Towards User-Awareness in Human-Robot Collaboration for Future Cyber-Physical Systems

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***Abstract*—Cyber-Physical Systems constitute one of the core concepts in Industry 4.0 aiming at realizing production systems that combine the efforts from human workers, robots and intelligent entities. This is particularly true in Human-Robot Collaboration manufacturing where a tight peer-to-peer interaction between humans and (intelligent) autonomous robots is necessary. Such production systems need a holistic integration along different levels of abstraction and coordination for deploying effective and safe control solutions. We propose the use of novel Artificial Intelligence technologies to enhance *flexibility* and *adaptability* of these collaborative systems. Our aim is to advance the classical *human-aware* paradigm that considers the worker as an *anonymous* acting entity, in favour of a *user-aware* paradigm, that considers a worker as *profiled user* characterized with a number of specific *features* influencing the "shape" of the collaboration.**

***Index Terms*—Cyber Physical Systems, Human-Robot Collaboration, User Modeling, Augmented Reality, Knowledge Representation and Reasoning, Timeline-based Planning**

I. INTRODUCTION

Cyber-Physical Systems (CPS) constitute one of the core concepts in Industry 4.0 integrating communication and computational capabilities with physical processes to endow physical components with additional and/or enhanced abilities [1]. Central to CPS is the coexistence and synergetic interaction between human and technological actors. As stated in [2], it is necessary to highlight the relevance of *human factors* and prepare the *skills* needed to master and sustain transformation towards Industry 4.0 [3]. One of the challenges of our society indeed is figure out how to steer the design and deployment of Industry 4.0 paradigm in the enterprises, and how to seamlessly integrate people within CPS.

According to [4], the combination of technical solutions and organization of work within CPS is supposed to evolve between two extreme alternatives: (i) the *techno-centric scenario* and; (ii) the *antropo-centric scenario*. The former scenario foresees CPSs in which technology dominates human work while the latter scenario foresees CPSs in which workers "keep control" and make decisions supported by technology.

Being the the most attractive and challenging scenario, the *antropo-centric scenario* research is focusing on the development of novel systems that combine human and automation [5].In [6], personalized support is achieved by creating a population of profiles for each individual. Each profile corresponds to different instruction element settings and it has a weight that is updated after receiving operator's feedback at the end of every task. A personalized user profile is structured based on the population's profile weights. Production systems should combine human workers, robots and intelligent entities by pursuing a multi-perspective integration along different levels of abstraction [7]. Recent works extend the concept of collaboration to transform it into a real symbiosis where human workers and artificial systems dynamically adapt to each other and cooperate to achieve common goals [8]. Such level of synergetic interaction brings several benefits. Technology becomes the mean for workers to: continue to work rather than being replaced [9]; accommodate issues related to ageing, disabilities or inexperience [10] and; increase skills, comfort and wellbeing [11]. However, due to the extreme complexity of CPS and the evolving state of technology there are many open research challenges and emerging needs. Two particularly relevant research issues concern: (i) how to understand and control the *interaction* between workers and CPS technologies and; (ii) how to take into account the *skills* and other (heterogeneous) *characteristics* of the workers in conjunction with the different production scenarios and production needs of CPS.

In the context of Human-Robot Collaboration (HRC), we address these two open issues by proposing the integration of novel technologies based on Artificial Intelligence (AI) and Augmented Reality (AR). AR is an imposing technology that can be used for overlaying instructions and knowledge from CPS's digital entities to the physical world inside operator's point of view [12]. Our aim is to pursue a *user-aware* approach to HRC in order to enhance the flexibility and adaptability of collaborative systems. In contrast to *human-aware* paradigms where the human is an *anonymous acting entity* in the environment, we propose a *user-centric* methodology in order to adapt the behavior of collaborative robots as well as the "shape" of the collaborative processes to the different *features* (e.g., age, skills, experience) and *preferences* (e.g., left-handed vs right-handed) that characterize different users. To this aim we propose the integration of three technological modules that allow the system to *know* users, *reason* on

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their characteristics and *adapt* the interaction accordingly. More specifically, an AI-based *knowledge representation & reasoning* module encapsulates the *user model* to represent relevant features of human workers and contextualize resulting *user profiles* with respect to production needs (e.g., match users' skills to the requirements of production tasks). An AI-based *task planning* module reasons on this *knowledge* from an *optimization perspective* in order to synthesize *collaborative plans* that take into account robot capabilities and *known* skills and features of the worker. An AR-based *human-system interaction module* then realizes advanced interaction mechanisms to contextualize communication to and from the worker.

The work presents the general methodology and shows the technical feasibility of the proposed approach by taking into account a realistic manufacturing scenario. The rest of the paper is thus structured as follows: Section II describes the general aim and objectives of the H2020 research project Sharework[1] within which the methodology has been developed; Section III discusses the defined user model and the knowledge-based formalism used to represent and reason about user and production information; Section IV shows how *user-awareness* is supported and specifically how the task planning and human-system interaction modules leverage user knowledge to adapt/personalize the collaboration; Section V concludes the paper by showing the integrated modules into a realistic HRC manufacturing scenario.

II. The Sharework Project

The Sharework project develops an effective and safe CPS system for anthropocentric Human Robot Collaboration with no fences. It defines a modular architecture that is comprised of 15 software and hardware modules, and allows a wide range of different module configurations so that it to be customized for different industrial needs. The Sharework project architecture has for instance demonstrated modules capable of understanding the environment and human actions through knowledge and sensors, future state predictions, smart data processing, augmented reality and gesture and speech recognition technology in order to make the robot overcome human barriers and ensure a more effective cooperation.

A. General Architecture and Module Overview

Figure 1 shows a high level overview of the Sharework architecture, the different modules and the high level flow of information. In the following, we specifically focus on the modules that are mainly considered to support *user-awareness*.

1) The Knowledge Base Module: The Knowledge Base Module stores a semantically rich representation of the current status of the production environment using the Sharework ontology. The Knowledge Base aggregates information from other modules and uses reasoning to produce new knowledge. The Knowledge Base module serves as an information repository and provides reasoning capabilities. In particular this module is responsible to store, update and provide access to the ontology-based model of workers, objectives, tasks, procedures and constraints that are described in section III.

2) The Task Planning Module: The Task Planning Module is responsible to a) identify and adapt in a time aware fashion the required tasks for humans and robots that carry out production processes within the Sharework CPS. The Task Planning module generates a schedule of tasks that need to be performed by taking into consideration the known human operator and the operational requirements of the production process. By using this information this module computes the planning strategy dynamically adapted to the the data received from the environment.

3) The Human-System Interaction Module: The Human-System Interaction Module's purpose is to enable and facilitate the interaction of human operators with the Sharework's system by providing a bidirectional communicating channel from operators to the system and vice-versa. This module serves as the main communication channel between human operators and the Sharework system and is used to both allow the human operator to provide data and goals to the Sharework system, as well to inform the human operator about pending tasks, robot movement, security alerts or recommendations to improve his ergonomic assessment results. The Human-System Interaction Module in collaboration with Knowledge Base are responsible to configure and customize the visualized information based on the specific user and the user's preferences and configurations, offering a user friendly, user-aware experience to the human operators that participate in the HRC production.

B. Module Integration Schema

Given the general responsibilities of the three considered modules, we here further discuss how they actually interact in order to support *user-awareness*. Figure 2 shows more details the general integration schema of these modules and the implemented "control flow".

First, the Human-System Interaction Interface registers or authenticates a particular user into the system and sends a request to the Knowledge Base to retrieve information about the production scenario (e.g., known production goals, descriptions of production procedures, user profile and any other information that can be useful). The Human-System Interaction Interface consumes a set of ROS services offered by the Knowledge Base and supports controlled access to the underlying information. The user then sends a production goal selection message to the Knowledge Base through this interface. The assumption here is that the operator decides the production goal to perform and sends the "starting signal". This message thus specifies the production goal to be achieved and the user that take part to the process.

The Knowledge Base contextualizes the requests and configure the Task Planner by defining the variables of the model according to the requested goal and the profile of the user (e.g,. robot capabilities, operator skills and performance profile, production goal decomposition, etc.); The Task Planner synthesizes and executes a task plan. During the execution

[1] https://sharework-project.eu

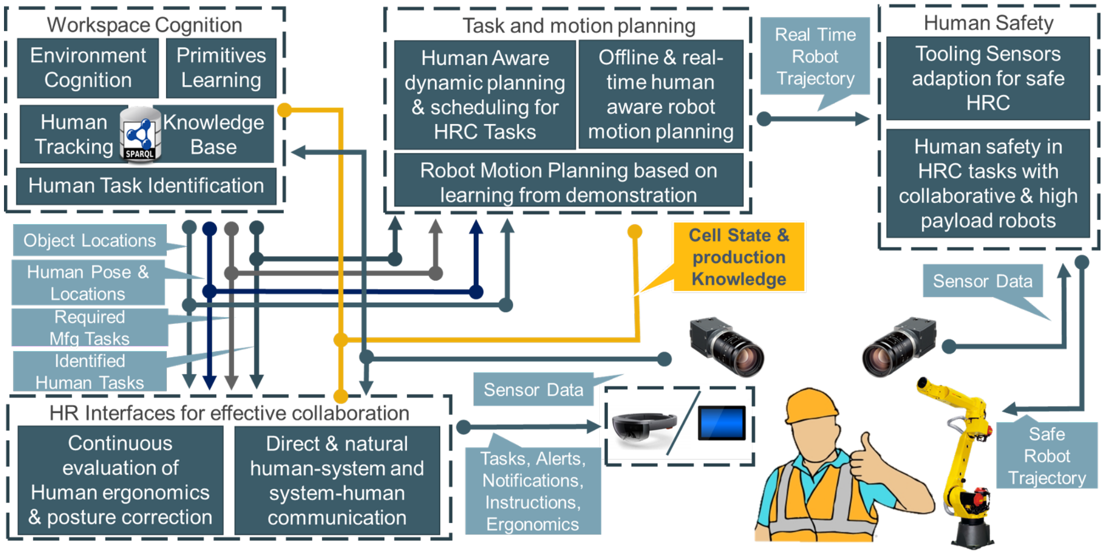

Fig. 1. Overview of the Sharework architecture

the module dispatches task execution requests to the Human-System Interaction Interface to interact with the human worker and task execution requests (or motion requests depending on the "functional layer") to the Motion Planner to interact with the robot. It receives execution feedback from both the modules in order to be notified about the actual execution of the requests tasks/commands (and possible failures). The Human-System Interaction Interface and Motion Planner offer a set of specific ROS Actions that enable initiation and monitoring of Human and Robot tasks.

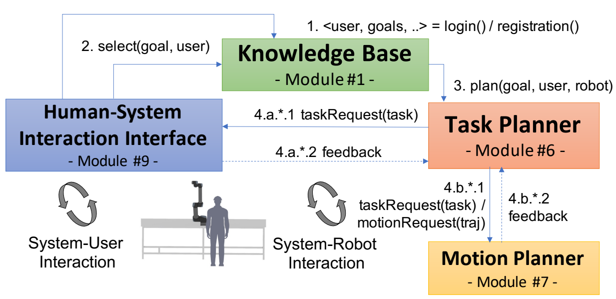

Fig. 2. Integration schema of the considered modules

III. Ontology-based Model of Workers

HRC scenarios should pursue a tight "team work" between the human and the robot that behave as two autonomous agents. In general terms, a prerequisite for effective team operations is that the members have a *shared view* of the *objective*, a *shared view* of the motivations, capabilities and limitations of other team members and an *agreement* about how to achieve the objective [13]–[15]. In addition, as pointed out in [16], team members should be able to use each other's data and knowledge to *learn* from each other.

From a coordination perspective this means that a (Sharework) HRC control system should be endowed with *knowledge* suitable to characterize a collaborative scenario. For the effective coordination of human and robotic agents is indeed necessary to: (i) represent production needs in terms of *objectives*, *tasks*, *procedures* and *constraints*; (ii) represent *capabilities* and *skills* of the robot and the human worker and; (iii) represent *performances*, *preferences* and any type of behavioral or physical *feature* that may a affect the way the human and the robot actually collaborate and interact. To this aim we pursue an ontology-based approach to formally define the *semantics* necessary to represent and reason about this knowledge. A clear and well-structured characterization of all this information is indeed crucial to achieve *user-awareness* and support flexible and effective coordination between the human actor and the robotic actor.

A. Context-based Ontology for Collaborative Scenarios

The *Knowledge Base Module* relies on the SOHO ontology [17] (TBox) to build and maintain a *knowledge base* (ABox) describing a specific collaborative scenario. SOHO is a domain ontology designed to characterize human-robot collaboration scenarios by combining multi-perspective views. SOHO builds on top of the foundational ontology DOLCE, the core ontology CORA [18] and the ontology SSN [19]. It is organized into a number of *contexts* each defining concepts and properties that characterize a collaborative scenario from a particular (coherent) viewpoint.

Knowledge Bases instantiate SOHO characterizing user profiles, robot capabilities and production processes in specific collaborative scenarios. Such knowledge is structured as a Knowledge Graph (KG) [20], [21] and related knowledge processing mechanisms rely on standard semantic technologies that are the OWL language [22] and the open-source software library Apache Jena [2].

[2] https://jena.apache.org

As shown in [17] the *environment*, *behavior* and *production* contexts define concepts and properties suitable to describe respectively: (i) *physical entities* and *observable properties* of a collaborative environment; (ii) *skills* and *capabilities* of *acting entities* of the environment (i.e., the human worker and the collaborative robot) and; (iii) *production goals*, *production tasks* and *constraints* of *collaborative processes*. In particular the behavior context uses the concept of `Function` [23] to dynamically "match" production tasks to the *functions* (i.e., the low-level operations) the human worker and the robot can actually perform.

B. Human Factor and User Model

The current work specifically focuses on the *Human Factor* context and elaborates on its correlations with the *behavior* and the *production* contexts. Figure 3 shows an excerpt of SOHO with a taxonomic representation of the *variables* considered to represent the features of human workers. Such variables define the *user model* and are interpreted as extension to the concept `DOLCE:Quality`. These variables therefore define a *representation space* of qualitative aspects of a worker that can be *measured* through some *value* (instance of some `DOLCE:Region`).

Figure 3(a) shows part of the taxonomy concerning the *physical body* of a worker. These variables are useful to model and observe physical, health and cognitive parameters during the collaboration. Such information allows the system to detect anomalous and/or wrong working conditions like e.g., *bad body ergonomics*, *body position in hazardous areas* or *mental and/or physical fatigue*. Figure 3(b) instead shows part of the taxonomy concerning the *behavior* of a human worker from a production perspective. These variables in particular characterize the *performance* of a worker in a given production scenario and are thus suitable to define *user profiles*.

The concept `WorkerExpertiseLevel` represents a *measure* of the *level of knowledge* of a human worker about a specific production scenario and the *reliability* of her performance. On the one hand, the expertise level determines the (sub)set of production tasks a human worker is actually able to carry out. Some tasks indeed could be "enabled" only when a worker has gained/acquired enough level of knowledge (i.e., expertise) in a specific collaborative scenario. On the other, the expertise level characterizes the expected *uncertainty* about the performance of a worker when executing tasks. Users with low expertise may have a significant *variance* in the time they take to complete assigned tasks, leading to high (temporal) uncertainty. More experienced users instead may achieve more "consolidated" performance leading to low variance and thus low (temporal) uncertainty.

The concepts associated with `WorkerPerformance` supports a numerical representation of the *observed* performance of users. We specifically distinguish between *accuracy* (`WorkerTaskAccuracy`) and *efficiency* (`WorkerTaskPerformance`). These variables support the incremental definition of a *dataset* that keeps historical data about performance of each user with respect to the production tasks of a specific collaborative scenario. Such a dataset can be analyzed to *infer* knowledge useful to coordinate and adapt the collaboration to the *known* (and *learned*) behaviors of different users. For example, knowledge gathered about *efficiency* can be used to *infer* an *efficiency matrix* that depicts *average completion times* of production tasks for each user. Given a set of known users $\mathcal{U} = \{0, ..., n\}$ and a set of production tasks $\mathcal{T} = \{0, ..., m\}$, for each user $u_i \in \mathcal{U}$ and for each task $t_j \in \mathcal{T}$, the matrix associate an average value $\delta_{i,j} \in \mathbb{R}$ denoting the (known) average time user u_i takes to complete task t_j. If no information is available the average duration $\delta_{i,j}$ is set to ∞. The same holds in case of "new users" without historical performance data.

IV. User-Aware Collaboration

The production and user-centered *knowledge* is at disposal of other modules to *adapt* production processes to the participating users and production context. Such a knowledge is necessary to push forward novel collaboration paradigms where the system adapts interactions and collaborative processes to the *known* features of participating users. This section explains with more details how the *task planning module* and the *human-system interaction module* take advantage of *user model* to support this level of personalization and adaptation.

A. Personalized Task Planning

Task planning and scheduling capabilities rely on the timeline-based paradigm formalized in [24]. A timeline-based specification consists of a number of *state variables* that describe possible behaviors of domain features to be controlled over time. A state variable is defined as a tuple $SV = \langle V, T, D, \gamma \rangle$ where: (i) V is a set of *values* $v_i \in V$ representing states or actions the feature can assume or perform over time; (ii) $T : V \rightarrow 2^V$ is a transition function specifying valid sequences of values $v_i \in V$; (iii) $D : V \rightarrow \mathbb{R} \times \mathbb{R}$ is a duration function associating to each value $v_i \in V$ lower and upper bounds to its execution (i.e., duration bounds); (iv) $\gamma : V \rightarrow \{c, pc, u\}$ is the *controllability tagging function* specifying if the execution of a value $v_i \in V$ is *controllable* (c), *partially controllable* (pc) or *uncontrollable* (u).

Information about *controllability* is necessary to reliably deal with *temporal uncertainty* and uncontrollable dynamics of the environment during the execution of a (timeline-based) plan. This is known as the *controllability problem* [25] and is particularly relevant in scenarios like HRC where an artificial system like e.g., a collaborative robot, interacts with "unpredictable" agents like e.g., a human worker.

Complex behaviors of a system (e.g., a HRC work-cell) are modeled by means of *synchronization rules* that constrain simultaneous behaviors of state variables whose temporal evolution are the *timelines* of a plan. A rule is a kind of *logical entailment* specifying a behavioral dependency among timelines. Every time a value v_x is assumed by a variable SV_i a number of values v_y should be assumed by other state variables SV_j. The temporal occurrences of such values should satisfy the set of temporal constraints of the rule.

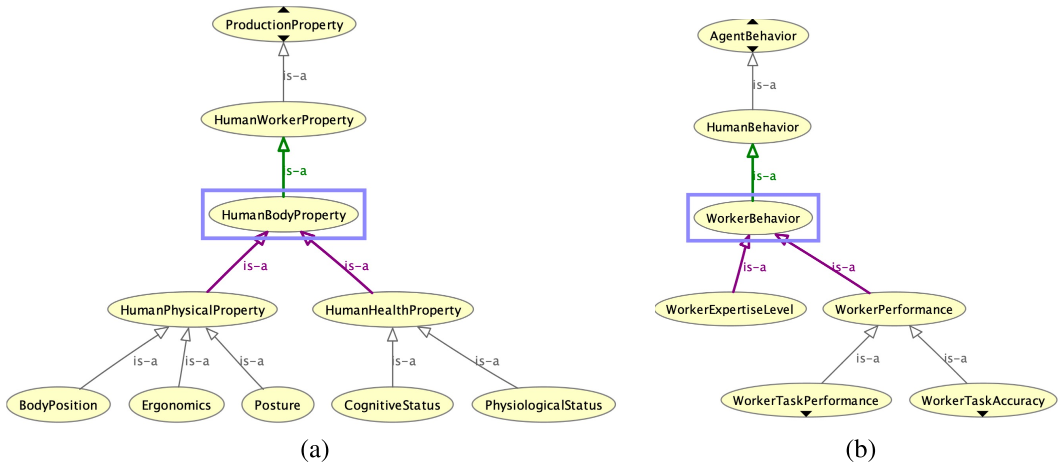

Fig. 3. Excerpt of SOHO concerning the variables of the user model

The task planning model follows a hierarchical decomposition methodology where: (i) a state variable SV_G describes the high-level production goals that can be performed within the HRC work-cell; (ii) a number of state variables SV_L^i where $i = 0, ..., K$ describe the production tasks to be performed at a specific abstraction level i, where K is the number of hierarchy levels of the procedure; (iii) a state variable SV_R and a state variable SV_H describe the low-level operations (i.e., instances of `Function`) the robot and the human can actually perform; (iv) a set of synchronization rules $\mathcal{S}$ describes the procedural decomposition of high-level goals (i.e., values of state variable SV_G) into increasingly simpler production tasks (i.e., values of state variables SV_L^i), until they are associated to a number of functions (i.e., values of state variables SV_R and SV_H) the human and the robot should perform to successfully complete production tasks and achieve high-level goals.

The state variable SV_H describes *known* skills and behavioral dynamics of the human worker that cooperate with the robot. The state variable $SV_H = \langle V_H, T_H, D_H, \gamma_H \rangle$ is thus generated from the knowledge base. The values $v_j \in V_H$ are defined according to the tasks/functions the worker is actually able to perform in the given production scenario. No assumptions can be made on the actual duration of tasks/functions assigned to the worker. Consequently the user is modeled as an *uncontrollable* entity of the environment and all the values are tagged as uncontrollable, $\gamma_H(v_j) = u, \forall\, v_j \in V_H$.

Flexible duration of each task $v_j \in V_H$ and thus the *duration function* $D_H : V_H \to \mathbb{R} \times \mathbb{R}$, is defined by taking into account the mentioned performance matrix. Specifically, a *performance vector* is extracted for the user $u_i \in \mathcal{U}$. Such a vector specifies for each value $v_j \in V_H$ the average time $\delta i, j$ that user u_i takes to accomplish the associated task *task* $(v_j) = t_j \in \mathcal{T}$ ($\delta_{i,j} = \infty$ if no information is available). This information, combined with the (known) *expertise level* of the user defines the expected *lower* and *upper* bounds of the *duration function* for each value $v_j \in SV_H$. Specifically, a certain amount of uncertainty is associated to each of the three expertise levels defined into the ontological model: (i) *novice*; (ii) *intermediate*; (iii) *expert*. The higher the expertise level the lower the uncertainty about the performance and vice versa. We thus define an *uncertainty index* as a constant associated to each expertise level. The uncertainty indices defined for the three expertise levels are (respectively) $\Omega = \{0.8, 0.5, 0.2\}$.

Given $\Upsilon : \mathcal{U} \to \Omega$, a function that for each user $u_i \in \mathcal{U}$ gives the uncertainty index corresponding to the associated expertise level, $\Upsilon(u_i) = \omega_i \in \Omega$, the duration bounds of the values $v_j \in V_H$ for a user u_i are defined as follows:

$$D(v_j) = (\delta_{i,j} - \omega_i * \delta_{i,j}, \delta_{i,j} + \omega_i * \delta_{i,j}) \quad (1)$$

In this way, the task planning model of a worker assumes a higher or lower *percentage deviation* from the average completion time of values $v_j \in V_H$ (i.e., higher or lower temporal uncertainty) depending on the expertise level. The finer the temporal model of the worker the better the overall efficiency of the resulting collaborative plans and thus the overall optimization of the production process [26].

B. Augmented Human-Robot Interaction

The objective of the *Human-System Interaction Module* is the design and implementation of a multi-modal interface that can establish seamless interaction between workers and the system. In hybrid systems involving humans and robots in common workspaces, it is integral to implement novel means for control, monitoring, and support. The novelty of those means is associated to the usage of human's senses [27] (i.e. vision, hearing, and touch) besides natural interaction actions (i.e. gestures, voice, etc.) for supporting Human-System (HS) and System-Human communication (SH). In the context of SH communication, the operator can be informed about manufacturing system's status, assembly operation steps and procedures as well as robot's current and future actions.

In the contrary, HS communication mostly serves monitoring and control. Human improvisation can be a lever in many modern industrial problems; however, it can generate issues in hybrid scenarios as operator's intentions and executed tasks are not known by task planning systems and robots. Through the years, research focused on vision monitoring and task execution identification based on learning techniques. Such schemes are subtle to production changes and require enormous datasets. In this context, the proposed multi-modal interface offers functionalities that allow operators to effortlessly declare their status without being distracted from the assembly process itself. Additional functionalities are also introduced for direct system and robot control. Starting, pausing or stopping the manufacturing process or robot actions are important when anthropocentric systems are attained.

Implementing user-aware interfaces pre-requires interpreting the information that operators need to exchange according to their experience and preferences. The multi-modal interface is designed for presenting or retrieving information via different means and at different levels. More specifically, operators are able to use independently or in parallel alternative front-end applications where each one of them supports different modals and comes with different environment features. This flexibility can be a solution in practical issues (e.g. wearable device autonomy) but also allows operators to select their most appropriate tools within a variety of devices. The anthropocentric design approach of the Sharework system is enhanced by the capability of each application to be adapted at operator needs and partialities. Based on operator's experience, the knowledge base can tailor the level of information detail that is provided to each user.

Extensive instructions via visuals, text etc. can be delivered to amateur users whereas plain task identifications is sufficient for the experienced ones. The same parametrization is available for operators themselves through customization options. Type and level of details of information as well as feature and spatial configuration inside the application's environment can be adapted by the user prior or withing the assembly process. Customization settings are stored and correlated to the operator's profile and will be retrieved upon future login.

The personalization of the system's front-end through customizable applications and selection of multiple devices is achieved through the implementation of a distinct hierarchical architecture. The bottom layer consists of all desirable communication modals. Those modals are correlated to the intermediate layer's applications where their host devices' specifications can support them. The upper layer entails the interaction module's node that is responsible for parsing data from end-devices to the rest of Sharework's modules and vise-versa. Operator profiles, goals, procedures, as well as other important information (e.g. robot trajectories, safety zones, ergonomic results, etc.) are communicated to/from the node through ROS messages. In case of HS interaction, even if operator can give inputs through various modals, the intermediate node will communicate normalized messages according to the attained functionality.

A similar approach is followed for the SH interaction, where Sharework modules dispatch data (e.g. assembly instructions, trajectories, etc.) to the intermediate node. This data is then transferred simultaneously at all connected devices and each application presents it according to the customization options.

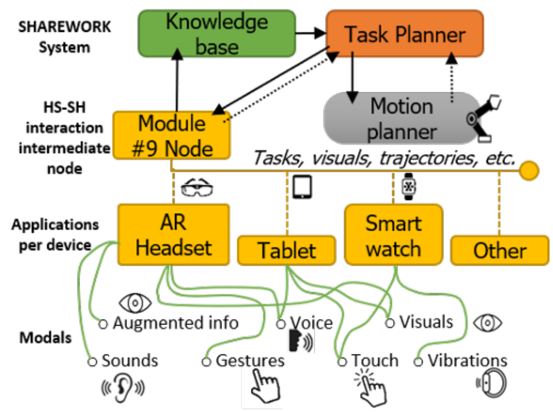

Fig. 4. Sharework's Human-System interaction module architecture

V. Automotive Assembly Scenario

The demonstration scenario derives from automotive industry and deals with the assembly of doors on pickup chassis. As presented in [28], for every door, the assembly procedure consists of a heavy object (i.e., door) transferring task followed by a number of handling operations for fastening door hinges and connecting harness. Former operations are allocated to human operators as they require high dexterity, whereas door transferring is assigned to industrial robots for preserving adequate ergonomics. In case door positioning fine-tuning is needed, operator guides the robot to final position via impedance control. For improving assembly line balancing, humans and robots may work in parallel at different doors or even at the car's bed. For attaining high productivity, quality and safety during collaboration the following requirements are considered to evaluate the implemented modules: (i) generate schedules based on production needs as well as robot and worker capabilities; (ii) share with the worker information about assigned tasks supported by suitable instructions; (iii) share with the worker updated information about the current and future tasks assigned to the robot; (iv) correct assembly of components ensuring alignment of chassis and doors.

First a complete and updated description of the production scenario is defined into the Knowledge Base Module. The associated OWL file describing the initial status of the knowledge can be found at the following URL [3]

Pursuing the same approach described in [29], a *knowledge extraction procedure* synthesizes a *contextualized* timeline-based specification defining: (i) production procedures for known goals and; (ii) robot and worker capabilities with associated *temporal dynamics* and *controllability properties*. The obtained specification provides the (general purpose) Task Planner Module with the rules necessary to synthesize collaborative plans in the considered manufacturing scenario. Figure 5 shows the production procedure automatically extracted and used to generate the task planning model. As can be seen, the procedure is organized into three hierarchical levels ($K = 3$)

[3]https://www.dropbox.com/s/1lso492avbpxshz/automotive.owl

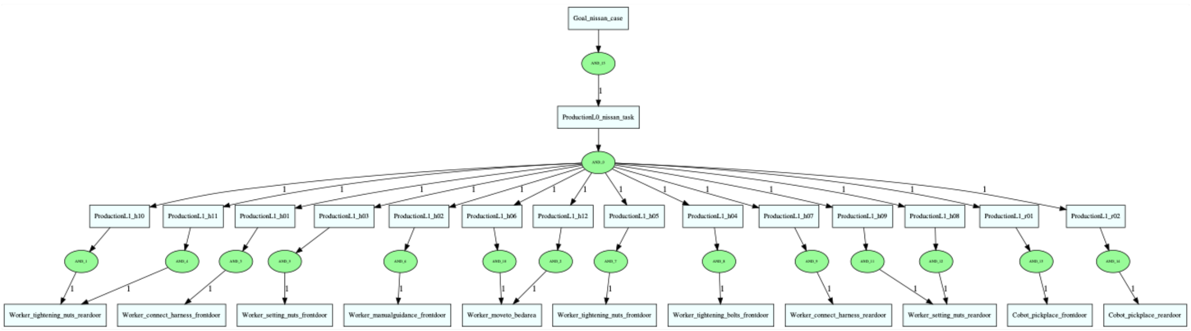

Fig. 5. Production procedure dynamically extracted from the Knowledge Base

and correlates high-level production goals (the root element of the procedure) with the low-level tasks the human and the robot should perform to achieve such goals.

The task planning model defines possible behaviors of the human and the robot (i.e., state variables SV_H and SV_R) according to the implemented `Function` that are extracted from the knowledge base. The temporal dynamics of the worker in particular are defined according to the expertise level of the operator and available data about performance, as described in Equation 1. When no data is available a "default" duration bound $(1, \infty)$ is set to the low-level tasks an operator could perform (i.e., $v_j \in V_H$). A complete description of the generated task planning model can be found at the following URL [4].

Such a model is given as input to the Task Planning Module which implements goal-oriented acting functionalities using the open-source ROSJava Package ROXANNE [5]. Once configured, the module can receive (asynchronous) production requests (i.e., planning goal) through a dedicated input topic. The underlying (ROXANNE-based) task planner synthesizes a collaborative plan which *minimizes* the *cycle time* of the production processes while taking into account worker (and robot) capabilities and (known) performance. The synthesis of a task plan consists in deciding the assignment of production tasks to the human and the robot that best take advantage of the collaboration (i.e., optimize the production process) in the given scenario [26]. The resulting assignment is then communicated to the worker and to the robot by online dispatching task execution requests to the Human-System Interaction Module and to the Motion Planning Module.

As for the HS interaction module is concerned, an android tablet and an AR application were deployed. Voice, gestures and touch were available for HS interaction while sound and vision were offered for SH communication. Seamless collaboration was supported by exchanging robot related information (e.g., actions, status, trajectories), assembly instructions (e.g., text, figures, augmented holograms, 2D figures, etc.), task execution goals and feedback. The type of modals, details of information and spatial configuration that are applied from the HS interaction module are configured by the knowledge base according to the expertise of the operator. Customization options were available to users for maximizing personalization through a series of options for each feature. Registry and authentication processes via operator profiles ensure that user models are updated with customization settings and that are linked to individuals.

[4]https://www.dropbox.com/s/4zqok1ynbhognqn/automotive.ddl

[5]https://github.com/pstlab/roxanne_rosjava.git

VI. Final Remarks and Future Works

This work shows an ongoing research activity within the H2020 project Sharework aiming at fostering *user-awareness* in Human-Robot Collaboration scenarios. The work builds on top of recent advancements in knowledge representation and reasoning, task planning and human-system interaction to support contextualized and user-centered collaborative production processes. A description of the system on a realistic manufacturing scenario shows the technical feasibility of the developed technological modules and how their integration promisingly support the desired level of personalization. Future works will concern a deeper analysis and evaluation of the integrated approach taking into account more flexible and complex collaborative process as well users with different skills and features.

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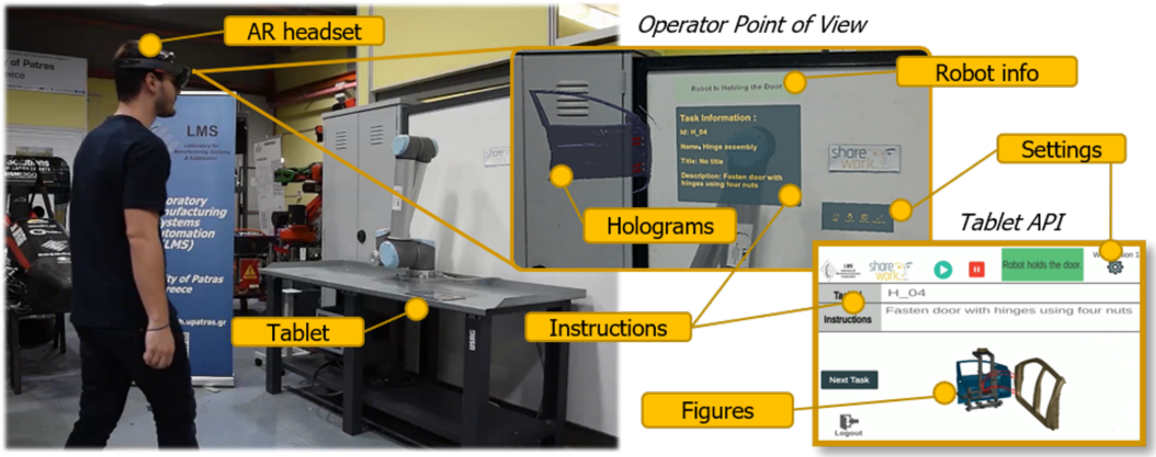

Fig. 6. Demonstration setup and HS interaction interface

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