"Cobotics" and human-robot interactions

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Abstract:
Thanks to advances in design and safety, industrial workstations now offer the possibility for robots and operatives to share the same workspace and interact. It thus becomes necessary to rethink the organization of workstations so that operatives can collaborate with "cobots". Examples are provided to illustrate how artificial intelligence techniques can facilitate the design of these new workstations and improve human-robot interactions.

Cobotics in industry

In industry, robots are gradually being installed at works stations where heavy or dangerous tasks are performed. Large sections of the assembly line in automobile plants have been automated: impressive robots occupy the workstations for soldering metal parts; and robots specially designed to withstand toxic vapors have been installed at workstations for painting. For the sake of safety, people are forbidden in the workspace area of these fully autonomous robots.[1]

However we cannot imagine robotizing all workstations in industry. Some stations require agility, flexibility, adaptability and the intelligence of human operatives. This holds for stations where workers assemble small parts in hard-to-reach places while keeping in pace with the assembly line and adapting to contingencies. At some stations, workers are assisted by machines that carry heavy loads (*e.g.*, a dashboard) but are still guided by human beings.

For reasons of ergonomics, performance and costs, it might be worthwhile coupling the skills of workers and robots at a single workstation. To enable workers and robots to work together in the same space, new types of robots — often called "cobots" (for collaborative or cooperative robots) — have to be installed. These cobots are by design guaranteed to see to the safety of nearby human operatives. It is thus possible for them to share the same space with workers (what is called "coexistence"), share activities but in successive operations ("sequential collaboration") or perform tasks together ("cooperation" or "co-manipulation").

The use of cobots in industry is subject to certifications and safety standards (*e.g.*, ISO 15066). These standards specify safety criteria related to the robot's speed, the energy and efforts to be used, and, too, the distance from operatives. Cobots are currently being rolled out for use in situations of coexistence, while manufacturers are still studying how to put them to more collaborative uses. Cobots are of interest to small and medium-sized businesses where manufacturing processes must be ever more flexible in order to respond to demands from customers.

[1] This article has been translated from French by Noal Mellott (Omaha Beach, France). All websites were consulted in March 2021.

Figure 1: Assembling a door on a vehicle in coexistence with a robot (WEISTROFFER 2014).

Contrary to conventional robotics in industry, cobotics allows for human interventions by making it possible for people and machines to share a workspace and interact. New problems related to safety, ergonomics and performance thus become topics for research. In this context, machine learning techniques opens perspectives worthy of thought.

Machine learning

With the emergence of cobotics, manufacturers have to reckon with new problems. One has to do with the transition from existing toward "collaborative" workstations and with the design of these new stations. Another concerns the interactions between people and robots, and the best way for them to cooperate. Let us look at these problems while illustrating, for each, how machine learning might make it easier to implement solutions.

Computer-aided design of cooperative workstations

The switch from a conventional to a more cooperative robotics in industry requires that manufacturers devote thought to the reorganization of workstations. In contrast with the usual organization where robots are fenced off, cobots allow for sharing workspaces with human operatives. Even though a cobot is designed to be inherently safe and therefore capable of detecting collisions with operatives and halting thanks to its sensors, external sensors might be needed for the sake of safety certifications. Designing these new "cooperative" workstations is more complicated, the larger the number of parameters that come into play. Conventional model-building turns out to be limited when it has to take into account the parameters for a robot that change in real time and has to make accurate calculations about safety conditions (such as the apparent mass or the efforts of the robot's end-effectors).

The SEEROB program (for the ergonomic simulation of work environments with collaborative robots) has been developed with PSA and Safran at CEA-List in FactoryLab.[2] Its computer-aided design (CAD) software visualizes future cooperative workstations and simulates a robot's actions. It helps make it easier to choose among safety sensors and calculate in real time a set of parameters for safety and ergonomics at the station. CAD can also be used for existing stations in order to generate a certification report. This software brings operatives into the work cycle by using virtual reality techniques to immerse them in simulation on scale 1 (by using headsets for virtual or mixed reality).

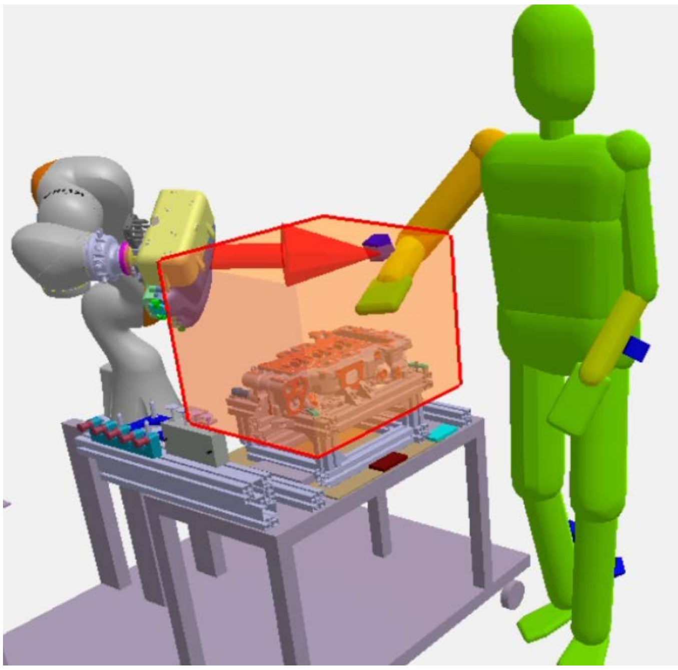

Figure 2: SEEROB software simulation for analyzing the ergonomics and safety of workstations with cobots.

As robotic engineers use this CAD software to design cooperative workstations, their job can prove arduous when a slue of parameters is to be taken into account. Expertise might be needed to optimize the positioning of a robot or set the parameters for safety sensors. For this, machine learning can come in handy, especially its reinforcement learning techniques. The agent chooses a set of parameters, and receives a reward (*e.g.*, a safety score) from the simulation. Through iterations with this feedback, the agent successively optimizes the set of parameters. These techniques are even more effective when simulations can be made in parallel on a bank of computers. Following simulations, the best results are selected and placed in a list of possible solutions for the future cooperative workstation.

These techniques of off-line simulation are put to use in other contexts, for example to generate itineraries. P. Maurice (2015) used them to determine a cobot's optimal configuration (position, structural kinetics) for relieving the musculoskeletal conditions for human operatives during the task of drilling. Genetic algorithms are used to simulate a large number of configurations and converge toward an optimal solution.

[2]Respectively: https://www.youtube.com/watch?v=9wMAvunW5M and http://factorylab.fr/.

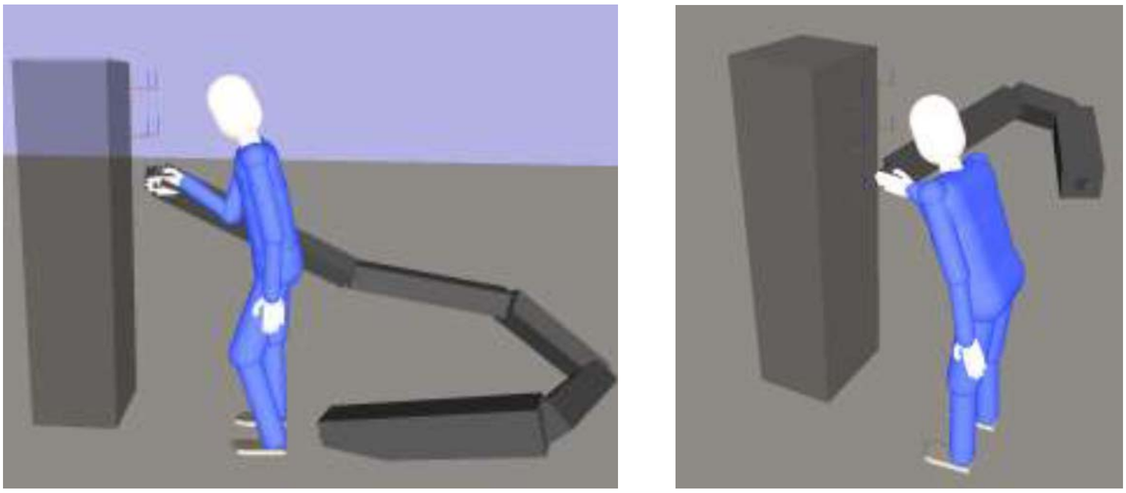

Figure 3: Use of genetic algorithms for designing a cobot for drilling. On the left, the 10th generation; and on the right: the 220th. Over generations, the robot's size has decreased while the virtual dummy's biomechanics has improved (MAURICE 2015).

Human-robot interactions

Once a collaborative workstation is designed at the macro level, we are led, for reasons of safety and ergonomics, to look more closely at robot-human interactions and the possibilities for collaboration. In conventional robotics, robots repeat the same operations in a set manner and do not interact with operatives. In the case of a shared workspace, cobotic robots have to adjust to the actions of nearby operatives, whether to avoid collisions or pass objects. Programming robots becomes more complex, as robots have to be made smarter so that they can recognize operatives' movements and adjust to them.

Some workstations are set up such that any contact between people and robots is forbidden for reasons of safety. At other stations, contact is necessary, since a human being and robot have to work together on the same parts or the operative has to guide the robot to specific places. Besides detecting collisions between people and robots, one challenge for collaborative robotics is to classify these collisions in order to distinguish, among intentional and accidental contacts, those that are potentially dangerous and demand immediate action. N. Briquet-Kerestedjian (2019) has proposed a solution that, once an impact is detected, classifies the interaction by using supervised learning techniques and neural network technology.

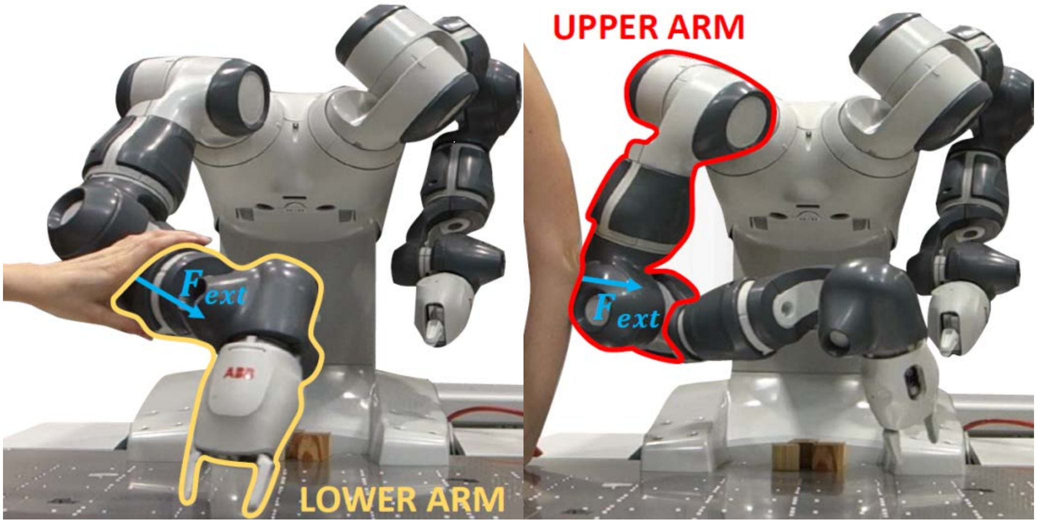

Figure 4: Neural network technology being used to describe contacts. On the left: an intentional interaction with the robot. On the right: an unwanted collision (BRIQUET-KERESTEDJIAN 2019).

Besides detecting and classifying contacts with operatives, a robot has to have a more granular knowledge of its activity so that interactions be smoother and more effective. Operatives' movements have to be analyzed to come up with a correct response and even prepare for them. External cameras for detecting movements are usually placed in the workspace to detect operatives' movements. Sensors might also be placed on operatives (in gloves or worn on the head), as Coupeté (2016) did to analyze human gestures during the assembly of automobile parts in collaboration with a two-armed robot. Algorithms based on a hidden Markov model serve to classify gestures in predefined categories. The results of recognition tests can be used as input to the robot. Using machine learning to recognize movements is not just for robot-human interactions. The same techniques can be used to ergonomically analyze a workstation, recognize the intention of a person at home, or assess an athlete's or artist's performance. These recognition techniques entail making a classification with categories that often depend on the case at hand. This can hamper an industrialized rollout of this method.*

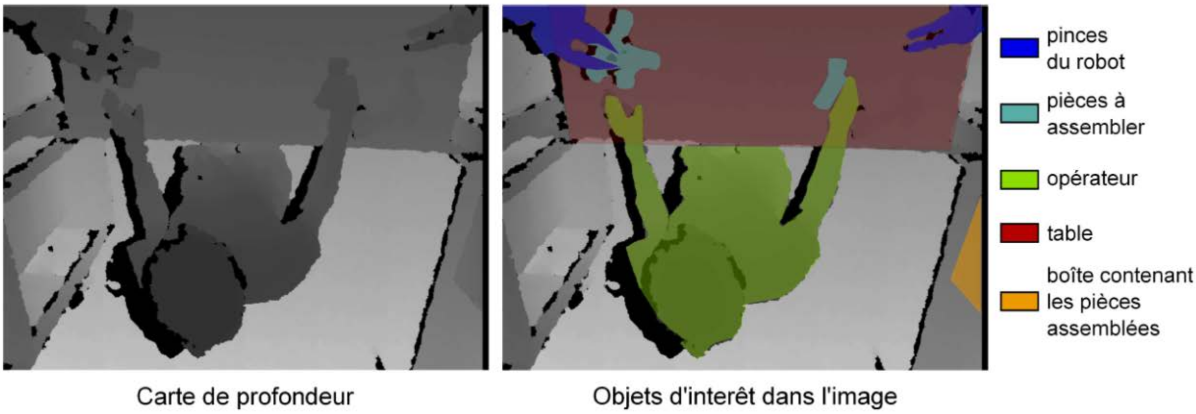

Figure 5: A depth camera analyzes an operative's movements and classifies gestures using a hidden Markov model (COUPETÉ 2016).

At some workstations, it is not enough for the robot to adapt to the movements of the persons with whom it interacts. It must also adjust to an operative's profile and level of expertise. A robot's behavior has a different impact on operatives depending on their level of expertise. Furthermore, after working with a robot for several hours, this level evolves, and the robot then has to adjust its parameters in real time to better adapt to the operative's adaptation of his/her own actions. This requires a granular model of user profiles. Blanchet *et al*. (2019) have proposed building models by extracting raw data from within the robot while operatives are manipulating it. Experiments have shown the worth of this approach for distinguishing between expert and rookie operatives. Different forms of assistance are needed depending on the operative's profile.

Limits and extensions of machine learning

These few examples illustrate the value of machine learning in cobotics, whether for the computer-aided design of new collaborative workstations or for improving human-robot interactions. They are not exhaustive, since other applications can be imagined. In some problem areas, it might be hard to apply machine learning.

A major problem is how to take into account an operative's actions and their variability. Current simulation tools are able to determine, ever more reliably, whether a collaborative workstation is acceptable in terms of safety and ergonomics, but they have yet to reckon with human behavior, its uncertainty and mistakes, so as to yield more satisfying results. Since these aspects are still hard to simulate, user tests have to be carried out at the station or in virtual reality (WEISTROFFER 2014).

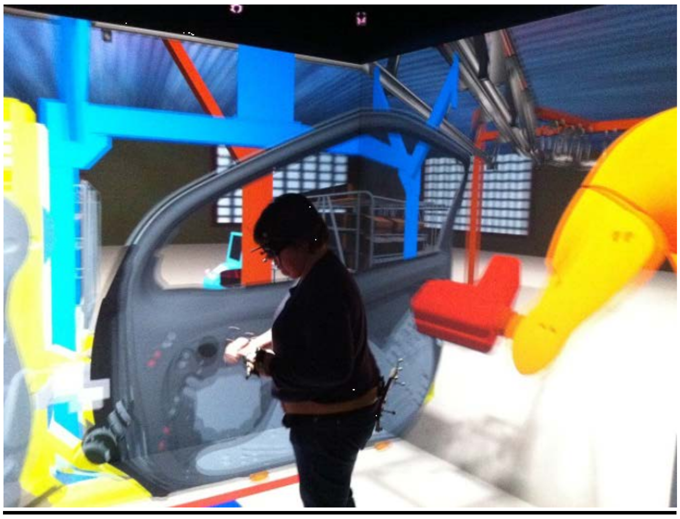

Figure 6: Virtual reality for simulating a workstation with a collaborative robot: the operative is interacting via an immersive system (WEISTROFFER 2014).

Safety, ergonomics and performance are but one necessary phase for developing collaborative workstations. Other phases are just as necessary for these stations to be accepted and deemed worthy of use by the operatives assigned to them. During all these phases, subjective criteria are essential even though they are hard to enter into a model for simulation. Unless it becomes possible to build an accurate model of operatives' behaviors (with their shortcomings and mistakes), simulation and machine learning will always have to be paired with supplementary tests for completing or validating the results.

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