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Data-driven framework to improve collaborative human-robot flexible manufacturing applications

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***Abstract*—The manufacturing assembly lines of the future are foreseen to dismiss fully unmanned systems in favour of anthropocentric solutions. However, bringing in the human complexity leads to modeling and control questions that only data can answer. Moreover, many human-robot collaborative applications in flexible manufacturing involve manipulator cobots, whereas little attention is given to the role of mobile robots. This work outlines a data-driven framework, which is the core of a brand new project to be fully developed in the very next future, to let human-robot collaborative processes overcome the barriers to successful interaction, leveraging mobile and fixed-base robots.**

***Index Terms*—Flexible manufacturing, Human-robot collaboration, Data-driven framework, Mobile robotics**

I. Motivations and State of the Art

The fourth industrial revolution marked the turning point towards the industrial integration of all the technological advances ranging from the Internet of Things (IoT) to 3D printing, which allowed the implementation of a series of new types of systems, leveraging the increase in computational power. The key concepts of Industry 4.0 are being slowly implemented as and where possible, but the direction of development is inevitably dictated by market demand. The ongoing revolution is not only linked to a further transformation of the tools used for the implementation of the production line itself but to the upheaval of the very concept of production/assembly line as it was intended before [1]. In fact, the production line structure has undergone morphological changes for quite a while now [2]. Recently, manufacturing have been shaped by lean principles applied to technology and decision-making processes to reduce material waste and non value-added activities [3], [4]. Lean manufacturing takes advantage of decentralised control to foster transparency and simplicity providing local autonomy to employees and, combined with Industry 4.0 concepts, upgrades the traditional centralised IT systems to achieve lean automation [5]. What is going to further transform the structure of production lines is today's market demand for products on request, fueled by a new awareness and sensitivity to sustainability. Indeed, current industries and production systems are not sustainable and seen as responsible for environmental degradation [6].

Products on request go beyond the concept of customized products (customization upon standard products): they require design, building and testing procedures specific to the individual product to achieve manufacturing levels that outbound the standard ones, making the whole process more expensive and time consuming. Mass production is in fact characterized by low costs and consequent low prices for customers but high risks linked to the failure to sell; conversely, custom manufacturing involves small batch productions, which improve sales security but imply higher production times and labor costs caused by the need to have human operators as an integral part of the assembly process. As a matter of fact, human intelligence in performing certain operations that require high cognitive capabilities is not replaceable by artificial intelligence yet. However, the use of automation reduces the amount of hands-on human involvement in the manufacture of each product and reduces human error [7]. When it comes to product on request, the optimization parameters change: quality is optimized by exploiting human capabilities (often experience-based) at the expense of production efficiency (especially in terms of time). Moreover, after the crisis due to COVID-19, many Small-and Medium-sized Enterprises (SMEs) became loss making, being more subject to a slow return to normal operation and less resilient to falling demand with respect to big players [8]. The custom product production vision can help SMEs and the relaunch of local enterprises. In particular, given the limited resources of an SME, an ideal solution would focus less on the optimization of machines for custom production but rather on a systematic enhancement of human manual operations through the collaboration with robots, exploiting artificial intelligence algorithms to improve the overall efficiency.

The challenge of custom manufacturing is to achieve the same standards of costs and production times of mass products. In order to achieve a sort of standardization of custom manufacturing production, collaborative robotics can represent a key enabler to fill the gap, evolving toward a smart custom manufacturing system. To do so, Human-Robot Collaboration (HRC) and Interaction (HRI) should aim at identifying a balanced synergy between the human and the robot (mobile or fixed base cobot) so as to value and enhance the cognitive skills and experience of the former and the accuracy, strength and efficiency of the latter. In a holistic vision, the HR system can be interpreted as a component within the context of the well-known and well-established concept of Cyber-Physical

System (CPS). In [9], the authors present an architecture to be used as a framework to achieve self-organization and self-adaptation using a multi-agent based technology, in order to achieve auto-reconfiguration without human intervention to comply with product customization requirements while reducing costs. The human operator is involved in the task execution but not considered as part of the multi-agent system.

The work presented in [10] reviews the role of Multi-Agent systems (MASs) as main tool for CPS implementation. According to the analysed works, a MAS technology reference architecture should be technology and system agnostic to ease its instantiation and to favour its co-existence and integration with pre-existing automation. The agent-based solution reconfiguration is interpreted as not strictly related to physical modification of the system but rather as a multi-objective reconfiguration, which could potentially include sustainability aspects as energy saving, reuse of equipment and optimal use of human resources. In [11], the human operator interacts with CPSs exploiting a modular robotic cell able to reconfigure itself according to the requested operation. In [12], the Decentralised Manufacturing System is presented as an enabler of distributed production layouts. To achieve optimal HR work distribution, the authors propose an algorithm that assigns a collaboration potential to each movement in order to distribute process capabilities. Moreover, in the context of MASs in smart manufacturing systems, the integration of human actions in the control system, also referred as human-in-the-loop (HITL), allows to consider the human-machine cell as a single agent with the ability of self-arranging its work locally [13]. The authors of [14] claim that fully unmanned factories cannot be implemented not only due to ethical or social reasons, but mainly to the unfeasibility of such complex control systems. To achieve interoperability, they propose augmented reality as a rapid learning solution and the use of machine learning (ML) techniques to enable self-predict capabilities for implementing dynamic reconfiguration. As a matter of fact, Human Cyber Physical Systems (HCPSs) are envisioned to become the core of the factory of the future [15], suggesting an increasingly clear transition towards anthropocentric approaches.

Therefore, a desirable solution would leverage human cognition skills and machines' processing and data mining capabilities to implement human capabilities augmentation. HRC potential could be unlocked if the different cognition models of human operators and robotic agents were suitably interfaced to allow effective and efficient communication [16]. One possibility is the emulation of human interaction paradigms that typically imply an anticipatory behaviour [17]. This, intuitively, is implementable if the system has prediction capabilities on its future states. However, being a human agent part of the considered system, inferring the overall dynamics of the system is not easy.

Indeed, much of the available literature on human intention recognition deals with the problem of modeling and interpreting the human motion itself. In order to infer the user intentions, many works consider a nonlinear joint model of the human to estimate muscle activations by monitoring electromyography (EMG) signals using wearable sensors [18]. However, given the measurement limitations linked to human physiological parameters, other solutions, as the one proposed in [19], utilise ML to estimate a neural network (NN) state model relating the human joint angles and EMG signals. In general, data-driven approaches using datasets to train activity models that link events to activities, allow to take into account the uncertainties of the model with the disadvantage that (i) large dataset are needed to learn the model and (ii) interpretability and generalization (reusability) are limited [20]. Note that the time required to produce such large datasets is not compliant with short setup times.

A large and growing body of literature has investigated the role of data synthesis and relative data augmentation to solve the data scarcity problem. In fact, this issue is becoming more and more relevant as the majority of AI-based methods heavily depend on data. Most works concern low-data regime image classification problems where small training datasets cause bad generalization, leading to models affected by overfitting. The latter can usually be reduced through regularization and dropout techniques that, nevertheless, do not tackle the problem at its roots: here is where data augmentation comes into play. Among the available techniques for data augmentation, Generative Adversarial Networks (GANs) have demonstrated their power allowing for much larger invariance space with respect to typical data augmentation techniques that usually rely on linear transformations [21]. The use of GANs as data augmentation method ranges from medical applications [22], to emotion classification [23] and, when considering the industrial context, several examples can be found that apply this technique to improve fault detection systems [24], [25].

To place the work presented in this paper, it is worth pointing out that HRC in manufacturing applications have showed to have numerous facets depending on specific parameters, such as the degree of collaboration, dictated by the product characteristics [26], and the human operator long and short term attributes [27]. Keeping in mind these aspects, several approaches when considering close-proximity interactions between human operators and robotic systems can be found in the literature on HITL. The framework presented in [28] provides a remote human-in-the-loop control mechanism that brings an enhanced reality visualization tool and a gesture recognition system together to implement a natural interaction between the human operator and two manipulator collaborative robots. The method provided in [29] aims at recognising patterns by identifying maneuvers or motifs in time series trajectory data generated in HITL applications. In particular, to perform pattern extraction, the authors exploit ML algorithms on symbolic representations obtained by clustering feature vectors, which in turn are derived from trajectory segments. The work in [30] provides a deep learning (DL)-based visual prediction method in which a multilayered neural network realizes recognition and prediction of various human manipulation actions. Specifically, the algorithm uses partial sequences of motion data, allowing to recognize and predict motions before the action takes place.

In [31], the human arm trajectory is segmented and partial segments are used for human intention inference. Specifically, they apply time series classification, which finds similarities between the current partial trajectory and each representative trajectory of each task, corresponding to the average of all training trajectories. Moreover, the methods in [32] exploit gaze approximations and skeletal data to estimate the reaching goal intention. This information initializes a learning algorithm on a nonlinear state-space model with the uncertain system dynamics modeled using a dynamic NN; the estimated human trajectory is then used as a reference for safe and efficient robot motion. These examples highlight that, while some research has been carried out on HITL collaborative applications involving standard cobots, i.e., collaborative manipulators, frameworks involving Autonomous Mobile Robots (AMRs) and mobile manipulators are not taken into account, supposedly due to the lack of clear mobile-cobots safety regulations [33]. Nevertheless, mobile robotics represents one of the key enablers of flexible manufacturing and should be considered in HITL applications. Namely, in passive HITL, i.e., when the human does not exercise control over the system [34], e.g., applications engaging the robotic system for monitoring the human operator and autonomously adapting to the situation.

The aim of this paper is to lay out the specifications for a data-driven framework, involving collaborative robotic systems at large, with the role of distributed sensors. The system goal is to recognise the executed process, inferring it from the human operator state, and make it known to the robotic system, with the aim of implementing a suitable control to maximize execution performances. The outlined solution seeks to reduce the complexity of available collaborative systems capable of behaviour recognition, to investigate if less information can be more significant than what has been considered so far.

The paper is organized as follows: Section II provides an outline of the framework within a proper manufacturing scenario. Then in Section III, development ideas and a feasibility analysis of the solution are discussed, based on the available tools and technologies. Finally, Section IV draws some conclusions and defines the project next steps.

II. Framework Outline

In this section, a preliminary definition of the proposed HITL framework is carried on. To better describe its components, a use case scenario posed as a problem scenario is considered and described hereafter. We consider a custom manufacturing context where flexible production lines are implemented using both fixed-base and mobile robots. This means that the execution of manufacturing processes is distributed among agents, with the aim of complying with the flexibility requirements of custom products and products on request, whose assembly often heavily relies on cognitive and experience-based capabilities of human operators. As mentioned before, fully-automated operations do not always represent the most suitable solution to certain operations. In fact, several operations are still necessarily brought on by hand, especially in the case of small-scale job shops. For this reason, the robotic system collaborating with the human operator can be considered as an apprentice, i.e., it exploits information coming from the human counterpart to autonomously learn and gain awareness about the executed operation or task. Note that we consider an operation as composed of a set of tasks, where tasks are performed by the operator in collaboration with cobots, moving from one workstation to the other.

An envisioned use case is that of a job shop operation where a human operator is needed for the successful finalization of the product. The operation to manipulate or assemble a product requires her/his presence at different manufacturing workstations placed in the shop floor, depending on the product to be delivered (Figure 1).

Fig. 1. A robot-assisted assembly use case for the presented collaborative framework. The human operator needs to carry out several tasks performed at ad-hoc workstations. The robotic system observes the operator to determine the current process to infer its own desired behaviour.

Given the above scenario, the problem statement can be defined as follows: given a collaborative operation, the robotic system should implement proactiveness to maximize execution effectiveness and efficiency, complying with lean manufacturing requirements. To face this problem, the idea is to have a robotic system able to autonomously understand the on-going process to behave accordingly. This improves the interaction during collaboration (the robotic system awareness allows for anticipatory behaviour) leading to effective execution. Furthermore, it reduces waiting times of the human operator, corresponding to a minimization of the overall process execution time, hence of the execution efficiency.

The solution implementing the described idea has the following main objectives: using human information to learn a model for process (operation or task) recognition, and controlling the robotic system based on the process recognition output to implement anticipatory behaviour. The resulting framework is composed of the following two physical components: (i) the human operator, representing the main source for process classification, and (ii) the robotic system, serving as sensor data source and used for anticipatory behaviour.

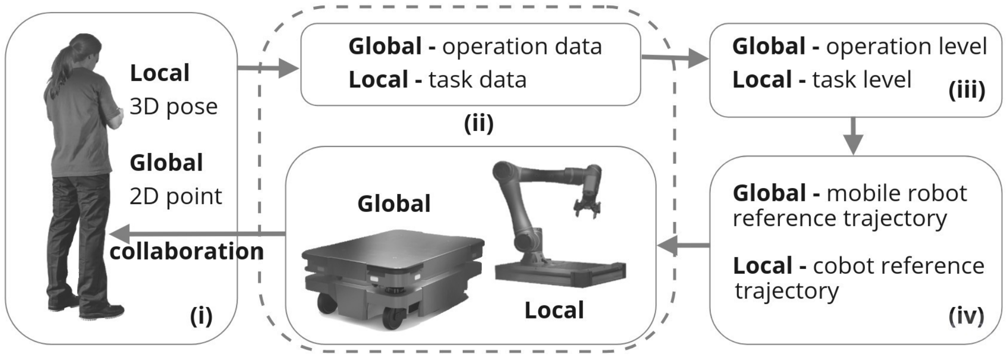

Fig. 2. Framework high level schema.

The framework considers the human-robot comprehensive system as a CPS that implements a passive HITL manufacturing application by abstracting from the mentioned two physical components what we refer to as the *system functions*. The combination of such functions determines two levels of abstraction: the *global functions* of the system consist in operation-oriented classification and associated control of AMRs and cobotic manipulators, and the *local functions*, in charge of task recognition and related actions on behalf of standard cobots. From a practical point of view, the system provides a global recognition of the human motion between workstations of the flexible production line (operation execution), and a local classification of human manipulation and actions (task execution). To stress the need to involve mobile robots in HITL manufacturing applications, the focus is put on the description of the global functions of the framework. The framework functions can be summarized as follows:

(i) *Human operator modeling*. From the global point of view, the human operator is approximated by a 2D point on the plant map. Indeed, human modeling is complex and with the goal of operation recognition, considering the 2D motion of the human operator should be sufficient.

(ii) *Data collection*. In order to identify the 2D point position corresponding to a human operator, an algorithm filters sensor data about the surrounding environment to retrieve the relevant piece of information. In this case, data are gathered by the robotic system itself, serving as a distributed network of sensors.

(iii) *Robotic system awareness*. Globally, the estimated sequence of 2D positions of the human operator is fed to a classification algorithm. Based on the classification capabilities of the model, the ongoing operation should be identified and a reference trajectory for the mobile robotic system generated.

(iv) *Robotic system control*. The computed robot reference trajectory is employed for controlling the mobile platform, which is then able to anticipate the expected motion of the human operator.

An overview of the framework is shown in Figure 2.

III. Development feasibility analysis

In this section, the development analysis of the proposed framework is tackled, mainly concerning the technical limitations and feasibility of the project itself. To do so, possible implementation choices are evaluated. As anticipated, this paper focuses on the description of the global functions of the framework and the physical components involved in it.

The following analysis can be interpreted as the evaluation of possible instantiations of the abstract global functions of the framework. The authors consider functions (i) and (ii), namely *Human operator modeling* and *Data collection*, as already available. In fact, the Sen3Bot meta-sensor [35] has the specific function of monitoring industrial scenarios while detecting human operators, implementing a safe behaviour when approaching them. The Sen3Bot can be considered a sensor itself, able to publish the 2D position of the human operators on a shared map, in order to make it available to all the robotic systems' components (Figure 3). In [36] the possibility of a

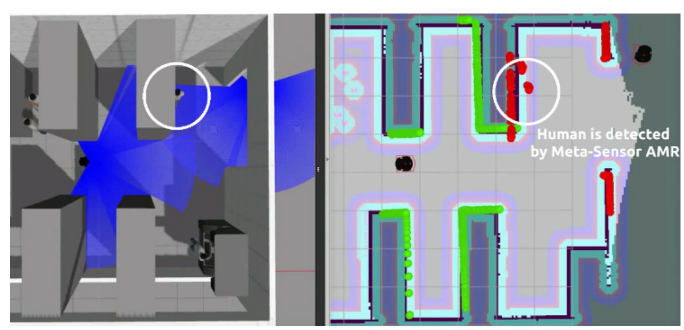

Fig. 3. Sen3bot 2D human position publishing on the plant map.

collaborative behaviour has been introduced: within this HITL framework the Sen3Bot would be upgraded to a collaborative Sen3Bot (Sen3CoBot) able both to autonomously navigate and be aware of the executed process. As a side note, to lighten the computer vision computational effort of the Sen3CoBot, downgrading the Sen3Bot original software choices to favour edge computing should be considered.

The *Robotic system awareness* (global function (iii)) development and implementation should take into account several

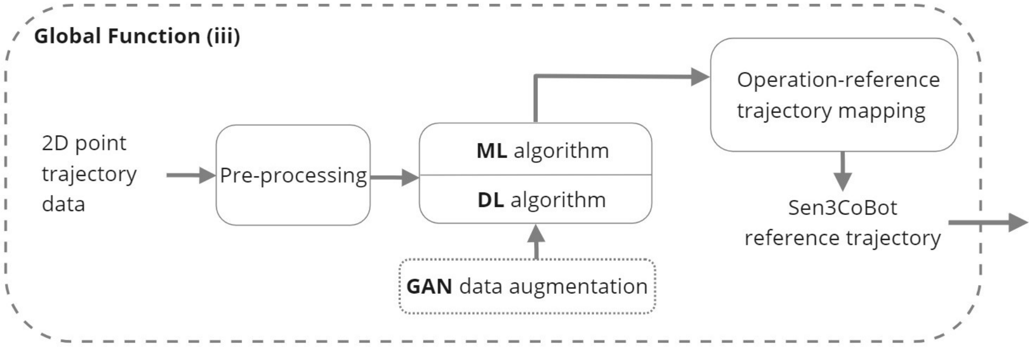

Fig. 4. Robotic system awareness summarizing schema.

feasibility aspects. Given the intention of employing Artificial Intelligence for this function, some technical details intrinsically influence the algorithmic choice. First of all, data availability must be considered: ML methods typically require structured data, implying accurate manipulation if not available; on the other hand, DL algorithms often require a large quantity of training data to avoid overfitting. Moreover, another aspect that must be taken into account is the available hardware. Operations performed within DL models, such as convolutions, are best executed on a GPU parallel architecture. A possible distributed solution could involve the use of edge computing systems, e.g., embedded GPUs. Additionally, Cloud deep learning services offer several solutions, which take advantage of shared powerful hardware.

Properly choosing an AI algorithm also implies selecting an unsupervised or a supervised learning technique. The function requires the recognition of the executed operation, thus a classification is necessary. Supervised learning requires a lot of labelled data to train the model. In this case, however, there are no readily available labelled datasets on 2D human trajectories during an operation, and labelling should be done for each new recorded trajectory, which can be quite time demanding. Conversely, unsupervised learning would allow to train and use the clustering model with unlabelled data but, because there are no labels, there is no way to identify the process and retrieve the associated reference trajectory for the robot. To face this problem, a mixed method supported by GAN-based data augmentation could provide a feasible solution. Clustering could be performed on large sets of synthetic data generated by a GAN, then the obtained clustered data could be used for training a classification model. Note that we assume the number of clusters c, i.e., the number of operations, to be known a-priori. However, depending on the required accuracy, it could be necessary to bring on the labelling and feature engineering processes for supervised classification.

Hence, to implement the operation recognition function, a suitable trajectory time series data classification algorithm should be identified. Ideally the model is trained and fed with partial trajectory data to implement the desired anticipatory behaviour and, based on the confidence with which the trajectory is classified, use the robot reference trajectory associated to the recognized operation to control the robotic system. The first development step should identify the best data structure to be used, since it must contain both the human operator trajectory and the Sen3CoBot trajectory. In fact, during training the robot should be teleoperated to assist the human operator when necessary, so as to record both the sampled human trajectory $\boldsymbol{x_h}$ and the Sen3CoBot trajectory $\boldsymbol{x_r}$. Once the operation is recognized by feeding the model partial trajectory data, the Sen3CoBot is given $\boldsymbol{x_r}$ from that instant k on, as the reference to be tracked. The sampling interval, at first, could be fixed and assigned, while a more dynamic tuning could be implemented to discretize the trajectory based on some relevant criteria. A summarizing schema of the *Robotic system awareness* function instantiation is shown in Figure 4.

Finally, the *Robotic system control* function will receive the Sen3bot reference trajectory $\boldsymbol{x_r}$ associated with the recognized operation. The Sen3CoBot control could implement a mission planner to deal with exceptions, such as an obstacle present in the next goal position in the reference trajectory. Moreover, if no robot motion is predicted to be necessary within the recognized operation, the Sen3CoBot could go in an energy saving mode/state to minimize battery consumption. A further functionality that would be interesting for the Sen3CoBot control, is a sort of proactiveness of the robotic system, that through visual or sound outputs could cause a reaction in the human behaviour, for example to signal possible delays with respect to the expected operation execution time.

IV. Conclusions and Next Steps

This paper presented a framework outline to improve collaborative human-robot flexible manufacturing processes. The main physical components and the desirable implemented functions have been provided introducing an envisioned use case scenario. Development feasibility has been carried on, to map the desired goals to available methodologies and evaluate the best implementation steps to be undertaken. Strong motivations and future trends have pushed towards the inclusion of mobile robotics in flexible manufacturing HITL applications.

Along with the global functions implementation, further research shall be put on the local implementation to monitor the execution at task level. Local functions would interest cobots equipped with proper sensors, e.g., hand-tracking or vision-based sensors, to track the approximated human motion corresponding to her/his end effectors (hands) 3D poses, in order to perform task recognition. Moreover if unsupervised learning were implemented, association methods could allow to identify dependencies and recognize what is a sequence of different tools needed by the operator to perform a certain task, and share this information to a manipulator in order to trigger a suitable interaction with the operator.

The authors future works will focus on the implementation of the framework global functions after carrying out a deeper investigation and choice of the most suitable methods to achieve the desired behaviour.

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