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A human-in-the-loop cyber-physical system for collaborative assembly in smart manufacturing

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Abstract

Industry 4.0 rose with the introduction of cyber-physical systems (CPS) and Internet of things (IoT) inside manufacturing systems. CPS represent self-controlled physical processes, having tight networking capabilities and efficient interfaces for human interaction. The interactive dimension of CPS reaches its maximum when defined in terms of natural human-machine interfaces (NHMI), i.e., those reducing the technological barriers required for the interaction. This paper presents a NHMI bringing the human decision-making capabilities inside the cybernetic control loop of a smart manufacturing assembly system. The interface allows to control, coordinate and cooperate with an industrial cobot during the task execution.

Keywords: smart manufacturing; Industry 4.0; collaborative robotics; natural human-machine-interfaces

1. Introduction

The logic of Industry 4.0 foresees humans and machines as indistinguishable parts of a larger heterogeneous body of distributed autonomous and cooperative entities. Under such a perspective, machines are endowed with self and environment awareness and can smartly interact with both humans and other machines [1]. This innovative standpoint brings forth the concept of cyber-physical system (CPS) [2], due the significant shift in embedded systems design that it entails: from dedicated devices operating and handling a limited number of resources, to fully featured perceptive interactive devices, able to handle intimate interactions with physical process and peers through networked communication systems.

In contrast to the third industrial revolution, CPS are not intended to substitute humans in industry, but to work with them in synergy. Accordingly, CPS not only perform their own tasks in autonomy or semi-autonomy, but also provide support to humans in terms of physical, perceptive and cognitive aid systems. Such a tight interaction between CPS and humans requires (i) a rich unambiguous bidirectional information flow and (ii) a proper set of abstract interactive *human-machine interfaces* (HMI). Each of the above listed requirement represents a fundamental contemporary research field in Industry 4.0.

The HMI of a CPS must allow the configuration of its behavior or set of automated actions to be performed in autonomy or in semi-autonomy along with other CPS or humans. This implies that a HMI must include methods for adapting and reacting to unexpected environmental conditions, without requiring explicit human intervention, thus improving the task execution in terms of accuracy, reliability and safety.

In less than half of a century, HMI methods in industry have seamlessly evolved from indicator lights, buttons and levers to every-day graphical user interfaces (GUI), keyboards, mouse and touch-screens reaching up to the concept of multi-modal interfaces [3], where voice, hands, and the entire body become a single communication channel. This HMI evolution reflects

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the intrinsic need of defining interaction between CPS and humans in terms of *natural* human-machine interfaces (NHMI) [4], i.e., the need of endowing CPS with an *anthropomorphic* dimension.

NHMI in cyber-physical productions system (CPPS) are expected to hide greater levels of complexity as the fourth industrial revolution will exhibit new work areas where, as remarked in [5][6][7], highly skilled occupations will increase while low-skilled and auxiliary occupations will decrease. In this context, a fundamental issue to be addressed is how to make accessible to the CPS the human expertise. A way to overcome such a technological challenge is to define a anthropocentric mechanism known as the *human-in-the-loop* approach [8][9], which allows a direct sharing or transfer of human skills into inside a subset of CPS control loops. The aim of this work is therefore to test and to validate some examples of possible NHMI for human-in-the-loop control, coordinate and cooperate with CPS in collaborative workspaces. Like in [9], we focus on the expertise transfer, but in contrast to both [8] and [9], we do not investigate mechanism for endowing the CPS with decision-making capabilities. The implementation was realized in a laboratory environment of a learning factory lab, a demonstrator for other researchers as well as students and practitioners from industry.

The rest of the paper is organized as follows. Section 2 introduces the state of the art in NHMI and human-in-the-loop approaches in industry. In Section 3 we provide a comprehensive description of the collaborative assembly case study and the laboratory facility. Then, Section 4 introduces the demonstrator of NHMI in human-in-the-loop CPS, describing and illustrating the different technologies and interfaces that have been applied in this laboratory case study. Finally, Section 5 summarizes the main findings described in the paper and provides an outlook for further research activities.

2. Theoretical background and state of the art

Gorecky et al. [4] suggest that the main enablers of NHMI in the Industry 4.0 era are the a*utomatic speech recognition*, the g*esture recognition* and the e*nhanced reality*. The latter enabler defined either in terms of a*ugmented reality* or v*irtual reality*. For us, it is also natural to consider as determinant factors for NHMI the p*hysical human-robot interaction* and the p*rediction of operator's intentions*.

Automatic speech recognition consists of the identification and recognition of patterns bearing the information content inside the speech waveform [10]. In industrial context, CPS implementing an automatic speech recognition system relies on a v*oice user interface* to interact with humans. Lotterbach et al. [11] identify a set of guidelines for the implementation of voice user interface in industrial environments. The authors state that voice user interfaces cannot represent a replacement to classical GUI but a complement to them, that under certain conditions and in certain contexts, provides the most comfortable and efficient way of interaction. An interesting overview of automatic speech recognition applications in industrial maintenance is given in [12].

Any expressive and meaningful body motion (including fingers, hands, arms, head motions, face expressions, body postures, etc.) with the intent of transmitting meaningful information or interacting with other entities in the workspace can be defined as a *gesture*. In many practical applications, gesture recognition relies on visual computing systems, either in terms of motion capture or pure image-based approaches. Regardless the approach, visual computing has been recognized as one of capital importance in Industry 4.0, specially in those cases where the *visual gesture recognition* system relies on multi-sensor measurements [13]. Visual gesture recognition has been long appreciated as a method for interacting with robots [15]. An interesting review of applications and technologies of this topic is given in [15]. Moreover, with the advent of RGB-D sensors the possibilities for visual gesture recognition have dramatically grown [16].

Augmented reality consists of the enrichment of the physical world information by means of digital information superimposed on top of a perceived representation of the physical world [17]. Under this definition, any of the human senses can be used to implement such kind of technology. However, nowadays augmented reality is primarily implemented at the visual, tactile and spatial perceptive levels by means of *spatially augmented reality*, where virtual objects are rendered directly within or on the user's physical space [18]. By mixing the perceptive capabilities of modern mobile devices and RGB-D sensors together with the visualization capabilities of smart glasses such experience can be built on top of virtual reality environments where the physical world superimposed on it [17]. In [19] a spatially augmented reality approach is developed to enhance the HMI of industrial computer numeric controlled (CNC) machines. In [20], the authors describe a use case of augmented reality in logistics.

Under the perspective of multi-modal interfaces, physical contact represents a natural mechanism to develop HMI for CPS. This concept has been extensively explored in the robotics community. In the field of collaborative robotics [21][22] the contact between humans as robot is expected to be frequent. The mechatronic design of a collaborative robot allows it to sense the qualities of the physical contact, making possible to convey information through the physical interaction. The introduction of such systems in industrial environments have been addressed in [23] and [24]. Also, in the field of human-robot augmentation systems, the mechanical capacities of a human involving motion control and force are augmented with wearable robotic systems [25]. Such systems allow, for example, to improve the patients mobility after injuries [26][27], improve the dexterity of surgeons [28] and reduce the hand fatigue of astronauts during extravehicular activities [29].

Prediction of operator's intentions enhance the effectiveness of collaboration between CPS and humans, especially in industrial scenarios where safety greatly depends on the understanding between humans and CPS. In fact, not only humans need to be aware of the CPS in collaborative tasks to guarantee their own safety. Also, CPS must identify and understand and human intentions in such scenarios to promptly react and adapt to both expected and unexpected operative conditions in a safe manner. It is worth noticing that a prediction system of this type can be built on top of visual gesture recognition frameworks, since the detection and prediction of human intentions relies on gestures recognition and tracking. Koppula et al. [30] show how the link between human actions and object affordances can be exploited to detect and anticipate human intentions. In [31], the authors predict grasping gestures using an eye-tracker device and wearable attached to the user's hand. Casalino et al. [32] propose a framework for the prediction of human intentions from RGB-D data while improving the human awareness by means of haptic feedback. Similarly, Zanchettin et al. [33] describe a framework to infer the most likely reaching target of the operator's hand based on RGB-D measurements. In [34] a method to predict human activity patterns is described. The method allows to anticipate when a specific collaborative operation will be requested by the operator, such that the cobot can perform other tasks in the meanwhile.

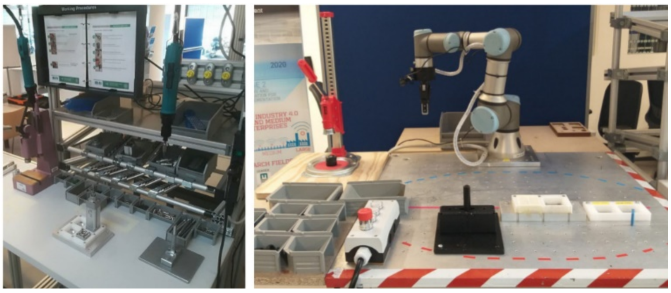

Fig. 1. Left: original manual assembly station of our case study. Right: toward a fully collaborative station based on the UR3 robot.

3. Description of the laboratory case study

This work refers to the transition of an existing manual assembly workstation to a collaborative one through the implementation of NHMI. To do so, an existing manual assembly workstation is used as a starting point for the concept development of the collaborative one. Such a starting point is a flexible working area for the study of manual assembly of light industrial products (see Fig. 1), located in the Smart Mini Factory Laboratory (SMF) of the Free University of Bozen-Bolzano. It is a training workstation where a single operator can completely assemble a pneumatic cylinder aimed to simulate different assembly conditions and applications to analyze the production system performances. It is equipped with a mobile workbench, a block-and-tackle for lightweight applications, an integrated Kanban rack, a working procedures panel, a double lighting system, an industrial screwer and a knee lever press. Main laboratory applications are the development of case studies for manual lean assembly, workplace organization, human-centered design and ergonomics. Other analyses refer to safe human-robot collaboration in hybrid assembly of light products.

The SMF counts with two collaborative robots of different sizes both produces by Universal Robots, the UR10 and UR3. They are respectively the larger and the smaller robots produced by such house. They have 6-axis anthropomorphic structure with an almost spherical workspace and 500mm and 1200mm of reach. Both are controlled by a Mini-ITX PC with a Linux system installed which runs, as a daemon, the low-level robot controller called URControl. A visual interface is available through a touch screen pendant, providing a Graphic User Interface (GUI) called PolyScope.

The main collaborative feature of these robots lies in their design for safe physical human-robot interaction according to the standards ISO 10218 and ISO/TS 15066. The former standard deals with hazards that traditional industrial robots may pose. The latter corresponds a Technical Specification for operation of collaborative robots where a person and the robot share the same workspace. In fact, these robots are endowed with a series an ergonomic and lightweight design, and its control system makes it a so called “force limited robot”, thanks to its built-in capability of collision identification and reaction as well as limitation of dynamical features. The user can configure thresholds for the dynamical properties of the robot and geometric boundaries that, once approached, trigger different handling procedures, as a protective stop to minimize the possibility of injuries.

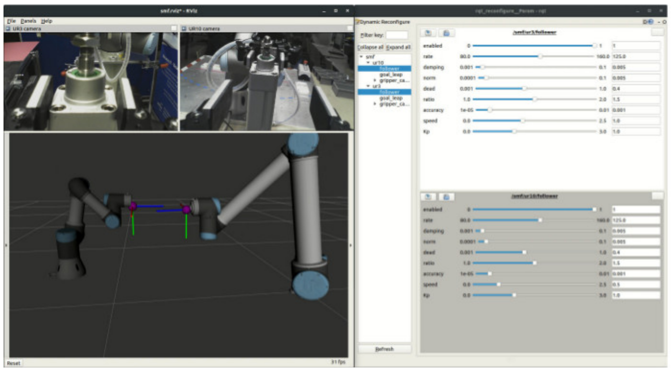

Fig. 2. Graphical user interface of the proposed framework. Left: visualization tool. Right: parameters setup screen.

4. Demonstrator of NHMI in human-in-the-loop CPS

As previously stated in Section 3, we focus our attention on collaborative robotics applications in industrial environments, so to provide solutions to the small and medium-sized enterprises (SME) sector. Therefore, one fundamental constraint is to define simplified robotic programming methodologies through NHMI. On the current collaborative robotics market, the so-called *hand-guiding waypoint programming* technique is well established human-on-the-loop approach, where the operator guides the robot in free-drive mode and stores in its memory a sequence of waypoints characterizing the task. After the operator has completed the sequence, the robot computes suitable joint motions and performs on-demand the given task.

Nevertheless, in many practical situations the physical interaction between the robot and the operator could represent a limitation (e.g., service-oriented robotics). In fact, considering that the CPS “nature” relies on the ability to handle intimate interactions with physical process and peers through networked communication systems, we impose as a research objective to implement a NHMI that doesn't rely on physical interaction and that can be implemented remotely on top of a networked communication system. Moreover, depending on the CPS capabilities, three distinct levels of autonomy can be identified: *direct* control of the CPS; *supervision* of actions executed in total autonomy by the CPS; *shared* execution of actions by combining human and machine skills. Like the case of hand-guiding waypoint programming, here we are focused on shared control architectures for task-oriented applications.

Our framework consists of a remote human-in-the-loop control mechanism the combines an enhanced reality visualization tool together with a gesture recognition system to implement a natural interaction between the human operator and two collaborative robots. The control mechanism translates a sequence of operator's gestures into corresponding motions of the end-effector of each robot independently. Moreover, our framework was developed on top of the *robot operating system* (ROS) middleware, that provides a publish-subscribe messaging infrastructure designed for rapid prototyping of distributed networked systems, a set of tools for handling such networked systems and an extensible collection of libraries for robotics programming. As a consequence, our framework can decomposed on three main units: NHMI (Section 4.1), motion controller (Section 4.2) and distributed communication network (Section 4.3).

4.1. Natural human-machine interfaces

Our NHMI is defined by the combination of a gesture recognition system and a powerful GUI composed by an enhanced reality visualization environment and a configuration panel (see Fig. 2). The gesture recognition system decodes and transmits the operator gestures, defining the input signals of the control unit (see Section 4.3). The enhanced reality environment provides to the operator the images acquired from the cameras mounted on both end-effectors and a simulation environment where to observe from any arbitrary viewpoint the robot states and mapped gestures in workspace. The configuration panel allows to set in real-time any parameter of the interface, the controller or the networked communications system.

Two different types of gesture recognition systems have been included in our framework:

Leap Motion Controller. This device is a small USB consumer-grade optical tracking sensor based on stereo vision, developed by Leap Motion. This sensor can recognize hand gestures and finger positions with sub-millimeter accuracy. To achieve this, it integrates two monochromatic IR cameras and three infrared sources to compute a 3D reconstruction of a roughly hemispherical area up to about 1 meter. A detailed analysis of the accuracy and robustness of the sensor is discussed in [35]. In conjunction with the sensor, an API in different programming languages is provided. This API allows to retrieve the positions in Cartesian space and orientations vectors of fingers, hands, and wrists. Unfortunately, the API doesn't provide any mechanism to obtain the underlying point cloud data. Based on the leap motion measurements we define six different type of gestures. Three of them associated to the orthogonal linear displacement of the hand (up/down, forward/backward and left/right), like the one depicted in **Error! Reference source not found.**. The remaining three to identify the orientation changes of the hand in terms of the roll, pitch and yaw angles.

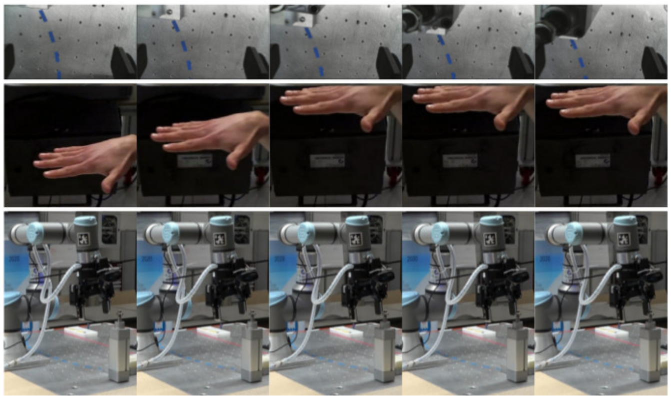

Fig. 3. Illustrative outcomes of the motion control of the UR3 robot using the leap motion controller (top row: UR3 camera frames; middle row: hand gesture; bottom row: robot motion). The relative motions are applied to the of the end-effector with respect to its corresponding camera frame: forward/backward gestures of the hand are mapped along the approaching direction (z-axis); up/down gestures along the vertical direction (y-axis); left/right gestures along the horizontal direction (x-axis).

Smartphones. Nowadays, in many consumer-grade and industrial applications, smartphones represent the first device choice on IoT applications design. On the one hand, modern smartphones are equipped with growing computing, storage and networking capabilities. On the other, they include cameras, microphones and a great number of motion and gesture sensors that can be used to implement NHMI. The Android platform provides a large set of standard motions sensors: gravity, linear acceleration, rotation vector, significant motion, step counter, step detector, accelerometer and gyroscope. The last two are always hardware-based, while the others depending on the specific device can be either software or hardware-based. Since the estimation of linear displacement from accelerometers measurements is heavily subject to drift [36], in our demonstrator we consider only measurements taken from orientation sensors. Orientation measurements are usually obtained from *micro electro-mechanical systems* (MEMS) gyroscopes, vibrating mechanical elements able to sense angular velocities based on the transfer of energy between two vibration modes caused by the Coriolis acceleration that undergoes the smartphone [37]. Based on the smartphone's sensor measurements we define three different type of gestures to identify orientation changes of the device in terms of the roll, pitch and yaw angles, as depicted in Fig. 4.

The human-in-the-loop mechanism is thus defined in terms of the visual feedback provided by the enhanced reality visualization environment. The operator will guide the robot motion based on the video streams generated by the cameras mounted on the end-effectors. Also, the robot states and mapped gestures in workspace can be observed inside the visualization environment. This visual feedback allows a more robust control of the robot since self-collisions or singular configurations can be easily predicted and avoided. The interface is based on the RViz visualization tool of ROS.

Fig. 4. Illustrative outcomes of the orientation tracking of the operator's smartphone orientation using the UR10 robot. As can be observed, the orientation of the end-effector mirrors the orientations of the smartphone.

4.2. Motion controller

The motion control of the UR3 and UR10 robots is defined in terms of a first order inverse differential kinematics controller. The implementation exploits the robotics programming libraries offered by the ROS framework to automatically generate a kinematic model of the robot from publicly available robots' descriptions in *unified robot description format* (URDF). We extract the geometrical description of the kinematic chain of the robot using the URDF parser of ROS to build a computational kinematic model with the *kinematics and dynamics library* (KDL). The kinematics inversion is based on a custom implementation of a damped pseudo-inverse of the Jacobian matrix. The controller as well as the rest of the framework was implemented in the C++ programming language.

The controller first maps the operators gestures into a set of primitive motions in the workspace of the robot with respect to the camera frame, then such motions are mapped in joint space through the inverse differential kinematics. Gestures are defined in terms of relative poses measured with respect to an initial measured sensor pose, that need to be defined through the initialization procedure before the start of the control loop (see Fig. 5). All control parameters, including gain, thresholds, control rate, etc., can be set in real-time through the configuration panel of the GUI described in Section4.1 (see Fig. 2).

4.3. Distributed communication network

ROS is based on a peer-to-peer network of processes called *nodes*, that process and share data together. Data is exchanged through a set of data structures with typed fields called *messages*. The ROS network relies on a *master* node to provide name registration and lookup services to the other nodes. This node also is responsibly to provide a centralized data storage mechanism available to all other nodes of the network. Messages can be exchanged either in terms of a many-to-many one-way communication transport layer (publish/subscribe model) or a request/reply based service transport layer. The ROS protocol is built on top of the stateless XMLRPC HTTP-based protocol. Peer-to-peer data connections between nodes are also negotiated through XMLRPC. Such data connections can be established through TCP/IP or UDP, depending on the applicative context.

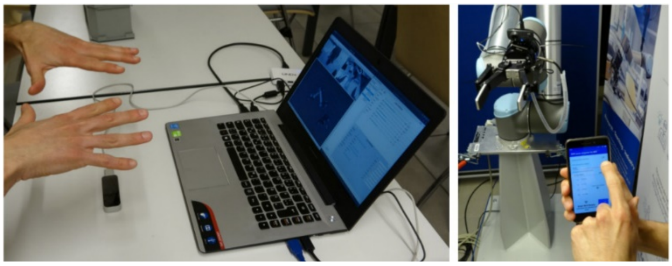

Fig. 5. Sensors initialization. Motions applied to the robots are the computed in terms of relative gestures between the initial sensor pose and successive poses after initialization. Left: initialization of hand poses based on Leap Motion measurements. Right: initialization of the smartphone orientation based on the filtered measurements provided by the Android SDK.

4.4. Realization

The entire system is composed by a consumer grade laptop with 8GB RAM and an Intel Core i5-5200U CPU, the UR3 robot and the UR10 robot sharing a common workspace. Since each input sensor can be used to control either robot, one fundamental issue to be addressed is the mapping of gestures into control inputs for the robots. In this regard, we found that many natural gestures (e.g., closing the hand) notably reduce the accuracy of the Leap Motion Controller. Also, the hand tracking was often lost when only small portions of the hand go beyond the measuring range.

Moreover, mapping gestures (i.e., relative poses measured by the sensors) into relative poses of the robot implies limiting the dexterity of the robot to the set of feasible relative motions that the human hand may reach inside the measuring range of the sensors. To increase the robot's range of operation an incremental gestures composition was adopted: gestures are not mapped as relative poses but as relative velocities.

With this new control modality, the smartphone's sensor presented the lowest orientation drift. This is due the high sensibility of the Leap Motion Controller measurements to the hand pose and gesture. However, by implementing a custom tracking mechanism on top of the sensor measurements (e.g., a Kalman or similar filter) improved levels of accuracy can be achieved with both sensors.

5. Discussion and future work

The main feature of our framework is that it doesn't need real physical interaction to program the robots and the implementation allows a remote control. This confirms that in contrast to classical remote interfaces, direct physical interaction is no longer required to control, collaborate, cooperate and coordinate CPS.

We tested two different gesture recognition approaches in our NHMI and the results are promising. One the one hand, the Leap Motion Controller allows to perform natural hand gestures without any physical or ergonomic constraint with sub-millimeter accuracy. On the other hand, we are used to manipulate smartphones every day and -most important- very accurate orientation measurements can be obtained from their motion sensors, allowing a fine-grained control on the end-effectors orientation.

It is worth noticing that our framework can be more efficient if information of the robot's environment is included inside the virtual scene. This will be accounted in a future work.

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