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Automatic Learning Improves Human-Robot Interaction in Productive Environments:
A Review

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ABSTRACT

In the creation of new industries, products and services -- all of which are advances of the Fourth Industrial Revolution -- the human-robot interaction that includes automatic learning and computer vision are elements to consider since they promote collaborative environments between people and robots. The use of machine learning and computer vision provides the tools needed to increase productivity and minimizes delivery reaction times by assisting in the optimization of complex production planning processes. This review of the state of the art presents the main trends that seek to improve human-robot interaction in productive environments, and identifies challenges in research as well as in industrial - technological development in this topic. In addition, this review offers a proposal on the needs of use of artificial intelligence in all processes of industry 4.0 as a crucial linking element among humans, robots, intelligent and traditional machines; as well as a mechanism for quality control and occupational safety.

KEYWORDS

Augmented Reality, Computer Vision, Machine Learning, Manufacturing, Robotics

INTRODUCTION

The fourth industrial revolution is not only trendy, but also defines the new rules to which the current industry must adapt to. Since this subject covers a wide variety of work fields, this research was carried out in order to summarize the ideas and findings of other researchers in this field. Thus, this paper presents a synopsis of the arguments that revolve around integrating robotics with operators in cyber manufactures to improve productivity, supported by the use of technologies such as computer vision, automatic learning, human-robot interaction, which at the same time allows the creation of collaborative and secure environments for humans as well as automated systems.

This paper profusely studies the applications of the fourth industrial revolution in intelligent manufacturing, especially in human-robot interaction through the use of computer vision from the perspectives of "display", information exchange, level of autonomy and its applications. In addition, it discusses the concepts of artificial neural networks and their use in the different phases of manufacturing.

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TECHNOLOGY APPLICATIONS

Specifically on the topics related to the Fourth Industrial Revolution, an emphasis is being placed on cybermanufacturing systems, also known as "cybermanufacturing", being the manufacturing interconnection of the various human elements with complex automated systems, involving computer systems for control and the exchange of information from manufacturing operations and robotic systems; in order to create work models supported with artificial intelligence to improve decision making and anticipation of problematic situations in the production flow (Siddique, Mitchell, O'Grady, & Jahankhani, 2011). In this type of environment, the most natural interconnection between humans and robots is sought, since as mentioned by (Meisner, Isler, & Trinkle, 2008) this can generate environments that minimize stress on operators when using complex robotic systems (Meisner et al., 2008).

Such environments -as mentioned by (Hedelind & Jackson, 2011; Hermann, Pentek, & Otto, 2016; J. Lee, Bagheri, & Jin, 2016) – are strongly related to the concept of automation and data exchange as a core in manufacturing technologies, where technologies such as robotics, systems, cyber physicists, Big Data, and Things Internet are the foundation in building a collaborative environment with people (Hedelind & Jackson, 2011; Hermann et al., 2016; J. Lee, Bagheri, & Kao, 2014).

As the complexity of systems increase, the main element to be considered for the construction of these new integrated production environments are humans, who can make use of technologies of interaction with robots and machines, as it is the case of augmented reality (AR). For example, (Tatic & Tešic, 2017) talk about a thermal energy plant in Bosnia and Herzegovina. The aim is to prevent workers from making mistakes and protect their physical integrity through the use of mobile devices that integrate systems AR, which makes it easier for them to use real-time checklists (Meisner et al., 2008). Cases like these can frequently be found in other investigations.

Continuing with the topics of the previous section, computer vision is an important element to consider in this new manufacture era, since its applications in human-robot interaction can be applied to manufacture for quality control, detection of collisions (Wang, Schmidt, & Nee, 2013), navigation (Hornung, Bennewitz, & Strasdat, 2010) and augmented reality (Makris, Karagiannis, Koukas, & Matthaiakis, 2016). However, implementing these applications requires the application of automatic learning as a whole. As mentioned by (Lee et al., 2016), they require the intervention of operators in order to be able to train artificial intelligence using robots. This requires established mechanisms for control and exchange of information to guarantee high quality mechanisms.

CV is also used in automatic inspection processes through supervised learning techniques. For example, (Ferreiro & Sierra, 2012) claim that these can be used in industrial processes where the quality in the workstations needs to be controlled (Ferreiro & Sierra, 2012). These quality inspection processes can be carried out by simple sensors as well as by weight, color, and size sensors (Fast-Berglund, Fässberg, Hellman, Davidsson, & Stahre, 2013). Quality can be assessed according to the shape the products processed at the workstations (Hedelind & Jackson, 2011).

Computer vision can be used to help to protect the integrity of operators, as described by (Xiao, Wang, & Folkesson, 2015). For example, RGB-D cameras can be used as tools that improve the HRI, since they allow the tracing of the operators' movements so that robots can predict the intentions and recognize the behavior of the people with whom they collaborate (Xiao et al., 2015). This allows the creation of more flexible working environments for human tasks, but this requires automatic learning algorithms to make decisions from data sets coming from environments with a supervised training level. If there are data limitations, unmonitored training can be administered. Thus, (Santoro, Marino, & Tamburrini, 2008) propose the use of a mixed scheme, using supervised and unsupervised learning in which datasets used for training are obtained from the behavioral patterns gathered by a human "trainer" (Santoro et al., 2008). This technique for obtaining information through patterns is also pointed out by (Ericson, Franks & Rohrer, 2016) as a powerful tool in productive environments. On the other hand, we find many contexts in which we do not know the relationships between inputs and outputs, so using algorithms to organize information or find patterns is necessary (Ericson, Franks & Rohrer, 2016).

Another application of the use of automatic learning, different from computer vision, is to provide help in decision making in cyber factories. For example, the initial production process, the definition of demand and the particular needs of each product, for which artificial intelligence must be fed with data, which is proposed by (Leng & Jiang, 2015). He fosters the utilization of social manufacture to take advantage of cross-company information by leveraging the benefits of information and communications technologies (Leng & Jiang, 2015) in addition to getting information from the Internet of Things, Big Data, cloud Technologies and advanced manufacturing processes (Cheng, Tao, Zhao, & Zhang, 2015). These social and cloud manufacturing environments generate large volumes of unstructured data, which generate conflicts in other data mining tools, so the use of automated learning technologies has made it possible to extract information using neural networks based on cases and rules (Leng & Jiang, 2015), as well as neural network techniques of retro propagation and case-based reasoning (CBR), in order to establish the rules to initiate production to reduce the time needed for production (Priore, De La Fuente, Puente, & Parreño, 2006).

INTERACTION

Industries seek to create work environments where the use of robots is greater than the use of humans, generating a series of new challenges, such as the protection of the integrity of people. Thus, the mechanisms of communication between humans and robots must be safer (Goodrich & Schultz, 2007). A factor that increases the complexity of this issue has to do with the noise produced by the machinery of the factories, which deteriorates verbal interaction. An important point to consider is occupational safety; especially in environments where there are young and inexperienced operators who usually do not read carefully, do not abide by safety standards, and do not follow instructions to avoid injury (Tatic & Tešic, 2017).

Among the different types of robots that can be found in an industrial environment, there are mobile robots, fixed robots and recently social robots. Mobile robots serve to move through the plant elements such as: raw material, supplies, and finished products, among others. Currently these robots follow predefined routes with colored lines, which they recognize through color sensors or cameras. A more dynamic production scheme with greater human-robot interaction is greater sharing physical space. (X. V. Wang, Wang, Mohammed, & Givehchi, 2015) propose a 3D detection plant model, which links motion sensors in real time (Kinect sensors) in order to imitate the models that have elements of reality. These are aimed at calculating the minimum distance between human and robot, generating a system of active detection of collisions between humans (Wang et al., 2013).

In an industrial environment, HRI can be improved by using computer vision and augmented reality. Computer vision allows to help in self-localization, mapping (SLAM), detection and tracing of people, identification of human activities and facial expressions. Digital content can be overlaid on images of the environment on mobile devices to create augmented reality systems that help operators interact in real time. In addition, wearables can be used to facilitate human activities using first-person vision (FPV) (Leo, Medioni, Trivedi, Kanade, & Farinella, 2015), according to (Mehlmann et al., 2014). A study revealed that using an eye tracking approach could cause problems over time.

As shown in Table 1, it can be seen that most of the interaction found in the scientific articles consulted was usually through mobile mechanisms, especially tablets, where the interaction was carried out through buttons which displayed graphical information about the processes and statistics on the use of devices (both intelligent and regular machines) in order to facilitate the movement of people. In a significant amount of occasions a traditional computer was used which showed similar information.

As for the level of autonomy, as shown in the Table 1, the main devices to perform the interaction are those controlled directly by humans, very few equipment provide total control capabilities by artificial intelligence or where artificial intelligence controls most of the decisions. Many of these automatic decision capabilities are being used to determine events (related to stimuli on each machine, events generated by interactions with other intelligent machines in complex processes are not being controlled). In addition, automatic learning capability is used in pattern recognition for navigation determination in controlled environments.

As for verbal or visual interaction, these forms have a greater relation with automatic learning, according to the data identified in the Table 1. These mechanisms seek a more natural interaction with people. In the case of visual form, most cases are computer vision systems, where eye-projection systems or mobile devices are being used to create augmented reality systems to facilitate interaction, which provide additional information about the work environment.

The analysis of Table 2 is a compilation of the evaluated articles where it is evident that the approach of greater use in the automatic learning are the neural networks with 68% of the identified occurrences in the investigation realized, along with the technique of supervised training, which is present in 88% of the occasions. Despite its intensive use there are high probabilities of research in these subjects since its applications are very broad. For example: manufacturing, navigation, optimization and metaheuristics, bioinformatics, interaction, collaborative, cognitive and social robotics, and finally computer perception, which provide 80% of the applications identified.

Adequate training of neural networks is required in new industries, since interaction of robots and operators must take place in the most natural way. In addition, they must collaborate with automatic decisions in production processes. Intelligent systems will be the basis on which the new industry will be based.

Although the new industry will focus on intelligent systems, interaction with people will always be present at some point in the overall process. Actually, it can be seen that most of the interaction is done by obtaining information through sensors, as can be seen in Table 2. It is necessary to establish an adequate interconnection beyond the use of sensors with Smart Manufacturing Equipment (SME), traditional machinery and operators with real-time monitoring and monitoring by artificial intelligence in order to maximize production, improve human robot interaction and minimize occupational health risks as well as physical risks in the productive elements.

Table 1. Human Robot-Interaction

Ref.	Display	Inf. Exchange	Autonomy (LOA)	Applications
(Tatic & Tešic, 2017)	Mobile	Visual	Reduced computational decision	Detecting events
(Lee et al., 2014)	Computer	Visual	Complete human decision	Controlling processes
(Wang et al., 2013)	Mobile	Touch	Complete human decision	Navigation, Detecting events, Interaction, Automatic inspection
(Leo et al., 2015)	Mobile	Touch	Reduced computational decision	Navigation, Detecting events, Interaction, Automatic inspection
(Mehlmann et al., 2014)	Computer	Voice	Complete human decision	Controlling processes
(Santoro et al., 2008)	Mobile	Visual	Reduced computational decision	Interaction
(Meisner et al., 2008)	Mobile	Voice	Reduced human decision	Navigation

Table 2. Machine Learning

Ref.	Applications	Approaches	Algorithms Type
(Monostori, 2002)	Manufacturing	Neural networks	Supervised, Unsupervised
(Leng & Jiang, 2015)	Manufacturing	Neural networks	Supervised, Unsupervised
(Ferreiro & Sierra, 2012)	Manufacturing	Neural networks	Supervised, Unsupervised
(Tatic & Tešic, 2017)	Bioinformatics	Clustering	Supervised
(Priore et al., 2006)	Manufacturing	Neural networks	Supervised
(Santoro et al., 2008)	Social	Neural Networks	Supervised, Unsupervised
(Meisner et al., 2008)	Navigation	Neural networks	Supervised
(Tsai & Li, 2008)	Manufacturing	Bootstrapping	Supervised
(Xiao et al., 2015)	Interaction	Non-parametric	Supervised
(Rani, Liu, Sarkar, & Vanman, 2006)	Bioinformatics	Support vector machines	Unsupervised
(Panait, Luke, Panait, & Luke, 2005)	Cooperative Robotics	Neural networks	Supervised, Unsupervised
(Mohammad & Nishida, 2009)	Social Robotics	Neural networks	Supervised
(Ramík, Madani, & Sabourin, 2014)	Cognitive Robotics	Genetic algorithms Supervised	
(Vlassis, Toussaint, Kontes, & Piperidis, 2009)	Navigation	Genetic algorithms	Supervised
(Hornung et al., 2010)	Navigation	Neural networks	Supervised, Unsupervised
(Guo, Hao, & Liu, 2014)	Optimization and metaheuristic	Neural networks	Unsupervised
(Li & Yeh, 2008)	Optimization and metaheuristic	Neural networks	Supervised
(J. H. Lee & Ha, 2009)	Machine perception	Neural networks	Supervised
(Sudha, Dillibabu, Srivatsa Srinivas, & Annamalai, 2016)	Optimization and metaheuristic	Neural networks	Supervised

CURRENT CHALLENGES

Manufacturing worldwide is exposed to a high level of competition in launching new products, so artificial intelligence can provide mechanisms to help with the planning and design of new products (Erdin & Atmaca, 2015). In order to carry out these strategies, pressure must be exerted on each of the engineering production processes; from the design phases (Puik, Telgen, van Moergestel, & Ceglarek, 2017), process planning, complex calculations, and production cell modifications (Erdin & Atmaca, 2015).

Production processes generate and consume high volumes of data from the beginning, starting with the definition of customer needs and moving on to the next stages such as design and planning of the solution, programming of the machines and robots in the sequence of production of product components. The integration of all these elements generates a very complex system to control and monitor, on which it is very difficult for a human being to make decisions. Thus, an artificial intelligence system can be implemented to facilitate these tasks (Puik et al., 2017). In addition, integrating humans and machines adds an additional level of complexity to decision makers and equipment programmers, so (Monostori, 2002) recommends using techniques of pattern recognition, expert systems, artificial neural networks, mixed manufacturing techniques and Artificial Intelligence (Monostori, 2002).

Another consideration on using robots and machinery together with people in productive environments has to do with protecting the physical integrity of operators, for which (Cherubini, Passama, Crosnier, Lasnier, & Fraisse, 2016), recommend using assisted tools with computer vision to better control the distance between elements. However, not only should computer vision be used as a simple distance sensor, as mentioned by (Schröter, Kuhlang, Finsterbusch, Kuhrke, & Verl, 2016) computer vision is a key element in determining large movement routes of actuators, such as robotic arms, tools that prevent collisions with people or other equipment. Evidently, artificial intelligence can prevent accidents or damage during work tasks. (Schröter et al., 2016).

As stated by (Herrero, Moughlbay, Outón, Sallé, & de Ipiña, 2017), computer vision not only allows to generate preventive actions, but to improve the HRI by using commands based on visual abilities that facilitate manipulation of robots by people (Herrero et al., 2017). (Ding et al., 2017) propose not only to search for more elaborate algorithms to define robot manipulation patterns, but also to accompany the computer vision of a database of visual elements to facilitate the interpretation of the environment to improve the learning and recognition of figures and objects in order to establish more natural reactions in a actions performed by robots (Ding et al., 2017).

An important point to consider is the control of robot movements to avoid hitting objects or people -including those that were not used in training- by using algorithms that predict potential collisions (Ahmad & Plapper, 2016). In order to get to these levels of prediction of possible collisions it is necessary for robots to learn through visual recognition systems, in daily life environments or in special lighting conditions that allow the identification of people and objects (Garrell, Villamizar, Moreno-Noguer, & Sanfeliu, 2017).

It is also important to investigate how to improve the level of accuracy in detection of human faces in real time by adjusting to different environments (Martinez-Martin & del Pobil, 2017). Not only is it important for robots to be able to distinguish people, human faces and objects, but also gestures in human interaction, which are so natural and will be transferred to robots. Thus, there are already advances in this area (Canal, Escalera, & Angulo, 2016).

CONCLUSION

This paper is mainly focused on the use of artificial intelligence applied to the industry, and explores several topics related to the central idea of cybermanufacturing, including robotics, computer vision, manufacturing, artificial intelligence and human-robot interaction. The paper reviews them from the perspective of an entire industrial production process, starting with the definition of the idea and needs of a product to its final production. It emphasizes how Smart Manufacturing Equipment (SME) interacts with each of its elements and the operators. Also, it proposes the creation of an intelligent environment for the development of an industrial production.

The main purpose is to discuss the need to use artificial intelligence as the core element for designing future cyber-factories based on the concepts of Industry 4.0. It will allow the interaction of intelligent and traditional equipment and the collaborative work between operators, considering elements such as computer vision to intrinsically promote the quality of the products and the occupational safety of people. Moreover, it will allow to consider the evolutionary proposal of production systems to make them more dynamic in response to times and flexibility of production of new products with variants caused by specific needs of consumers.

Future research lines propose the integration of intelligent logistic systems. The production planning in real time will allow intelligent distribution channels to integrate distribution schemes with robots directly from the factory. While HRI has made significant advances there are several challenges, including the use of two-way communication natural interfaces in real time between humans and robots. In this way, humans would feel that devices are really workmates rather than collaborative tools.

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