Industrial Platform for Rapid Prototyping of Intelligent Diagnostic Systems

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Abstract. In this paper the industrial platform for rapid prototyping of intelligent real-time monitoring and diagnostic system was proposed. Its architecture is ready to utilize advanced computational intelligence methods, especially devoted to novelty detection such as autoassociative neural network, local outlier factor, one-class support vector machines, or to solve multiclass classification problems. The rapid prototyping tool set based on Matlab/Simulink and industrial automation equipment was described in details. As an example of the use of the proposed platform, CNC milling tool head mechanical imbalance online prediction system was described.

Keywords: diagnostic systems, computational intelligence, rapid prototyping, mechanical imbalance prediction, Intelligent Manufacturing System, Industry 4.0

1 Introduction

Complicated manufacturing processes include different machining operations and involve many process variables, which complex interactions determine machines performance and components quality. Current challenge is to develop a new production monitoring and diagnostic system structure that exhibit intelligence, robustness and adaptation to environment changes and disturbances [1,2], and simultaneously satisfy industrial requirements and standards. Modern industrial system structure constitutes a hardware and software platform for practical implementation of Intelligent Manufacturing System (IMS) and Industry 4.0 concepts in metal processing industry, e.g. aerospace manufacturing. This concepts require an intensive use of Information and Communication Technologies (ICT) to support reliable management of production processes and utilize Artificial Intelligence (AI) and Computational Intelligence (CI) techniques [3,4] to: monitor, control and diagnose machines and production processes; support a human in manufacturing activities; automatically arrange materials, tools and production compositions; recommend and perform actions to prevent faulty production, performance reduction and machines breakdowns; automatically discover and provide knowledge about manufacturing process, equipment efficiency

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and condition; provide knowledge and tools for reliable management decisions; support techniques for production process optimization.

The main role of the intelligent real-time monitoring and diagnostic platform is to provide human operators and maintenance personnel with information, alarms and early warning signals to prevent production of out-of-specification components and to avoid machines breakdowns. The platform should also deliver advanced Human-System Interface (HSI) for efficient interaction between operators and computer systems, which can significantly improve overall production effectiveness [5]. Moreover, the intelligent platform should support maintenance management system and enable practical implementation of Predictive Maintenance (PdM) strategy and Failure Mode Avoidance paradigm to avoid potential failures in high precision machining facilities [6,7]

Due to the complexity of CNC machines, different working conditions in individual factory floors, diversity of machines history and technical condition as well as CI methods specificity, process of intelligent diagnostic system implementation for each particular machine should be treated individually. The measurement signals types and features as well as CI methods, and parameters should be adjusted to the particular machine or technological process. To fulfil this requirement, data used to develop and test intelligent diagnostic methods should be registered on particular machines in their destination location and in typical industrial working conditions. To have the ability to conduct experiments in industrial environment and shorten time of solutions development, the appropriate tool set must be used.

This paper is composed of the following Sections. In Section 2, new architecture concept and implementation details of the intelligent real-time monitoring and diagnostic industrial platform are presented. In Section 3, rapid prototyping tool set for intelligent diagnostic systems development is described. In Section 4, an exemplary application of the tool set for CNC milling tool head mechanical imbalance diagnostic is demonstrated. In Section 5, the conclusions are formulated.

2 Architecture of Industrial Platform for Intelligent Diagnostic Systems

The architecture of the intelligent diagnostic industrial platform proposed in this paper, consists of the three major modules: monitoring and feature extraction (MFE), real-time anomaly detection (RTAD) and fault diagnosis (FD) (Fig. 1). In the MFE module, signal processing (noise reduction, filtering, signal transformations, etc.) and feature extraction methods are used in real-time to receive operating parameters of the machine on the basis of sensors signals acquisition and data acquired from machines control systems. Operators observations are input to the system via HSI which is a part of monitoring module. Different methods for data processing and feature extraction can be used in MFE [14,15] The selection of appropriate sensors and signals features adjusted to the problem

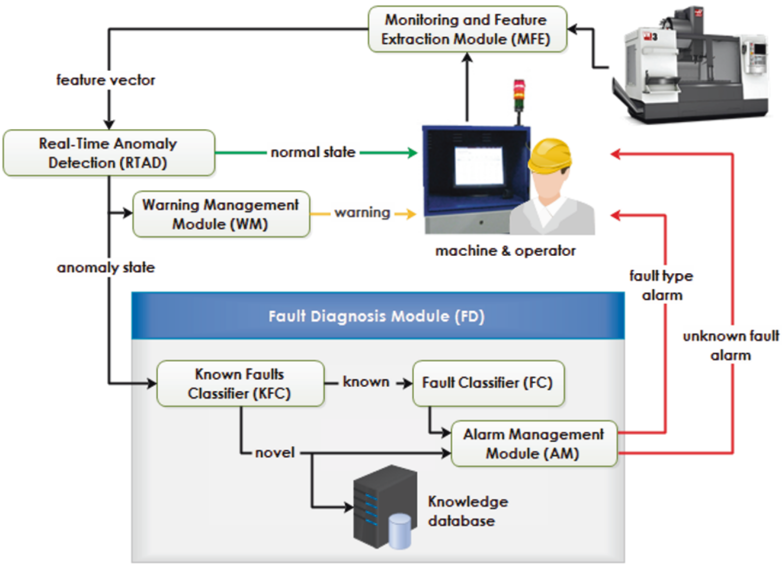

Fig. 1. Architecture of real-time monitoring and diagnostic system.

specificity is the crucial element of monitoring and diagnostic system development and is supported by rapid prototyping platform described in Section 3.

The signals features calculated by MFE are provided to RTAD module which is devoted to detect in real-time any forms of deviations (novelty/anomaly) in normal machine operation. In this module different novelty detection methods can be used, i.e. probabilistic, distance-based, etc. [16]. To develop novelty detection algorithm, only data for normal machine operation is required. When novelty is detected, RTAD sends the warning signal to the operator. In this work like in [16], normal condition is treated as positive example and novelty condition is treated as negative example. This convention is opposite to the one used in medical papers and in work [18], but is more common in the technical diagnostics field. Classifiers used in RTAD module should be characterized by as high as possible value of specificity defined as Spe=TN/(TN+FP)·100% parameter and as low as possible false alarm rate value defined as FAR=FN/(TP+FN)·100% (TP – true positive, TN – true negative, FP – false positive, FN – false negative).

In the FD module, the anomaly detected by RTAD is examined and the appropriate fault type alarm or unknown fault alarm is provided to the operator. The FD module consists of the two major subsystems, i.e. known faults classifier (KFC) and fault classifier (FC). KFC is used to examine anomaly state and determine if FC module is able to perform its correct classification on the basis of the knowledge gathered by the system. In this module, novelty detection methods can also be used, but in the opposite manner than in RTAD. To develop known fault type detection algorithm only data for known faults (positive examples) is used. If the particular fault type is known by the system, the appropriate fault type is identified by FC module and the alarm signal is provided to the operator. If the fault type is unknown, then data is stored in the system knowledge database and the unknown fault alarm is sent to the operator. Classifiers used in KFC module should be characterized by as high as possible value of sensitivity (Sen) parameter, defined as Sen=TP/(TP+FN)·100%. In the FC module, either classical multiclass classifiers [9] or hierarchical structure of one-class classifiers [17,18] can be used.

Additional modules, i.e. warning management (WM) and alarm management (AM) are used to limit the number of faulty warnings and alarms on the basis of information provided by the operator via HSI. If the short-term factor of faulty warnings exceeds configured value, then basic parameters (e.g. threshold) of classifiers used in RTAD can be changed temporarily or permanently. If the global system factor of faulty warnings or alarms exceeds configured value, then the system reconfiguration is needed, e.g. classifiers advanced parameters or structure modification. In nowadays industrial practice, human experts are employed to reconfigure the system in such case.

Main elements of the architecture described above, was implemented on the basis of production process monitoring system described in [8]. The system consists of modern industrial automation equipment and custom-made software modules for data acquisition, monitoring and intelligent diagnosis.

For data acquisition and processing as well as for communication purposes, programmable automation controller (PAC) or industrial personal computer (IPC) equipped with real-time subsystem (e.g. TwinCAT 3) and general operating system (e.g. Windows, Linux) can be used. Dedicated, custom-made software, that works on IPC, performs diverse tasks simultaneously, both in real-time, and in general operating system layer. The real-time software automatically acquires data concerning machine state on the basis of communication with machine control system and by the use of electrical signals provided by additional sensors. The application for general operating system, written in C# language, provides HSI for machine operators as well as performs diagnostic operations (FD module) which are not time critical. The application also communicates with real-time software modules, peripheral devices (e.g. barcode reader) and with the server layer. Ethernet is used for communication between PAC/IPC and the server. Data is stored in PostgreSQL database and web services are used for communication between PAC/IPC and the server. In the real-time layer software, a separate programmable logic controller (PLC) task created using ST language (structured text - norm IEC 61131-3) is used to read data from CNC machine control system and from digital and analog input terminals. Another real-time task created using Matlab/Simulink software and automatic code generation tools (Matlab Coder and Simulink Coder) is used to perform data and signals processing (MFE module) and diagnostic operations (RTAD module) which are time critical. Communication between C# application and PLC real-time module is performed by using ADS (automation device specification) protocol.

3 Rapid Prototyping Tool Set for Intelligent Diagnostic Systems Development

The idea of the rapid prototyping tool set for intelligent diagnostic systems was developed as the extension of the rapid control prototyping (RCP) concept and authors experience in the RCP field [19,20,21]. RCP gives tools for quick and convenient control strategy verification and iterative controller development. RCP involves a controller simulated in real-time (on PC equipped with computer-aided control system design software, e.g. Matlab/Simulink, Scilab/Xcos) coupled with a real plant via hardware input/output devices [19,20,22]. A typical RCP structure can be modified in order to use the same PAC or IPC controllers during experiments and a development process as well as for industrial implementation of the final solution [21]. Nowadays, such scenario can be applied for industrial purposes by the use of commercial TwinCAT 3 platform from Beckhoff integrated with Matlab and Simulink software. As it was mentioned in the introduction, the development process of the intelligent diagnostic system should be performed individually for each particular machine. It can be seen that the development of a control system is analogous to development of intelligent diagnostic system and needs similar approach and tools. On the basis of this observation, rapid prototyping tool set for intelligent diagnostic system was developed. Four main phases of the intelligent diagnostic system development process can be distinguished: (1) collecting data from real object (dedicated experiments or normal operation) and creating data base (real-time); (2) analyzing and processing registered data/signals, choosing and computing signal features (offline); (3) choosing and testing diagnostic algorithm on the basis of collected data base (offline); (4) testing chosen algorithm on real object (real-time).

It is desirable to perform all the operations mentioned above on integrated hardware and software platform. A procedure for intelligent diagnostic system rapid prototyping process is shown in Fig. 2.

The rapid prototyping tool set consists of: (a) slx Simulink framework project for collecting data during real-time dedicated experiments performed on a real object, External Mode of Simulink is used in this case - supports phase 1; (b) PLC program framework and communication software for collecting data of normal object operation, data is directly stored in PostgreSQL database - supports phase 1; (c) set of m-files which use standard Matlab functions as well as custom made functions for iterative realization of phases 2-3; (d) slx Simulink framework project for MFE and RTAD implementation and TwinCAT 3 framework project - supports phase 4.

The block schema of the Simulink framework for phase 5 is shown in Fig. 3. The tool set includes many different custom-made libraries in the form of m-files as well as auxiliary software tools, e.g. conversion of DTREG [25] output code to convention used in Simulink framework, conversion of decision tree code obtained from Matlab to m-function which can be used in slx project, etc. The subsystem created as a final slx project (Fig. 3) can also be tested offline, before real-time tests, by the use of data from experiments.

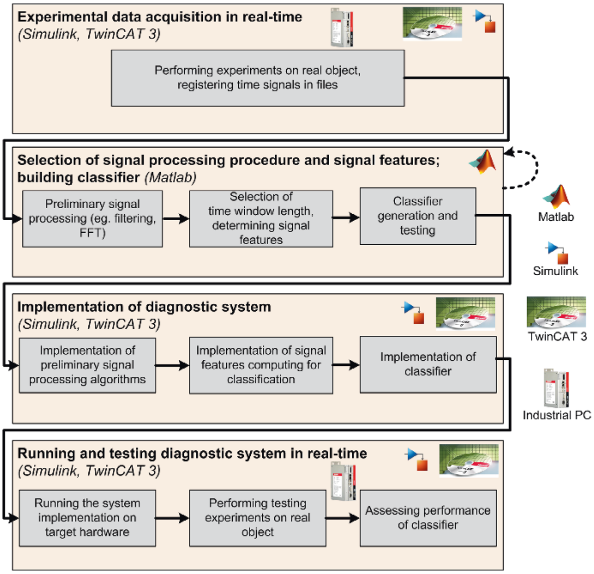

Fig. 2. Procedure for rapid prototyping of intelligent diagnostic system.

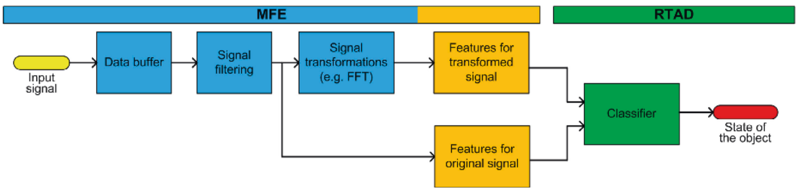

Fig. 3. Implementation of diagnostic system in real-time layer.

4 Application of the Platform for Milling Tool Head Imbalance Prediction

Detection of spindle or tool head mechanical imbalance is an important task in industrial practice. The mechanical imbalance of rotating parts, i.e. spindle, cutting tools (milling, cutters, drills) has significant negative influence on durability of CNC machines and quality of produced parts. Current industrial practice involves periodical imbalance spindle tests performed by maintenance personnel and balancing procedure of cutting tools performed by qualified personnel with the use of special balancing machines as a part of the process setting phase. Online imbalance monitoring of CNC machines rotating parts is a crucial part of PdM paradigm and Industry 4.0 requirements.

The platform described in Sections 2 and 3 was used to develop CNC milling tool head (Fig. 4) online imbalance prediction system in Haas Factory Out-

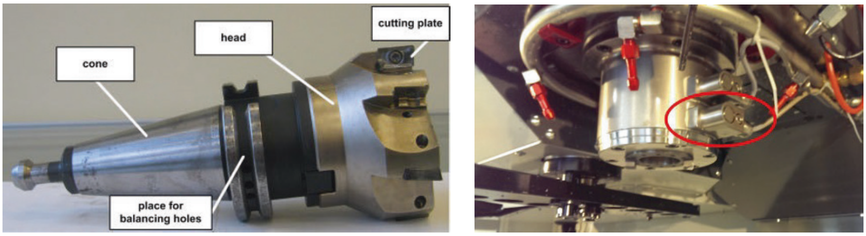

Fig. 4. Milling tool head and spindle with acceleration sensors.

let (HFO) and Haas Technical Education Center (HTEC) located in Rzeszow University of Technology. The industrial testbed consists of Haas VM-3 CNC machine equipped with an inline direct-drive spindle and set of sensors: acceleration and temperature (6 on the spindle: 2 on lower bearing, 2 on upper bearing, 2 on Z axis; 1 on sample), acoustic emission, spindle velocity, spindle load, three axis force and momentum (on sample). The rapid prototyping platform consists of IPC C6920 from Beckhoff, equipped with distributed input-output system (EtherCAT protocol, analog and digital inputs) and software modules (Matlab/Simulink custom-made m-files and slx projects, TwinCAT3 project and custom-made software modules).

The balance quality grade adequate for individual elements (i.e. spindle unit, drawbar components, milling tool) of the spindle-tool system is specified in the ISO 19401:2003 norm [23]. Four imbalance classes were examined in this study, i.e. class 1: G 0.4, class 2: G 2.5, class 3: G 6.3 and class 4: G 40. Preferable balance quality grade for milling tool is G 0.4. The grade G 2.5 is acceptable but not preferable. Grade G 6.3 is not permitted due to deterioration of machining quality. G 40 level is forbidden and may result in damage of the spindle unit. During conducted tests, diverse imbalance classes were obtained by mounting cutting plates of different weight in the milling tool. Precise imbalance value for each milling tool configuration and class as well as for each experiment was evaluated using the Haimer Tool Dynamic 2009 balancing machine.

The rapid prototyping tool set described in Section 3, was applied to perform experiments and collect data in the testbed as well as to develop the main elements (MFE, RTAD, FD) of CNC milling tool head imbalance prediction system. The imbalance test was performed for service speed of the spindle, i.e. 12000 rpm.

The research devoted to select: appropriate sensors, signals features (in time and frequency domain) and computational intelligence methods appropriate for the tool head imbalance prediction was described in [9] and [18]. On the basis of the research results, the acceleration sensor (Hansford HS-100ST) mounted on the spindle lower bearing (Fig 4) was chosen. Different methods for selection of sensors/signals and their features were used, e.g. support vector machine, Sherrod's method [25], principal component analysis, single decision tree. The acceleration signal measurements were divided into the constant length buffers with duration equal to 640 ms. Sampling interval was 40 μs. Fourteen acceleration signal features, calculated for each buffer, were examined during the research [9], [18], both in time and frequency domain.

For RTAD module autoassociative neural network (AANN) was selected due to its low computational power demands and availability of Matlab/Simulink tools which enable automatic code generation of the trained network. Data collected for G 0.4 (class 1) was treated as normal state (9625 records) and used to train AANN. Data for grades: G 2.5 (class 2), G 6.3 (class 3) and G 40 (class 4) was treated as anomaly state (17709 records) and used to perform offline classifiers tests. The final AANN structure was 3-4-1-4-3, the threshold value δ was calculated as $\delta = \mu + r \cdot \sigma$ [24], where μ is a mean value and σ - standard deviation. The obtained indicators were: Spe=100% and FAR=0%.

For KFC module in FD subsystem the local outlier factor (LOF) method was selected [18]. Three novelty detection methods were examined, i.e. AANN, LOF and one-class support vector machine (OC-SVM). During the offline experiments, data for grades G 2.5 (class 2), G 6.3 (class 3) and G 40 (class 4) was considered as normal state, i.e. known by FC module. These classes represent imbalance grades which should be recognized by the FC module (Fig. 1). Data for G 0.4 (class 1) was used for testing the classifier's ability to detect unknown state, as data for this class should never be provided to the FD in normal system operation. The LOF classifier achieved the best results, i.e. Sen=98.7%.

For FC module in FD subsystem the classifier based on multilayer perceptron (MLP) was chosen. During the research described in [9] seven methods were examined, i.e. K-Means, probabilistic neural network, single decision tree, boosted decision trees, radial basis function neural network, support vector machine and MLP, to detect four defined above classes. The results were adopted to the 3 class classification problem, i.e. G 2.5, G 6.3, G 40. The indicators: accuracy defined as Acc=(TP+TN)/(TP+FP+TN+FN)·100%, Sen and Spe were used to assess the performance of the algorithms. The values of all indicators were very high independently of the method. The MLP classifier was chosen due to the same reasons like in the case of AANN in RTAD. The final structure of MLP was: 3-5-3. Three normalized attributes were used and scaled conjugate gradient method was applied for MLP training.

The main elements of CNC milling tool head imbalance prediction system were developed and tested during offline and real-time tests. In the future work the real-time experiments are to be performed for the whole integrated system.

5 Conclusions

The new real-time monitoring and diagnostic industrial platform architecture which utilizes novelty detection CI methods, known also as one-class classifiers, multiclass classifiers, rapid prototyping tool set and industrial automation equipment was described. In contrast to monitoring and diagnostic system structures known from literature [12,13], the proposed platform utilizes only industrial automation equipment, what enables its direct implementation in real production environments. The main elements of the platform were developed and tested for the prototype CNC milling tool head mechanical imbalance online prediction system. Online imbalance monitoring of CNC machines is a crucial part of PdM and Industry 4.0 paradigms and is particularly important in aviation industry. In the future work, the real-time tests for the complete system are to be performed for long time operation of Haas VM-3 CNC machine. The main elements of the intelligent platform architecture proposed in this paper, has been created in co-operation between Rzeszów University of Technology (Department of Computer and Control Engineering), Żbik company and companies from clusters: Green Forge Innovation Cluster and Aviation Valley located in southeastern Poland region. The system has been used to conduct research in different aspects of IMS practical implementations [4,5], [9,10,11]. The basic hardware and software tools which satisfy industrial requirements and allow intelligent monitoring methods development were defined.

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