	52	33	54	25	80	69	58	86	93	4
4	55	67	54	11	8	4	12	18	7	4

TP : Testing Pattern ; EP : Estimating Pattern

same processing, and their grinding parameters are also referred to table 2. The experiment indicates that the accuracy of condition identification is about 87%, and able to meet the industrial need on the whole. In fact, the accuracy of condition identification is influenced with the variables of sample size N, cloning rate a, muting rate β and the affinity of training and monitoring. The reasons leading to the low accuracy could be: (1) sample size N is too small; (2) pattern samples lack of comprehensive choosing; (3) the actual appraisal of grinding condition is fuzzy, and fault diagnosis only distinguish breakdown or not, whereas in this experiment need distinguish the normal operating state under different machining conditions.

5. Conclusions

The multiple sensor system refers to an integrated combination containing a variety of sensors to gather some features or interesting information from the system's environment. The competitive structure sensor system has been applied in many scenarios with advantages that each sensor provides equivalent information about the environment. Since real world sensor data inevitably contains noise and has finite accuracy and limited reliability, it is hard to implement multiple sensor system perfectly. Hence, merging readings from competitive sensors to form a more complete and reliable picture of the environment becomes an important and challenging problem. Based on artificial immune algorithm (AIA), a multi-sensor data fusion system for condition monitoring within grinding process is presented in this paper. Of course, like other emerging industrial techniques, applied issues on AIA reaffirm the due commitment to their further development and investigation, such as the problems how to design the representation scheme of grinding process and how to set the affinity function to make the industrial data fusion model development more easily. Some complicated signal aberrations in the data acquisition didn't be discussed in our works; however, it has been observed that the multi-sensor data fusion system for grinding monitoring is promising. One looks forward to the era in which much of the condition monitoring in manufacture process will be replaced by more intelligent systems.

Acknowledgements

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