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Visual Analytics Framework for Condition Monitoring in Cyber-Physical Systems

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***Abstract*—One of the biggest challenges facing the factory of the future today is to reduce the time-to-market access and increase through the improvement of competitiveness and efficiency. In order to achieve this target, data analytics in Industrial Cyber-Physical System becomes a feasible option. In this paper, a visual analytics framework for condition monitoring of the machine tool is presented with the aim to manage events and alarms at factory level. The framework is assessed in a particular use case that consists in a multi-threaded cloud-based solution for the global analysis of the behaviour of variables acquired from PLC, CNC and robot manipulator. A human-machine interface is also designed for the real-time visualization of the key performance indicators according to the user's criteria. This tool implemented is a great solution for condition monitoring and decision-making process based on data analytics from simple statistics to complex machine learning methods. The results achieved are part of the vision and implementation of the industrial test bed of "Industry and Society 5.0" platform.**

Keywords*—*industrial cyber-physical systems, condition monitoring, visual analytics

I. Introduction

Nowadays, a continuous digital transformation is currently taking place in the current manufacturing industry due in large part to information and communication technologies (ICT), betting on the digitalization, personalization and traceability of processes, products and services [1]. The combination of Internet of Things (IoT), Cloud-based Manufacturing, and Cyber-Physical Systems (CPS) are new tools within the industrial sector with new strategies and methods for smart manufacturing [2].

The Industry 4.0 approach within the paradigm of the industrial cyber-physical systems (ICPS) is focused on the complete interconnection between manufacturing processes and consumers of final products [3, 4]. This aims to provide manufacturing systems with capabilities to adapt to market demand and be able to manufacture products adapted to consumers [5]. Nowadays, there are several technical challenges related, among other areas, with control systems with self-learning capabilities [6-9] and new optimization methods [10-14], the development of software-intensive solutions that serve as an interface for mutual feedback between the factory and the end user, also supported by the development of new technologies or new concepts, for instance, IoT or CPS [15, 16].

The design and development of CPS is getting the attention of the scientific and technical community with the aim to be applied in the manufacturing and industrial sectors. Specifically, ICPS has a key role for the Industry 4.0 (4th Industrial Revolution) which includes digitization, networks, and the embedded intelligence of the manufacturing industry [17, 18].

This paper presents a visual analytics framework for condition monitoring in ICPS to manage events and alarms at factory level. The proposal includes two main modules: a local node collecting information of all systems for real-time monitoring with an active supervision; and a global module based on cloud computing which collect, process and store the most representative data in order to perform global monitoring and reconfiguration.

For a better understanding of this work, the structure chosen is the following. After this introduction, a review of state-of-the-art and the main areas taken into account in this research is described. Next, a particular implementation of a CPS framework is presented in section III. Then, a case study is designed and implemented with the objective of experimentally validating the proposed framework. Finally, the conclusions and future research steps are addressed.

II. Related works

In general, the development of ICPS architectures and frameworks is a research and development priority in Industry 4.0 paradigm when dealing with complexity is truly challenging [19]. In this direction, the standardization of device communication protocols (sensors, actuators, etc.), and heterogeneous data acquisition from different machines play an essential role in visual analytics, facing important limitations. For example, the way to access (interfaces and communications) to each type of machine is different since it depends on the manufacturer. Therefore, the functionality of any visual analytics framework should include data acquisition, data storage, signal processing, event correlation and operation characterization for effective monitoring [20, 21]. Figure 1 shows a general outline of the current vision focused on the integration, interconnection and interaction of multiple layers or levels from a physical layer composed of all devices (e.g., machine tools, robots, etc.) up to more abstract layers to perform monitoring, control and self-reconfiguration functions in order to consider the whole value chain.

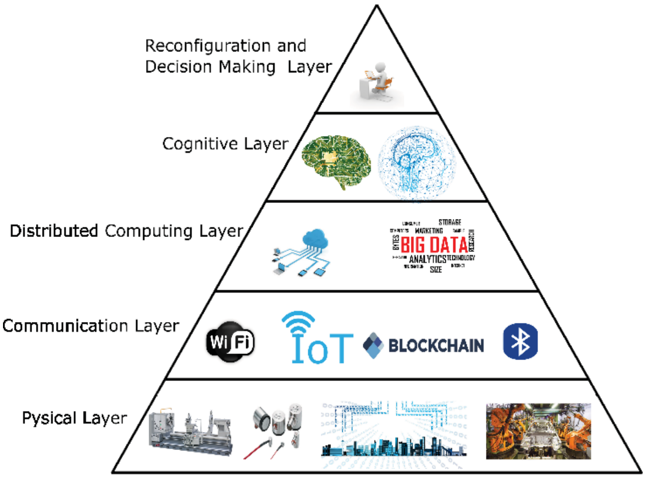

Fig. 1. General outline of the current version of a CPS Framework.

ICPS has the key enabling that a set of tools and methods, such as, the integration of TIC and control, make possible the smart manufacturing [22]. The framework is generally structured in five layers, i.e., computer, detection, network, cognitive and control. In addition, a digitalized machine is configured to emulate the physical machine in the cybernetic space and it is called the digital model or digital twin of the CPS. This is possible thanks to the previous stage consisting of detecting, collecting, transmitting, storing, extracting and analysing data from representative variables of the machine and the physical environment [23]. The ICPS should be able to self-learn and store and update its knowledge base using the sensory data and information provided by a machine tool or a set of machines [24]. System knowledge may include possible conditions, such as manufacturing parameters, operation of the machine, error or anomalies and wear of certain components. On the other hand, the configuration and architecture of the CPS is fundamental along with the high priority of autonomous processing of data and learning models [25].

In the industrial sector and more specifically, in the manufacturing sector, a process of adaptation to the ICPS is taking place, which is still quite slow [26]. For this, in order to obtain good results in terms of cost, quality and flexibility, the development of new architectures becomes indispensable with an approach based on adaptive controllers, intelligent decision making and use of resources [27].

Specifically, the main function of the condition-based monitoring (CM) is to determine recognizable patterns of behaviour in sensory information and internal variables provided by sensors and the CNC of machine, detect them and relate them to possible failures. CM are of vital importance to the operation of any production process, by enabling the decision making to be made for correction or adjustment of certain parameters, with the aim of achieving an optimal and efficient operation. The maintenance can be proactively programmed when it is necessary and not before [28, 29]. In the literature, CMs are applied in most cases within the industry sector in the detection and maintenance of certain critical elements to analyse vibrations, lubricants, acoustic emission, infrared thermography, ultrasounds, currents and consumptions, among others [30].

III. CPS Proposed Framework

Figure 2 illustrates the particular implementation of the proposed CPS architecture.

Fig. 2. Proposed Architecture.

The information flow between the different levels is described below. At the shop floor level, sensors, actuators and internal variables of the machine are in charge of capturing and storage data from the environment. At the second level, nodes receive data through the communication protocol stablished between nodes and the physical layer. Internally, these nodes are composed of pre-processing methods with the aim of being able to extract the most relevant behaviour patterns and, in addition, to be visualized by the operator at the local level. This information is also shared with the global node or cloud. The main components of the visual analytic framework are nodes and the cloud, where all the information is processed.

A. *Nodes*

Nodes contain all the communication protocols to interact with the different physical devices. Furthermore, they also contain pre-processing information methods (e.g., fast Fourier transform, wavelet transform, statistics) in order to get the most important features of the data, and machine learning based algorithms (e.g., support vector machine, multi-layer perceptron, hybrid incremental modelling, among others) to model and to estimate the current status of the process to take actions and reconfigure the system in order to avoid failures. Fig 3 shows the most important elements of a node in each subsystem.

The machine parameters to be monitored are spindle temperature, working time of gear and component, etc. These representative variables are obtained from multiple local sensors distributed in the shop floor. This procedure that is executed in the nodes includes the machine condition-based monitoring and diagnosis method.

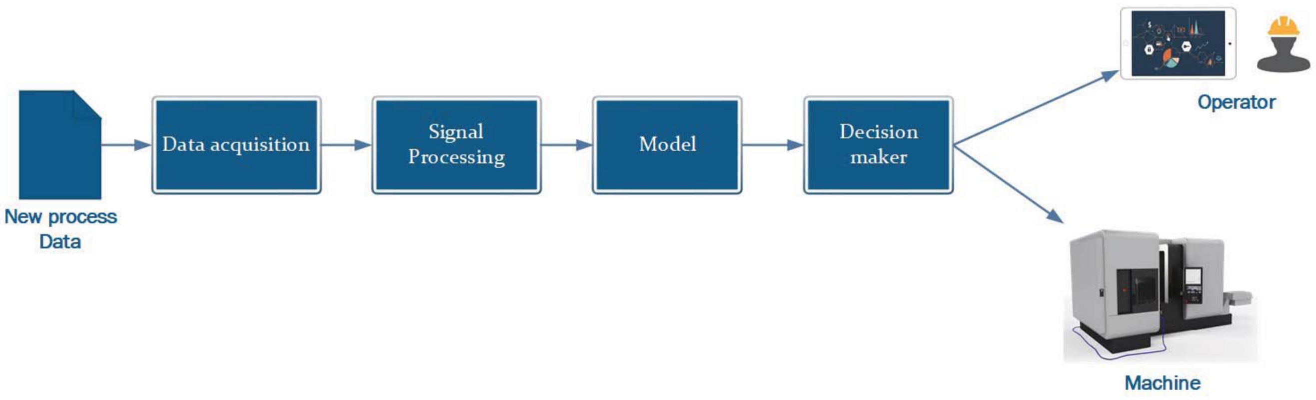

Fig. 3. Scheme of the main elements of a node

B. Cloud

In general, the global module, located in the cloud, serves to enable the supervision of all events and alarms that occur at the shop floor level in the industry. The steps that follow this monitoring process are described below. First, if an error or failure is detected in one of the local nodes in the shop floor, an interchange of messages (configuration, events, alarms, errors, etc.) are carried out between the local nodes and the cloud service, and then the cloud notifies to the user about recommendations or mandatory actions to be taken into account in each instant. Secondly, the system provides the option to perform optimization of the local module parameters and the reconfiguration of the system, using algorithms based on machine learning (artificial neural networks, clustering and others), and a reinforcement learning [31-33]. Obviously, the connectivity between the different nodes and the global modules is fully controlled by the user. Fig 4 shows the general diagram of the cloud subsystems.

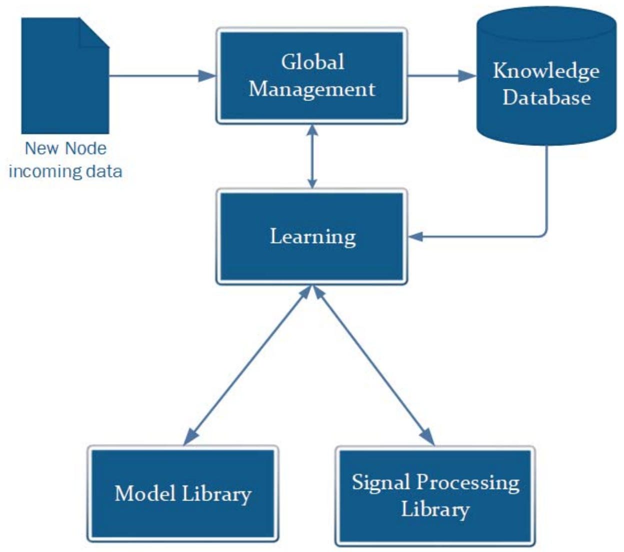

Fig. 4. General diagram of the main components of the cloud for visual analytics.

IV. CASE STUDY

In this work, specifically, the use case is a particular implementation of the visual analytics framework for CPS-based condition monitoring.

Fig. 5 shows a general overview of the particular implementation in the laboratory GAMHE 5.0 located in the Centre for Automation and Robotics (CAR). From left to right, Fig. 5 shows from the lowest layer (floor layer with machines and robots), in which physical systems are located, to the highest layer (cloud). According to the above description, multiple nodes that compose multiple physical systems are included, enabling the ability to exchange information among them for global condition monitoring and thus improving production efficiency.

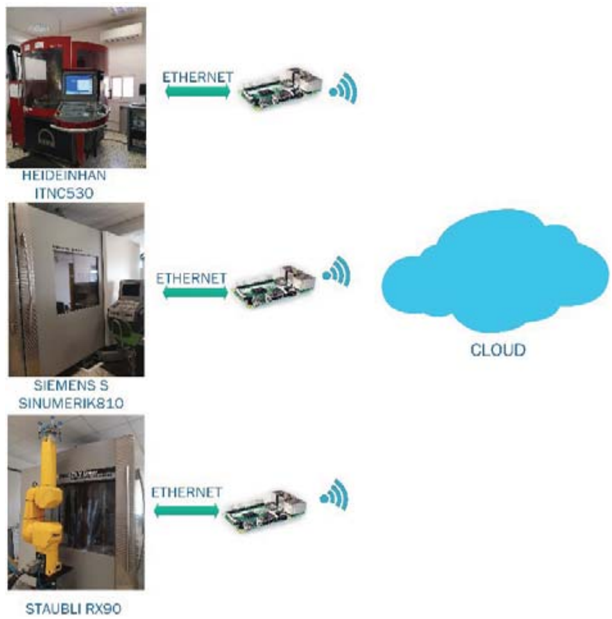

Fig. 5. Diagram of the GAMHE 5.0 Laboratory.

In more detail, the use case consists of visual analytics for condition monitoring and visualization of representative variables of simultaneous manufacturing operations running in two machines tools and a collaborative robot. This use case is part of the “Industry and Society 5.0” laboratory of the GAMHE group. This infrastructure includes two universal machine tools fully equipped with sensors and measurement systems (Deckel Maho Linear 75v and Kern Evo micromachining center); and a manipulator robot with 6 degrees of freedom (Staubli RX90).

For each physical node, there is a low-cost computing unit to enable monitoring and communication capabilities and to guarantee security. For the sake of simplicity, the hardware chosen was a Raspberry pi 2 model B for the nodes that connect to the cloud.

A. Communication protocol

The specific protocol contains an automatic procedure for incorporating new nodes to a wireless network in the following way. First, a socket is created by establishing the type of connection, the IP address and the port through which the cloud will wait for node connections.

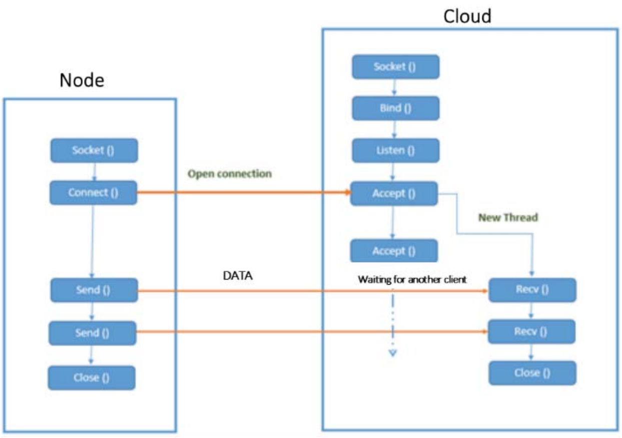

Fig. 6. Connections diagram between nodes and cloud.

Secondly, when a request is received, a thread to handle this request is launched. In this way the cloud, on the one hand, delegates the necessary work to meet the request and, on the other hand, returns to the waiting state of requests. Finally, the nodes developed in Python software and deployed in the Raspberry hardware are in charge of requesting the setting of connections to the corresponding IP address and port determined in the cloud. The client has the ability to inform the cloud about the success or failure in setting up connections.

B. Human-Machine interface

The information is available for computing and visualization through the human-machine interface implemented.

Fig. 7 shows the developed visual analytics interface, in which the real-time values of the main variables in each machine are shown. The correct operation of different indicators of the process condition is also depicted, as well as the trend of the main selected variables.

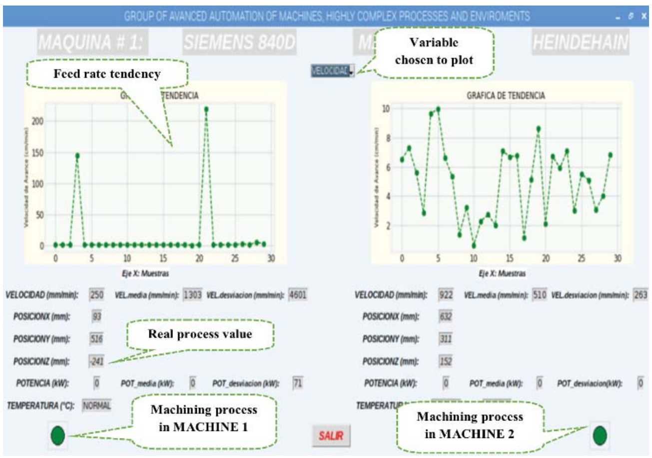

Fig. 7. Visual analytics interface for monitoring the main variables.

In addition, the application software generates machine connection and data storage reports. In this way, the stored data from the monitoring system can be exported to standard file formats such as TXT and XML, being freely available to all users from machine to factory level. Fig. 7 represents the connecting diagram between nodes and the cloud. An important difference of the HMI implemented in this work is that it is multi-platform.

C. Results

In this section, the analysis of certain representative variables related with the machine condition state is presented by applying the visual analytics framework with the aim to show the behaviour of the machining processes and to make use of stored data. From the experimental collected data, 60 clusters with 50 data were selected. For example, some of the simple statistic computations chosen for the analysis of the behaviour of some variables were the mean value and the standard deviation.

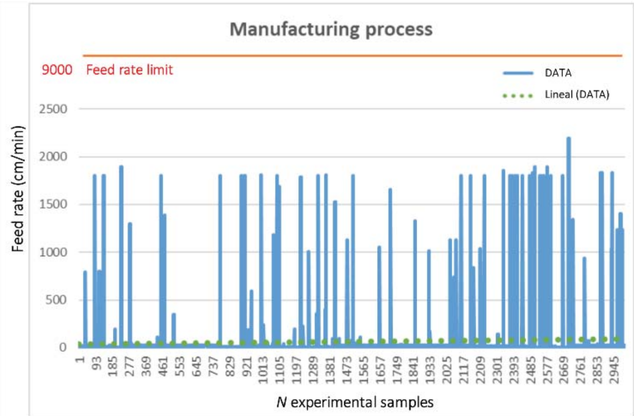

Fig. 8. Samples used to validate the visual analytics procedure.

Fig. 8 depicts the behaviour of the feed rate in a real machining process. The monitored values are within the theoretical maximum allowable limit, which means that the machine operates in normal condition. In addition, another way to visualize information is through a history over time of different statistical metrics that reflect the behaviour of these representative variables in a typical manufacturing process.

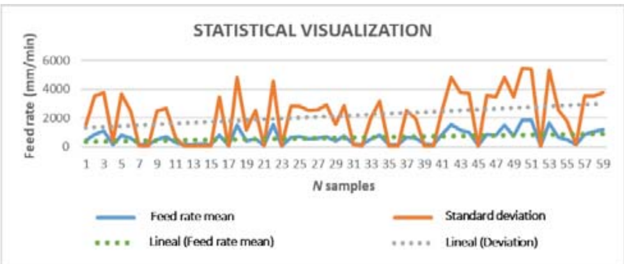

Fig. 9. Statistical of the feed rate in visual analytics for a particular machining process.

Fig. 9 shows another example of these visual analytics. The information and results obtained can be used to develop predictive models for estimating the mechanical failures and the remaining useful life of the manufacturing sub-systems or components and to estimate what resources will be necessary to replace them, as well as take necessary actions to anticipate future abnormal events.

V. Conclusions

This work presents a visual analytics framework for addressing some of the challenges within ICPS paradigm that is the condition monitoring of the machines. Therefore, the visual analytics framework is able to management events and alarms in machine tools and driver's robot manipulators.

The proposed framework includes, at global level, a server for managing the supervision of all local nodes based on the global knowledge. The procedure consists of collecting data from each local node incorporated into the network. In addition, the run-time monitoring method is executing in the local node of each machine or robot, converting data into useful information.

A multi-threaded local-cloud framework based on a CPS was implemented for the analytics visualization of the main variables acquired of the PLC, CNC and drivers of the manipulators of each of the interconnected machines. A HMI interface was also developed for real-time visualization of key indicators to be monitored according to technologist's criteria, becoming a useful tool for decision-making process based on current information, statistics and historical data trends of each machine.

Therefore, the developed framework also supports the use of low cost platforms. Moreover, this reported work is part of the vision and implementation of an industrial demonstrator of the "Industry and Society 5.0" platform.

Finally, this work has considered only the application of three nodes, two machine tools and a collaborative robot. However, the integration and interconnection of different types of systems and sub-systems is currently growing so that other strategies will explored in short terms such as collaborative robotics, industrial cognitive systems, self-learning systems, cloud programming, among others.

Future research will take into account issues such as the use of web sockets and, even, security, which are not included in this work since they are not the objective of it.

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