Empowering Field Workers:
A Cognitive Architecture for Human-Robot Collaboration *

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Abstract— **This paper presents an earlier stage of development towards this ambitious goal by proposing a conceptual architecture for human-robot collaboration in challenging applications and its envisaged future direction. Field robots are adaptable and sensitive to dynamic, unstructured and, therefore, challenging environments, such as in agriculture, forestry and construction. These robots perform demanding tasks that require too much time, labour and, most of the time, that are even hazardous for humans. Although humans still outperform robots in these domains with the ability to have critical thinking, strategy, empathy and physical skills, there is plenty of room for humans to outperform themselves by collaborating with robots. This position paper aims to explore the concept of human-robot collaboration in field robotics, wherein human operators take advantage of a multi-robot system for physically unendurable tasks, and robots benefit from the shared control and assessment of humans in dynamic and unknown environments.**

I. INTRODUCTION

Field robotics is a domain comprising single or multiple robots that are designed to achieve physically unendurable tasks in unstructured wild environments, such as forests. Due to the fact that these domains of application mostly requires a large amount of human labour, it is reasonable to think as to why not replace humans with robots, as we have witnessed in the other service robotics applications. The main reason for that falls on the life-long autonomy maintenance of the system under these challenging, unstructured and dynamic scenarios [1]. On the other hand, by having empathy, critical thinking, strategy and complex physical skills, humans are not removable from the loop, especially in such complex domains. Still, it is possible to combine the advantage of a robotic system, that is convenient for physically unendurable tasks, with human cognitive skills and assessment in these wild environments, fostering a symbiotic relationship between both agents, i.e, human-robot collaboration (HRC).

Although human-robot interaction (HRI) falls under the umbrella of the broader domain HRC, most of the research in HRI focuses on developing interaction modalities that are socially acceptable and natural using various different forms and interfaces, such as verbal and non-verbal interactions, using a wide range of different modalities, from touchscreens to wearable technologies. The most traditional domain HRI has revolved around is social robotics [2]. However, these multimodal interaction modalities can also take place in other applications, like field robotics, going beyond the interaction using touchscreens, thus calling upon a more immersive and natural bi-directional interaction between humans and robots. Furthermore, as opposed to vast majority of social robotics studies, field robotics is likely to imply multi-human and multi-robot collaboration. This has been the case of many R&D projects in field robotics, which, despite not including humans in-the-loop as foreseen to be needed in a near future, they stood on the idea of having heterogeneous multi-robot systems (MRS) to tackle the wide variety of tasks inherent to such scenarios. These networked robots are expected to be more efficient than a single robot operating in such complex tasks due to the team labour they perform.

However, to plan how to achieve a goal cooperatively with humans requires robots to have a continuous self and human awareness. In addition to that, environment observation is needed, especially in dynamic scenarios. Although robots in a MRS can share the knowledge and computation workload with each other, the joint task achievement process requires high computation power and storage capacity. These result in extra weight which limits the mobility of the robot and its operational time. Another limitation of using the shared information effectively is due to the potential difference of hardware and software components that each robot has - the so-called embodiment problem [3]. All this together leads to the lack of robust HRC architectures able to cope with the uncertainty of humans operating under such challenging scenarios, with the time-sensitive decision-making ability needed to fulfil the complex tasks at hand, and the access to an evolving universal knowledge for self-organizing human-robot teamwork.

In this position paper, we present an early stage of development of a human-robot collaboration architecture, starting with simple interactions and system monitoring in a networked shared MRS deployed in the field. This is the stepping stone to propose a future direction established to empower field workers with an intelligent MRS to enable robust, fast and efficient collaborative cognitive skills needed to assist and cooperatively work with its human teammates. To achieve this, we propose the development of the cognitive architecture for human-robot collaboration (CA4HRC), which comprises a threefold contribution:

- Human-like decision-making modelling with enhanced fuzzy finite state machines;
- Spatio-temporal decision-making with multi-agent deep reinforcement learning;

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- Knowledge transfer and distributed processing with fog-enabled federated learning.

The next section presents the literature review which paves the way to the herein proposed proposed approach.

II. RELATED WORK

This section reviews various studies, challenges and suggested approaches in the HRC domain. HRC is an emerging multidisciplinary research field that focuses on understanding humans' cognitive abilities and designing robotic systems for cognitive and social interaction to expand these abilities and skills [4]. HRC focuses on the design and evaluation of robotic systems and related interfaces so that these are able to communicate, share physical spaces, and ultimately work with humans to achieve shared goals.

While collaborating with a robot as seamlessly as if it was another human being may sound futuristic, many robotic systems cannot yet be fully autonomously deployed in certain applications and require systematic human input. This is particularly true when addressing complex tasks to be fulfilled in dynamic environments, where these systems often take advantage of humans' cognitive abilities [5]. For instance, agricultural robots are successful mostly as human-operated, or semi-operated, machines, being designed to reduce the farmer's workload and optimizing time and cost in repetitive tasks, such as harvesting, pruning, watering and spraying [6], [7]. However, many believe that these could offer more and further increasing the productivity, while providing lower workload and security, if endowed with strategic interfaces. Adamises et al. [7], [8] proposed different user interface modes (with a mouse, a Wiimote and a digital pen) in a pesticide spraying robot, preventing farmers from being exposed to pesticides. Similarly, Bergerman et al. [9] described a tree fruit production process, in which the robot could localize itself and use this knowledge to select an interaction mode from three options: mule mode, pace mode, and scaffold mode. In mule mode, the user would be next to the robot and control its position, starting and stopping it via the user interface. In pace mode, the user would define the required arguments, such as speed and row offset, and the robot would automatically spray or lead the product. Scaffold mode enabled a certain level of HRC, where the robot navigates along the row and the farmer standing on top of it performs the pruning. While these applications are certainly promising in reducing human workload and optimizing their time by enabling a certain level of peer-to-peer collaboration, they still require a demanding interface to constantly command each robot individually, leaving no room for any real collaboration to take place.

However, as today in many of situations, robots are expected to work with human in collaboration as teammates to achieve a common goal, i.e. human-robot joint action. Many researcher from cognitive science and psychology investigate these joint-task mechanisms, namely how humans coordinate together to accomplish a common goal. Sebanz et al. [10] identified the three important components of a successful joint task: the 'what', the 'when' and the 'where'. More specifically, the 'what' refers to the understanding of the agents intentions. The 'when' refers to the understanding of when such joint actions should be performed. At last, the 'where' focuses on where and how to perform the joint action. This spatio-temporal reasoning is key in HRC, not only to cope with the uncertainty of human actions, but also to foster decision-making ahead of the time, which is vital for a successful joint task achievement between humans and robots.

This direction has been followed in some recent studies addressing HRC as a joint task achievement, in which the robot perceives the environment and the multiple surrounding agents, be it humans or robots, coming up with a plan to achieve a goal and asking for human help if needed [11], [12]. Although these studies are promising, their use cases mostly rely on peer-to-peer (i.e., single human and single robot) collaboration and under simple prototype scenarios. Despite this drawback, most works on HRC already contemplate a high degree of multimodal communication (gesture, voice, tactile) [13], context awareness of human movement [14], and adaptive control [15]. In addition, some authors address proactive HRC as a way to provide bi-directional cognition between humans and robots and self-organized teamwork, which are the current weaknesses of traditional HRC [16]. The authors state that a proactive HRC should go beyond a traditional master/slave model and enable humans and robots to dynamically change their roles with empathetic cognition. One of the main challenges identified by the authors, however, lies on the spatio-temporal cooperation prediction of humans' next intentions by eliminating their inherent level of uncertainty [17], [18], [19]. The authors also point out to a direction on how to solve this by extracting more information and rapidly processing it to handle rapid decision-making, though no clear plans are established on how this can be achievable under the constrained computing power of MRS [16].

Still, many researchers believe that successful HRC can only be achieved if a certain level of situation awareness is guaranteed which relies on extracting more information. While MRS is more efficient than a single robot at creating situational awareness by extracting and sharing more information, the level of situational awareness is strictly dependent on fast processing, i.e. computational power. Cloud robotics, merging cloud computing technologies with networked robotics, has emerged as a promising approach to tackle these challenges in networked MRS [20]. Cloud robotics employs computation, memory and intelligence features over a cloud infrastructure, instead of integrating into a single standalone system, providing a higher computational power and memory to store and process enormous amount of sensory data, such as the one needed for mapping, and to run other demanding processes for computer vision, speech recognition, among others. Due to its potential, several studies focus on developing cloud-based solutions, be it to store and process data as shown by the RoboEarth [21] project (later known as Rapyuta), or to share the knowledge of skills such as perception, planning and control as RoboBrain

[22]. These and other studies propose efficient approaches to take the computation off from robots and into the cloud. However, be it for collaboration or not, in any human-robot interaction, latency is one of the most critical issue which may cause undesired late responses. Furthermore, it can even cause several safety issues for both humans and robots, especially in dynamically changing environments. Some authors have been proposing solutions to mitigate these problems by optimizing the task assignment and scheduling of cloud robotic operations [23], while others have decided to completely redesign these architectures and exploit the concept of fog computing instead. Gudi et al. [24] proposed a fog robotics architecture that consists of a fog robot server and a sub-fog robot server. According to the authors, fog robotics is capable of tackling not only the issues related to latency and speed, but it also provided an additional layer of security and privacy.

III. A COGNITIVE ARCHITECTURE FOR HUMAN-ROBOT COLLABORATION

A. Current Architecture

This section starts by presenting the proposed initial architecture, which has been implemented and preliminary evaluated, comprising *Database (CoachroachDB)* as a distributed SQL database built on a transactional and strongly-consistent key-value store and provides a familiar SQL API for structuring, manipulating, and querying data, *Robot Operating System (ROS)* as an open-source robotics middleware suite as a collection of software frameworks for robot software development, including low-level device control, message-passing between processes, package management, among others, *Unity* as a cross-platform game engine that can be used to create 3D and 2D games, as well as interactive simulations and HRI and *Nakama* as an open-source distributed social and real-time server for games and apps which includes large set of services for users, data storage, real-time client/server communication, real-time multiplayer, groups/guilds, and chat.

Fig. 1 illustrates the multi-robot system architecture currently employed. *Nakama* is used as a bridge component between robots and users. In other words, it is the core unit that manages read/write data to the database, send action requests to robots for scheduled tasks, receive feedback from them and transfer this feedback to the UI by using JSON object structures. This allows communicating with robots through the ROS network by implementing the *goroslib*[1] library. In other words, according to the user requests or programmed schedules, *Nakama* creates ROS publishers, subscribers, action servers and action clients to communicate with the decision-making system of the robots, implemented using *(FlexBe)*[2]. Scheduling is carried out by using Cron jobs[3].

With this architecture in place, the system coordinator unit in Fig. 1 manages the requests from multiple users according to their hierarchical level. Such requests are currently carried out over a *UI* where the human-robot interaction occurs, allowing the user to remotely operate the robot using the keyboard, a gamepad or a touchscreen, including motion or other actuators (e.g., lights), stream cameras of robots and other relevant sensors, request the execution of tasks in real-time and schedule the execution of tasks for a forthcoming date and time. Besides allowing the user to perform these operational features, the UI is the main component for system monitoring and visualization, including access to real time positional data of robots in the field. The data collections available in the CoachroachDB are visualised as a list for the operator to view the overall system and to manipulate the database by inserting and deleting data, depending on each specific use case. The architecture has been developed as generic for any specific behavior integration. In other words, new services or actions following the ROS standard do not reflect any changes in the framework.

B. Proposed Direction

In this section and related subsections, we describe the direction that will be adopted to achieve an effective HRC architecture.

1) Human-like Decision-Making: As addressed in section II, identifying the current human behaviour and responding to it by providing adapting control is essential in any proactive HRC architecture. However, taking human behaviour into account is a challenge due to their inherent level of uncertainty. To tackle this, we intend to propose a human-like decision-making modelling with fuzzy finite state machines. Finite state machines (FSM) are known to robustly model dynamic events which change over time, containing states as behaviours and transitions between states. These FMS can be improved in a number of ways by modelling these transitions, be it by integrating probabilistic models (known as PFSM) or fuzzy logics (known as FFSM) [25]. The latter allows triggering the state transitions with a sense of fuzziness, dealing with uncertain data and reasoning with a certain degree of truth. Therefore, the FFSM can have more than one state active at a given time, based on the truth degree for each state, such as human can be cooking while watching television [26]. Mohmed et al. [27] proposed an enhanced fuzzy finite state machine (FFSM) by integrating Long Short-Term Memory (LSTM-FFSM) and Convolutional Neural Network (CNN-FFSM). LSTM is used to learn the temporal sequences from the data and use this information within the fuzzy rules controlling the transition between the activity states. CNN allows the system to select the most effective features from the inputs and learn the temporal relationship from these features to be used in the formulation of fuzzy rules. However, FFSM has not been used for multimodal intention recognition so far. Therefore, starting where Mohmed et al. [27] left, we intend to use FFSM with a multi-modal input system to reduce the uncertainty while increasing the representative features of the action behavior. This multi-modal system will include

[1]https://github.com/aler9/goroslib
[2]http://wiki.ros.org/flexbe
[3]https://github.com/robfig/cron

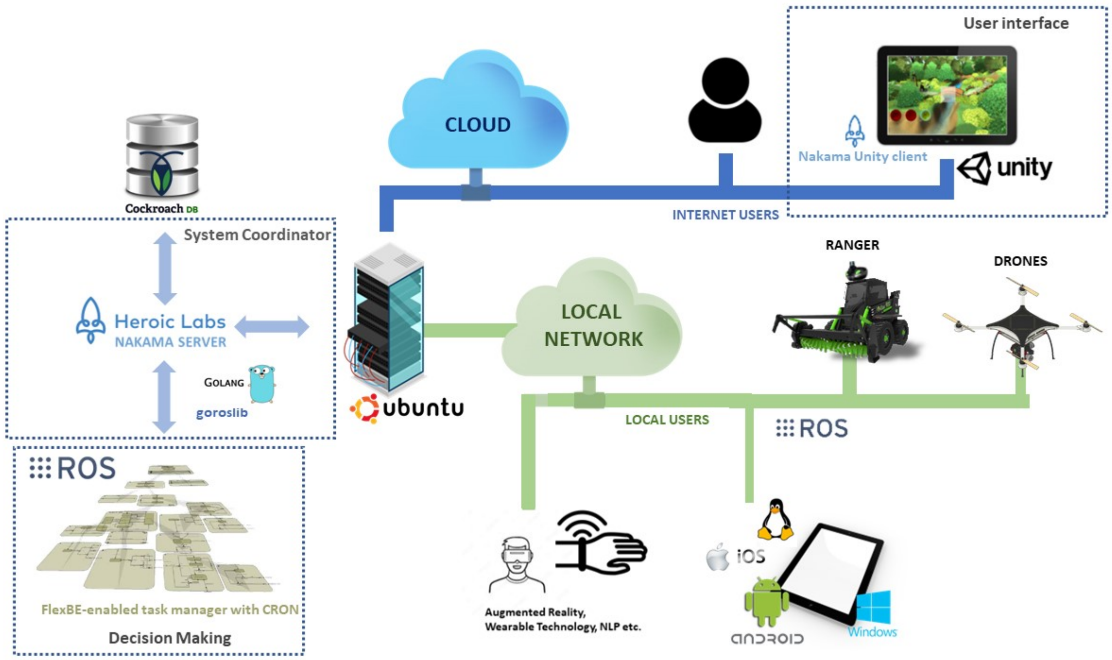

Fig. 1. Conceptual overview of the multirobot system

data from wearable technology with several sequential features, such as heartbeat, kinematics, localization and speech, as well as streams of images acquired through the user head-mounted displays (HMD). For instance, inertial data from a field worker cutting a tree with chainsaw might be too noisy to assess such behavioural intention. However, combining this with image data from the HMD can dramatically increase the likelihood of correctly identifying the behaviour, thus reducing its uncertainty. There are other works addressing the uncertainty of human behaviours and related classification by employing multiple modalities [28]. However, these alternative approaches end up predicting one behaviour at a time, while a certain degree of multitasking is still inherently human and can affect the decision making of the system. This can be captured by the proposed multimodal FFSM, which can output multiple states with different truth degrees.

2) Spatio-Temporal Decision-Making: Besides overcoming uncertainty problems, efficient and reliable multi-agent decision making is demanded by any safe and effective HRC architecture. Games research has been in the cutting edge of multi-agent decision making approaches by adopting deep reinforcement learning (DRL) methods [29]. Nevertheless, in interactive scenarios, such as HRC, without representation of the environments and symbiotic relations between the agents, these methods generate low cooperative behaviours, or may even cause danger. Therefore, this calls upon a description of the environment and the mutual effects between agents, which can be achieved by adopting concepts from graph theory [30]. In other words, the interactive relationship between the agents (robot-robot, human-human, human-robot) should be modeled so that an efficient spatio-temporal decision-making system is provided. Graph neural network, in combination with RL, has been used for spatio-temporal decision making in some studies. For instance, in [31], the authors proposed a spatio-temporal multi-agent reinforcement learning model for multi-intersection traffic light control. We proposed to leverage this approach by employing an extended version for HRC, considering the agents' current action state and uncertainty of human agents, being these modelled by the previously described FFSM. In our proposed approach, the graph consists of nodes representing agents and edges that are formed based on the interaction between these agents. The relationships between the agents can be modeled as explicit and implicit relational graphs using Graph Neural Networks (GNN) [32]. Explicit relations can be predefined or knowledge-based, such as a command given from the human to the robot. On the other hand, an implicit relation changes dynamically based on the distance between the agents. For example, the closest available robot should be the one performing assistance to a given human whenever needed. The output of GNN can then be used in a DRL to model the spatial dependent decision-making, which can be trained, once again, with a LSTM capable of learning the temporal dependency of collaborative behaviours.

3) Fog-Enabled Federated Learning: The previously addressed topics fall on the use of computationally demanding approaches, such as deep learning methods, which can make it unfeasible to completely execute the proposed comprehensive decision-making architecture locally. Researchers have been looking for solutions to build machine learning models without relying on collecting all large amounts of data in one central storage. They came up with an idea to train a model in different local machines where the data source was kept private, but only parameters were exchanged between these decentralized machines, known as federated learning [33]. However, federated learning still suffers from communication overheads and high computational requirements. Taking this into account, we intend to explore fog computing for knowledge transfer and distributed processing in MRS, adopting federated learning concepts in a fog distributed architecture. The conceptual overview presented in Fig. 1 can be seen as a first step in this direction, wherein that particular HRC-enabled MRS can be seen as a fog node, with a local server offering storage and computational power for its own MRS. This allows for any relevant training to take place in each decentralized fog servers locally, which can be then combined in the cloud and can be fetched whenever needed from any robot, regardless of a new or an already existing robot.

IV. USE CASE AND PRELIMINARY RESULTS

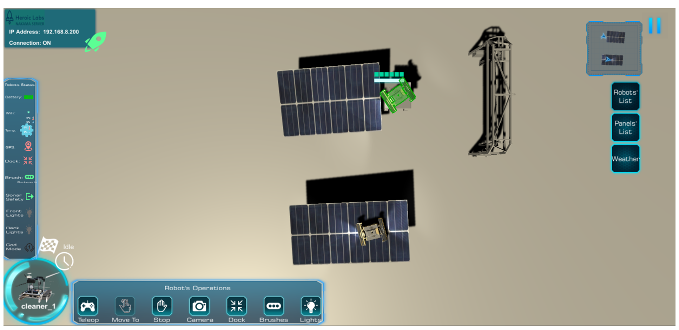

Fig. 2. Use case: SolarCleano UI with an MRS; *Cleaners* (on top of the panels), *Transporter* (loading a Cleaner on the panel above) and *Bridge*.

Some preliminary experiments were carried out to assess the usability of the proposed architecture within a use case scenario with an MRS designed for solar panel cleaning. At this stage, only interactions using touchscreen-enabled devices have been considered. The usability of the system has been evaulated by adopting an experimental setup in which the client from the manufacturing company of the robots who has the required knowledge and awareness of the solar panel installation, was asked to perform cleaning of solar panels via UI, enabling robots to perform all behavioural operations such as cleaning a whole panel, cleaning a panel along a previously recorded path, parking at a given location for loading/unloading robots to/from panels and dock/undock to/from the charging station. Afterwards, the client has filled out a questionnaire which is designed to evaluate usability and acceptance in human-robot interaction systems adopted in [34] and reorganized for our GUI-based interaction. We used a seven-point Likert scale. According to the results shown in Fig. 3, the client has a positive attitude with the idea of adopting the UI for collaboration in future tasks and he assessed it as a useful and easy tool.

V. CONCLUSIONS

This position paper provided an overview of the human-robot collaboration spectrum, addressing traditional and proactive approaches. Finally, the paper ends with a description of the first implementation of the preliminary architecture, quantifying the current usability of the system. Based on the preliminary results, although at this stage, the proposed approach does not affect the tasks' performance individually, it certainly increases the level of consistent and stable system monitoring and interaction. As future work, our main goal is to go beyond the semi autonomous management system to proactive HRC. With this motivation our direction is to expand the presented architecture and include humans to the loop by achieving three proposed criterias presented in section III-B. Following this direction, our next step is to develop an HRC simulator by employing the presented architecture to be used in human-behavior modeling which will be an efficient output for the community to benefit in such applications that demand large scales of human joint data.

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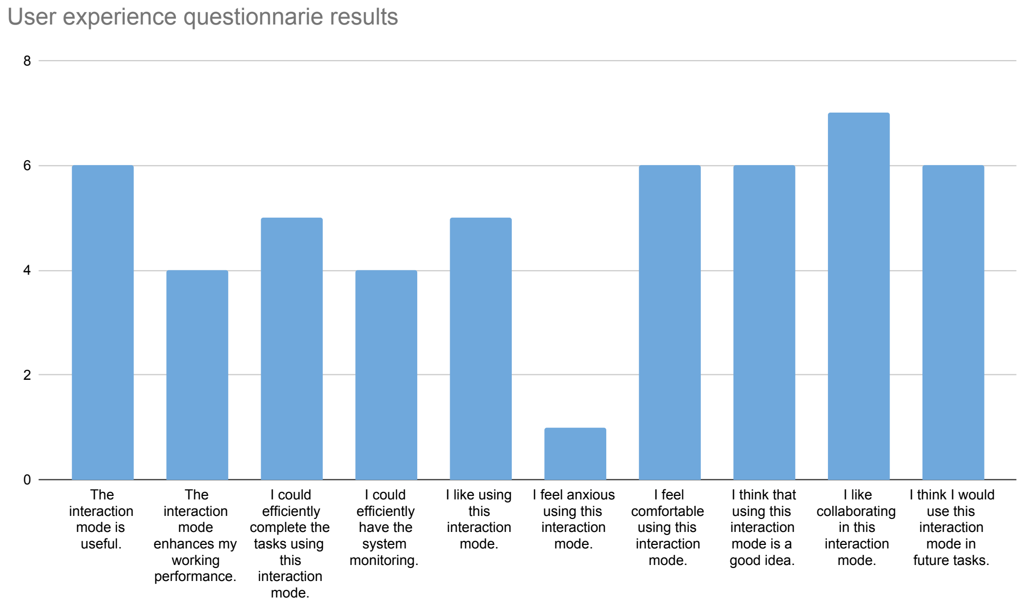

Fig. 3. The results of the questionnaire filled out by the client.

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