The impact of digital technologies and artificial intelligence on production systems in today Industry 4.0 environment

Francesco Pilati and Alberto Regattieri*

The industrial environment is currently experiencing its fourth industrial revolution, distinguished by the ubiquitous use of sensors that are able to capture large volumes of data regarding production processes. This vast quantity of digital information represents the raw material of the 21st century, which is able to fuel the decision processes of the factories of the future. The development and exploitation of novel algorithms and methods derived from cognitive processes of human beings represents the latest trend, both for research and application in the industrial sector. The adoption of artificial intelligence tools and techniques to design and manage smart assembly and manufacturing systems is the core of this manuscript. Two real industrial applications are presented to test and validate the afore-described approach, analysing both the advantages and the drawbacks of such solutions. In particular, a hardware/software architecture based on depth cameras is developed to digitalize the operator motions within assembly or manufacturing systems, whereas a set of neural algorithms defines the maintenance policies for continuously condition-monitored production systems.

Introduction

The industrial environment is currently experiencing what has been described as the fourth industrial revolution, namely Industry 4.0 (I40). The ubiquitous usage of sensors, which communicate through a world-wide network, make it possible to connect, in real-time, several entities of production systems, such as machinery, equipment, final products, components, workers, suppliers, customers, etc. Together, these elements comprise the Internet of things (IoT) (Stankovic, 2014). The huge volume of data produced by these connect objects is the raw material of the 21st century (Bortolini et al., 2017). These technologies facilitate the development of a new production paradigm, which has been termed personalized production. This paradigm satisfies the customer's contemporary need to participate in the production process since the product design phase (Hu et al., 2011).

Furthermore, today's industrial environment is distinguished by three trends of extreme importance. First, the workforce is aging alarmingly. In the last three lustrums, the percentage of European employees older than 50 years increased by 10 percent; that is, from 20 percent to 30 percent of the total working population (OECD, 2015). Currently, 5.8 million European workers are 60 years or older (7.4 percent of the entire workforce). Second, Western countries, Europe in particular, are experiencing the re-shoring of production plants that were previously off-shored to emerging countries (Ellram et al., 2013). This important trend is driven by growing labour costs in emerging countries that are almost equal to those in Western countries; the higher soft and digital skills of Western workers compared to those of emerging country competitors; the remarkable savings in transportation costs, which benefits local supply chains; as well as the flexibility and responsiveness needed to meet customer expectations (Davies, 2015).

Such a digital industrial environment generates a huge volume of date at high pace. Therefore, the development

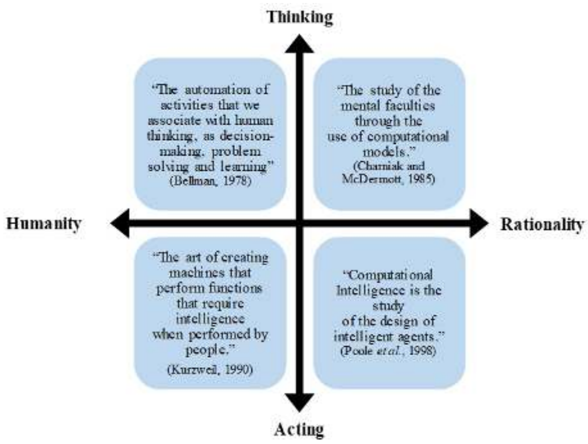

Figure 1. Artificial intelligence definitions proposed in the literature considering the thinking-acting and humanity-rationality dimensions

Source: Russel and Norvig, 2003

and adoption of appropriate models and methods, as well as algorithms and techniques, is of major importance to obtain meaningful information from these data sets. One of the latest trends is represented by the adoption of biology-inspired algorithm, as artificial intelligence (AI). The definition of AI can be provided considering two relevant

* Francesco Pilati and Alberto Regattieri, Department of Industrial Engineering – University of Bologna, Viale del Risorgimento 2, 40136 Bologna, Italy, francesco.pilati3@unibo.it, alberto.regattieri@unibo.it

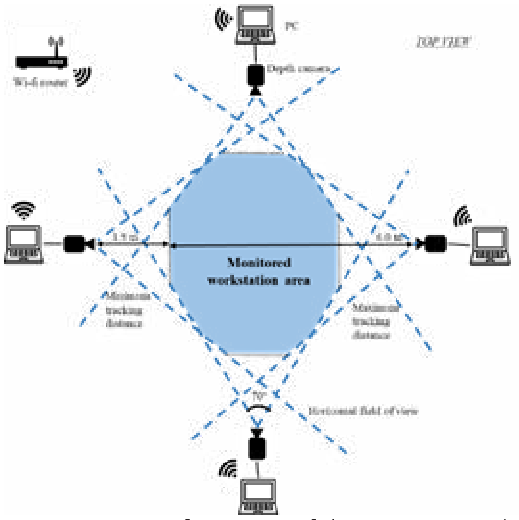

Figure 2a. Configuration of the MAS network of depth cameras

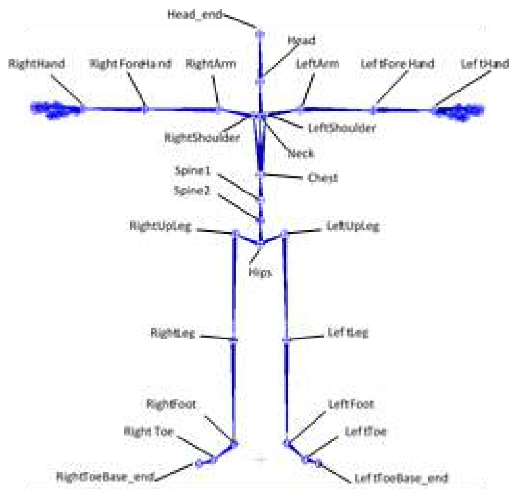

Figure 2b. Skeleton joints of the acquired human body

Source: Author's own compilation

dimensions: thinking vs. acting and humanity vs. rationality (Russel and Norvig, 2003). The former measures the degree of reasoning against behaviour in a decision process, whereas the latter compares the decision process with human versus purely rational approaches. Considering these dimensions, Figure 1 proposes four relevant but different definitions of AI that have been suggested in the literature.

This technology ensures a precise measurement of the operator absolute positons in the industrial 3D environment in relation to the difference pieces of equipment, products, and furniture displaced in the shop floor area. The MAS automatically, quantitatively, and dynamically evaluates a set of key performance indicators (KPIs) that deal with the monitored production process both from an ergonomic and a logistic perspective.

The large volume of data acquired by the MOCAP system represents the absolute geometric coordinates of each joint of the operator's body on the shop floor, and therefore his skeleton posture. The developed MAS leverages this information from an ergonomic perspective to dynamically evaluate the angle of every human body articulation and the related movement over the monitored time (Figure 3a). These data are further processed by the MAS to dynamically and automatically assess several ergonomic indices that evaluate the postures and movements of operators during working activities. For instance, the OWAS, REBA, NIOSH and EAWS can be easily evaluated by leveraging the distinctive features of the MAS. A useful tool provided by the MAS is the automatic analysis of index trends in relation to the risk categories and specific body parts,

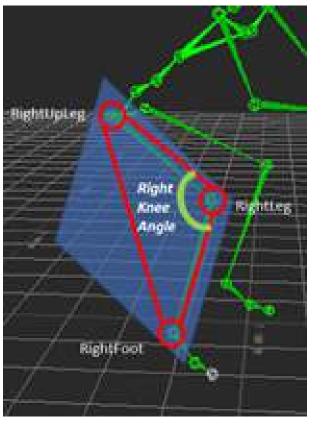

Figure 3a. Body articulation angles, knee exemplification.

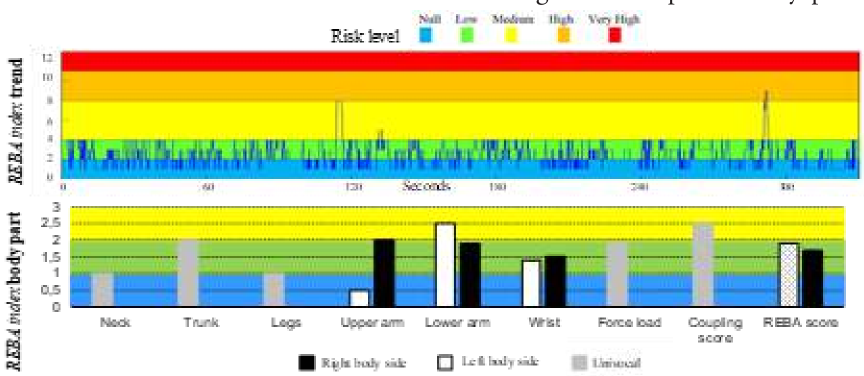

Figure 3b. Ergonomic index trend over time and per body part.

Source: Author's own compilation

which makes it possible to identify those tasks or manual activities that require corrective actions (Figure 3b).

Concerning the productive performances of the monitored operator within the shop floor, the MAS automatically and quantitatively evaluates the following set of KPIs: travelled distance and velocity of the operator and his different body parts; vertical movements due to lifting and lowering activities; worker's travelled paths and trajectories of his hands (Figure 4a); picking activity in-depth assessment (visited locations, duration, frequency, etc.) (Figure 4b); and working time partitioning, such as the distinction between added-value (task execution) and no added-value (walking, picking, etc.) activities.

an immediate maintenance intervention. A real industrial application of the proposed approach is represented by a fresh pasta production system. A particular system component determined several severe breakdowns in the entire production process. A customized AI algorithm has been developed to determine which operating parameter to monitor, along with its value, which distinguishes between a safe, warning and breakdown working zone. The following Figure 5 presents this exemplification.

The approach describe above is distinguished by several opportunities that positively affect the technical and economic performances of the analyzed production system during its entire lifetime. In particular, the most relevant advantages of maintenance policies based on the continuous condition monitoring of an operating parameter are listed below (Alsina et al., 2018):

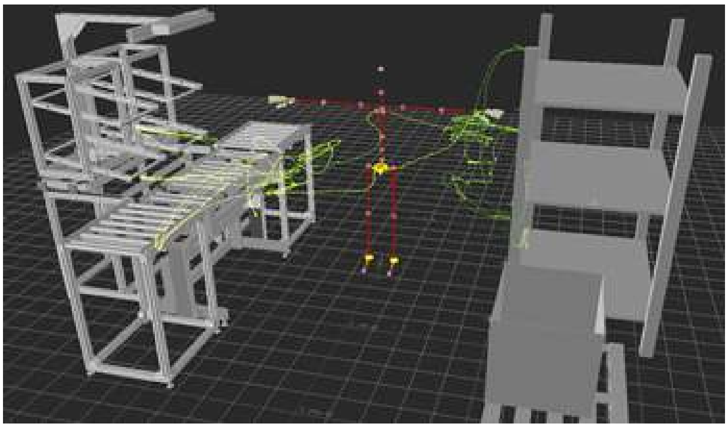

Figure 4a. Travelled paths and trajectories of operator and his hands.

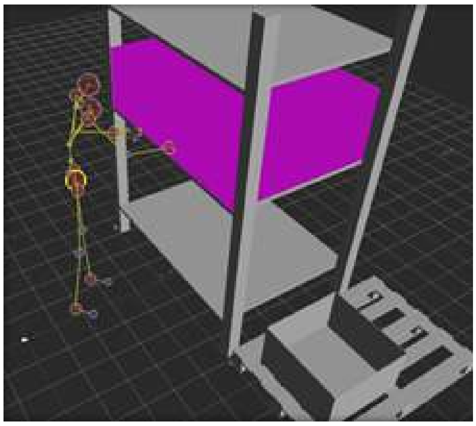

Figure 4b. Assessment of component picking from shelves.

Source: Author's own compilation

Data analytics for condition based maintenance

A remarkable opportunity in the field of production system maintenance is represented by the adoption of data analytics tools and techniques that exploit AI algorithms, in particular for continuous condition monitoring. The aim of the maintenance policies is to define the optimal instant to perform a maintenance intervention, whether a component repair or replacement, in order to minimize the production system total breakdowns and maximize its techno-economic performance. A recent trend in this field of research is represented by the definition of the maintenance policies through the continuous monitoring of one or more relevant operating parameters of the considered production system. Thus, the maintenance interventions are defined considering the real-time conditions of one or more continuously measured parameters. Appropriate AI algorithms have to be developed and trained to define which alert threshold of the monitored parameter requests

- Enhanced plant, production system, or machine availability
- Lower total cost of ownership of the considered production system
- Improvement in the design of complex production systems
- Potential revenue source for the maintenance department due to the sale of added-value services such as RAM analysis, maintenance strategy optimization, and forecasting of spare-part consumption.

Beside these positive aspects, the adoption of AI algorithm for the definition of maintenance policies, in particular the exploiting of continuous condition monitoring, is distinguished by some possible but severe threats.

Figure 5. Maintenance policy based on the continuous condition monitoring of an operating parameter.

Source: Author's own compilation

First, the determination of the link between a weak monitored signal and the component or system reliability is significantly challenging. The most relevant decisions deal with the definition of which parameter to monitor, which is the link between the parameter value and the time before failure and whether or not to link the condition information with a known failure state of the monitored component. Furthermore, a major challenge is represented by the definition of a proper measurement chain and the storage of the collected data. The relevant decisions deal with the identification of which sensor is appropriate for the monitored process, where to place the sensor considering the appropriate necessary space, the storage capacity of the collected data with a demanding amount of data to be managed, and customer unwillingness to provide the data about their production processes. Finally, the first signals to be used, at low cost, are those typically needed to control the technological process of machines; these are often available but neglected, such as positions, speed, currents, and temperatures.

The application of different AI algorithms to several real industrial production processes to define the optimal maintenance policy confirms this conflicting trend. Some of the approaches that have been tested in various case studies, with mixed results, are listed below:

- An artificial neural network was developed and adopted to forecast the spare-part consumption of packaging machinery, with very positive results.
- A support vector machine was adopted to forecast the reliability of mechanical and electric components in a refrigerating plant, with positive results along with some potential threats.
- A random forest algorithm was implemented to remote monitor a cutting machine reliability assessing the different occurring alarms. The difficulty of assessing and subsequently exploiting the different clusters of alarms led to negative results.

Conclusion and further research

This paper proposes the adoption of AI tools and techniques to design and manage production systems in the *Industry 4.0* environment. Two real industrial applications have been presented to test and validate the approach described above, analysing both the advantages and also the drawbacks that distinguish such solutions. In particular, a hardware/software architecture based on depth cameras was developed to digitalize the operator motions within assembly or manufacturing systems, whereas a set of neural algorithms defines the maintenance policies for continuously condition monitored production systems.

The main outcomes of this research suggest that current and future technological resources offer interesting opportunities to exploit AI tools and algorithms for production systems. AI can accelerate the development of strategies to monitor these systems, with a particular focus on human performances and to define proper and efficient maintenance approaches. A relevant risk is represented by the fact that this new paradigm could eventually emphasize the current problems related to data collection and interpretation. Unfortunately, from an engineering perspective, it is not foreseeable to significantly reduce the difficulty determined by the monitored data interpretation. Thus, further research should focus the effort to reinforce the process to analyze the huge quantity of collected data, along with providing meaningful information that has strong relations and backgrounds to real industrial applications.

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