Annual Reviews in Control 44 (2017) 342–354

Contents lists available at ScienceDirect

Annual Reviews in Control

journal homepage: www.elsevier.com/locate/arcontrol

Review article

Control sharing in human-robot team interaction

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A R T I C L E I N F O

Article history:
Received 15 July 2017
Revised 28 September 2017
Accepted 29 September 2017
Available online 25 October 2017

Keywords:
Human-robot team interaction
Shared control
Human behavior modeling
Robot team

A B S T R A C T

The interaction between humans and robot teams is highly relevant in many application domains, for example in collaborative manufacturing, search and rescue, and logistics. It is well-known that humans and robots have complementary capabilities: Humans are excellent in reasoning and planning in unstructured environments, while robots are very good in performing tasks repetitively and precisely. In consequence, one of the key research questions is how to combine human and robot team decision making and task execution capabilities in order to exploit their complementary skills. From a controls perspective this question boils down to *how control should be shared* among them. This article surveys advances in human-robot team interaction with special attention devoted to control sharing methodologies. Additionally, aspects affecting the control sharing design, such as human behavior modeling, level of autonomy and human-machine interfaces are identified. Open problems and future research directions towards joint decision making and task execution in human-robot teams are discussed.

Contents

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https://doi.org/10.1016/j.arcontrol.2017.09.017

1. Introduction

Human-robot team interaction describes the interaction between a human and multiple robots, which collaborate to achieve a common goal. Its envisioned benefits are superior performance in highly unstructured tasks in unknown and/or remote environments, reduced human workload, execution of tasks which are not possible with a single robot, flexibility in task execution, and robustness. Application domains of human-robot team interaction include for example search and rescue, collaborative manufacturing, logistics, maintenance, and construction.

The reduction in price, size, and operational complexity has considerably increased the availability of robotic systems, while the advancements in communication technology allow a seamless information exchange between them. These developments are enablers for *multi-robot systems*. They provide increased flexibility and robustness and are capable to conduct more complex tasks then single-robot systems (Iocchi, Nardi, & Salerno, 2000; Parker, 2008). Even though the autonomous task execution capabilities of robots have progressed rapidly in recent years, human intervention in the form of high-level reasoning and planning is still needed in a priori unknown environments. As a consequence, novel forms of human-robot interaction beyond single-human-single-robot have become a current and important topic of research covering the areas of multiple humans-single robot interaction (Malysz & Sirouspour, 2011), multiple humans-multiple robots interaction (Franchi, Secchi, Ryll, Bulthoff, & Giordano, 2012), and single human-multiple robots interaction (Cummings, How, Whitten, & Toupet, 2012).

The main scientific challenge of human-robot team interaction is to fuse the cognitive capabilities of the human and the autonomous capabilities of the robot team, while maximizing task performance, efficiency, and intuitiveness of the interaction. This leads to the consideration of suitable levels of autonomy, control sharing and human cognitive and behavioral aspects in the interaction design.

The aim of this article is to provide a survey on existing concepts and approaches for human-robot team interaction with special focus on control sharing aspects. The article is organized as follows: Section 2 concerns the modeling and control of robot teams and modeling of human behavior, Section 3 addresses the human-robot team interface design, and Section 4 reviews existing control sharing concepts. For an overview see also Fig. 1.

2. Modeling robot teams & human behavior

In this section we briefly review modeling and control approaches for robot teams and models for human behavior.

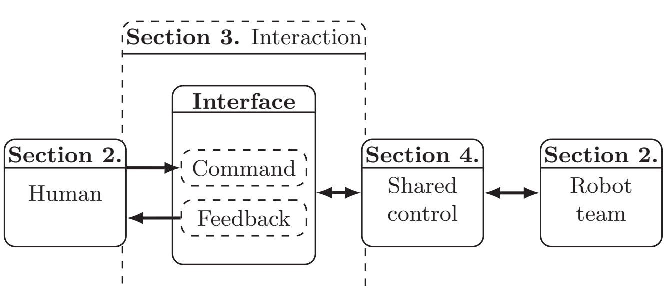

Fig. 1. Article overview in a block structure.

2.1. Robot teams

This subsection focuses on the modeling and control concepts for robot teams, which are suitable and/or used in human-robot team interaction. There are extensive reviews on multi-robot systems control in general, for example Cao, Fukunaga, and Kahng (1997), Iocchi et al. (2000), Arai, Pagello, and Parker (2002), Dudek, Jenkin, and Milios (2002), Farinelli, Iocchi, and Nardi (2004), Gazi and Fidan (2007), Murray (2007).

In this article the term *robot team* refers to a multi-robot system which cooperates to achieve a global objective. For example, robot teams can be a set of mobile manipulators (Khatib, Yokoi, Chang, Ruspini, Holmberg, and Casal, 1996; Sugar & Kumar, 2002), wheeled robots (Desai, Ostrowski, & Kumar, 2001) or UAVs (Jin, Minai, & Polycarpou, 2003; Ryan, Zennaro, Howell, Sengupta, & Hedrick, 2004). In the literature there is further the distinction between robot *swarms*, i.e. multi-robot systems with a relatively large number of "simple" and homogeneous robots, and heterogeneous multi-robot systems with more complex individual robotic agents. Under the term of robot team we will subsume both types, even though the related control problems can be quite different, see also Section 2.1.2.

2.1.1. Modeling of robot teams

Robot teams are modeled as a set of differential equations describing the models of individual robots. Most frequently used models are:

- *Kinematic* (*single integrator*) model (Tanner, Jadbabaie, & Pappas, 2003; Oh & Ahn, 2014)

$$\dot{\boldsymbol{x}}_i = \boldsymbol{u}_i \quad i = 1, \dots, N, \tag{1}$$

  where $\boldsymbol{x}_i \in \mathbb{R}^n$ is the pose of the ith robot, $\boldsymbol{u}_i \in \mathbb{R}^n$ its control input, and N the number of robots. This is the simplest of all models and often used to model robot agents in a swarm.

- *Point mass* (*double integrator*) model (Oh & Ahn, 2014; Liu, 2015)

$$\ddot{\boldsymbol{x}}_i = \frac{1}{m_i}\boldsymbol{u}_i, \tag{2}$$

  where m_i is the mass of the ith robot. This model is slightly more complex than the kinematic model and also often used in the analysis of robot swarms.

- *Euler-Lagrange* model (Khatib et al., 1996; Erhart & Hirche, 2016)

$$\boldsymbol{M}_i(\boldsymbol{x}_i)\ddot{\boldsymbol{x}}_i + \boldsymbol{c}(\boldsymbol{x}_i, \dot{\boldsymbol{x}}_i) + \boldsymbol{g}_i(\boldsymbol{x}_i) = \boldsymbol{h}_i, \tag{3}$$

  where $\boldsymbol{M}_i\ (\boldsymbol{x}_i) \in \mathbb{R}^{n\times n}$ is the inertia matrix, $\boldsymbol{c}(\boldsymbol{x}_i, \dot{\boldsymbol{x}}_i) \in \mathbb{R}^n$ the vector of Coriolis and centrifugal forces, $\boldsymbol{g}_i\ (\boldsymbol{x}_i) \in \mathbb{R}^n$ the vector of gravitational forces, and $\boldsymbol{h}_i \in \mathbb{R}^n$ is the vector of control wrenches. This is the classical model typically employed for an individual manipulator and for small heterogeneous robot teams.

If a robot interacts with its environment, for example touches an object, then the input $\boldsymbol{u}_i$ in (1) and (2) and $\boldsymbol{\tau}_i$ in (3), does not only contain the control input, but also the external force from the environment. Analogously, if multiple robots perform a cooperative manipulation tasks, i.e. are physically coupled through the object, then additionally the applied forces from the other robots acting through the object are contained in this input. For more details on modeling this type of systems, see for example (Erhart & Hirche, 2015; 2016).

Together with the continuous states, a discrete state, termed as *role* (Murray, 2007), can be assigned to each robot in the team. The role can refer to a set of responsibilities or capabilities a robot has within the team (Yanco & Drury, 2002), and is particularly relevant for heterogeneous teams. Roles can also determine to what extent the individual robots are capable of making decisions. Examples are *leader* and *follower* roles, where a leader does not use information of other robots to make a decision, while a follower considers the information of other robots to make its decision.

2.1.2. Control in robot teams

Control architectures for robot teams largely depend on the way in which robots interact to accomplish a task. In general we distinguish robot teams based on the coupling between the individual robots: Robot teams can be *uncoupled*, *loosely coupled* or *tightly coupled* systems. Loose and tight couplings are achieved through partial and full coordination control, respectively. Furthermore, we distinguish between *centralized* and *distributed* control approaches. In a centralized control architecture the team is coordinated from a single point (e.g. through the robot leader). The design of a centralized control architecture is simple compared to the distributed alternative, but is less resilient as there is a single point of failure. In a distributed control architecture the coordination among the team members is achieved via locally implemented control on each robot and communication of relevant information among the controllers of neighbouring robots. Achieving team behaviors is more challenging in this case, but resilience is higher. For complex control tasks hierarchical control schemes have been developed, where the overall control task is decomposed into smaller subproblems, often associated with *layers* in a hierarchical tree structure. Given the complementary capabilities of humans and robots one of the promising control paradigms for human-robot team interaction is to assign the low-level coordination to the robot team through distributed control and the high-level coordination of the whole team to the human in a hierarchical fashion.

Hierarchical robot team control: In the following we describe a hierarchical control architecture which has been originally developed for robot teams (see e.g. Parker, 1998), but can be suitably extended for human-robot team interaction. The team control comprises six layers: the *task*, *planning*, *subtask*, *action*, *robot team* and *interaction* layer, see Fig. 2 for illustration. The functionalities of the layers are described with particular focus on the task and the subtask layers.

The task goal is stored within the task layer. Often it is represented as a performance function to be optimized (Murray, 2007)

$$J = \int_0^T L(\boldsymbol{x}, \boldsymbol{\alpha}, \boldsymbol{u})dt + V(\boldsymbol{x}(T), \boldsymbol{\alpha}(T)), \tag{4}$$

where L and V are incremental and terminal costs, respectively. Continuous states of the robots, $\boldsymbol{x}_i$, are stacked in the vector $\boldsymbol{x} \in \mathbb{R}^{nN}$, discrete states (roles) of the individual robots are stacked into the vector $\boldsymbol{\alpha}$, the control inputs are stacked into $\boldsymbol{u} = \boldsymbol{\gamma}(\boldsymbol{x}, \boldsymbol{\alpha})$ with the control policy $\boldsymbol{\gamma}$ being a function of the continuous and discrete states, and T is the time horizon in which the task should be accomplished. The control input to the individual robots is determined through computations in the planning, subtask, and action layer. Highlevel planning in terms of the suitable combination of elementary behaviors or subtasks is performed within the planning layer. The elementary behaviors are represented in the subtask layer. The action layer is concerned with the local low-level control actions.

Global and local behaviors: We distinguish between *global* behaviors (or subtasks), which require information exchange among the robots within the team, and *local* behaviors, which require only the local information of an individual robot. Typical examples

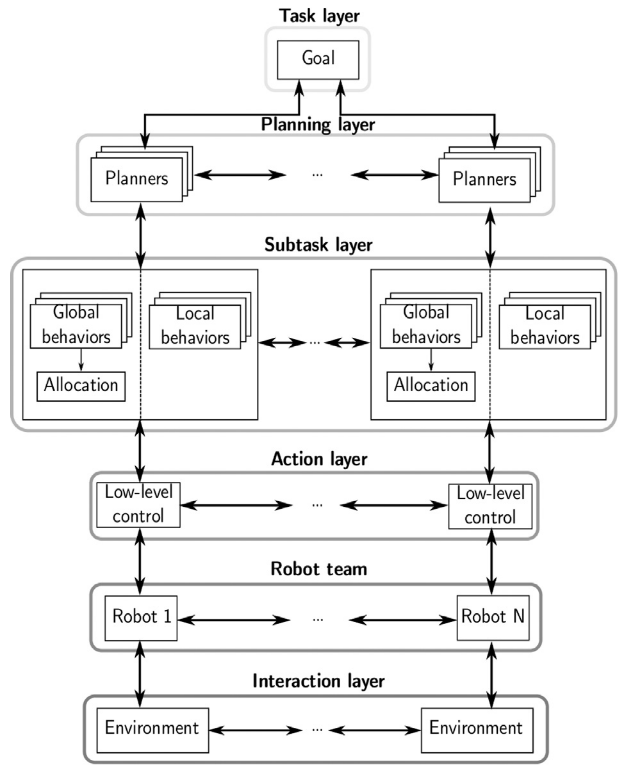

Fig. 2. Hierarchical control architecture for robot teams. Goal of the robot team is determined and monitored in the *task layer*. Based on the goal, a set of global and local behaviors are activated in the *subtask layer* through the *planning layer*. The outputs of this layer are control inputs for the low-level controllers of robots in the *action layer*.

of global behaviors are *rendezvous*, *foraging*, *cooperative manipulation*, *formation*, *coverage*, and *inter-robot avoidance*. Rendezvous describes a behavior in which the robots meet at a common point at a common time (Murray, 2007). Foraging refers to a behavior of collecting and delivering an object (Gazi & Passino, 2004; Winfield, 2009). Cooperative manipulation refers to the joint handling of an object (Spletzer, Fierro, Taylor, Kumar, & Ostrowski, 2001; Michael, Fink, & Kumar, 2011; Erhart & Hirche, 2016), and formation to the maintenance of robot poses relative to each other or to a reference (Dunbar & Murray, 2006; Egerstedt & Hu, 2001; Leonard & Fiorelli, 2001). Coverage refers to visiting areas of an environment for information acquisition (Choset, 2001; Cortes, Martinez, Karatas, & Bullo, 2004). Coordination control approaches from the area of multi-agent systems are suitable for accomplishing global behaviors by exchanging individual state information through communication between agents (robots). In this context, *consensus* is one of the canonical control problems (Olfati-Saber & Murray, 2004). For example, in order to accomplish a rendezvous behavior, the robots need to perform consensus on the position. The idea behind the consensus control is that each robot moves towards the weighted average of the states of its neighbors. There are multiple other control approaches that are used for cooperation of robot teams, e.g. artificial potential functions (Leonard & Fiorelli, 2001; Song & Kumar, 2002), Lyapunov-based approach (Ogren, Egerstedt, & Hu, 2001; Olfati-Saber & Murray, 2004; Hong, Gao, Cheng, & Hu, 2007), sliding mode control (Gazi, 2005; Defoort, Floquet, Kokosy, & Perruquetti, 2008), behavioral control (Balch & Arkin, 1998; Antonelli, Arrichiello, & Chiaverini, 2008), virtual structures (Lewis & Tan, 1997; Ren & Beard, 2004), to name a few.

Examples for local behaviors are *obstacle avoidance* and *self-collision avoidance*. It should be noted, that the classification of these behavior examples is not strict, but rather considers the "typical" case. If for example, inter-robot avoidance is performed using only local sensors of the robots without information exchange, then this would be called a local behavior.

Simultaneous execution of subtasks: In complex tasks, often, multiple subtasks need to be performed simultaneously. In order to achieve this, a *subtask-based* control approach is suitable (Musić et al., 2017). It is designed by defining subtasks as transformations of the system states in the form

$$\begin{aligned} \boldsymbol{x}_{s_i} &= \boldsymbol{f}_{s_i}(\boldsymbol{x}) \\ \dot{\boldsymbol{x}}_{s_i} &= \boldsymbol{J}_{s_i}(\boldsymbol{x})\dot{\boldsymbol{x}}, \end{aligned} \tag{5}$$

where $\boldsymbol{x}_{s_i}$ are the coordinates of the ith subtask s_i, $\boldsymbol{J}_{s_i}(\boldsymbol{x})$ is the corresponding subtask Jacobian, and $\boldsymbol{x} = [\boldsymbol{x}_1^T, \dots, \boldsymbol{x}_N^T]^T$ is the stacked pose vector of individual robots.

Example 2.1. In order to manipulate a common object in $\mathbb{R}^2$ from an initial to a final configuration, a team of N robot manipulators needs to collectively move to a desired location, while maintaining a fixed formation. Therefore, we can define two subtask functions of collective motion $\boldsymbol{f}_{s,1}(\cdot)$ and formation control $\boldsymbol{f}_{s,2}(\cdot)$

$$\begin{aligned} \boldsymbol{f}_{s,1}(\boldsymbol{x}) &= \frac{1}{N}\Sigma_{i=1}^N \boldsymbol{x}_i - \boldsymbol{x}_m^d, \\ \boldsymbol{f}_{s,2}(\boldsymbol{x}) &= \begin{bmatrix} (\boldsymbol{x}_2 - \boldsymbol{x}_1)^T - \boldsymbol{d}_{12}^d \\ \vdots \\ (\boldsymbol{x}_N - \boldsymbol{x}_{N-1}) - \boldsymbol{d}_{(N-1)N}^d \end{bmatrix}, \end{aligned} \tag{6}$$

where $\boldsymbol{x}_i \in \mathbb{R}^2$ is the position of the ith robot in the plane, $\boldsymbol{x}_m^d \in \mathbb{R}^2$ is the desired value of the mean position of the robot team, and $\boldsymbol{d}_{(i-1)i}^d \in \mathbb{R}^2$ is the desired relative position of robots $i-1$ and i. In a similar scenario, the human directly controls the object position (i.e. the mean position of the robots here) and formation control is performed autonomously in Franchi et al. (2012), Chipalkatty, Droge, and Egerstedt (2013), Sieber, Musić, and Hirche (2015), Setter, Kawashima, and Egerstedt (2015). In Musić et al. (2017) both subtasks are performed by the human.

Subtasks can be conducted according to a predefined priority. A common control strategy that ensures the prioritization is termed as *null-space based behavioral control* (Antonelli et al., 2008). It is based on the projection of lower priority subtasks onto the null-space of the higher priority subtask. For example, in the case of two subtasks, the control input $\dot{\boldsymbol{x}}^d$ would be

$$\dot{\boldsymbol{x}}^d = \boldsymbol{J}_{s_1}^\dagger \boldsymbol{x}_{s_1} + (\boldsymbol{I} - \boldsymbol{J}_{s_1}^\dagger \boldsymbol{J}_{s_1})\boldsymbol{J}_{s_2}^\dagger \boldsymbol{x}_{s_2}, \tag{7}$$

where $\boldsymbol{J}^\dagger$ denotes the pseudo-inverse of a Jacobian $\boldsymbol{J}$ and $(\boldsymbol{I} - \boldsymbol{J}_{s_1}^\dagger \boldsymbol{J}_{s_1})$ is the null-space projector. Note though, that the approach is kinematic, which makes it unsuitable for the control of dynamic behaviors, e.g. when the inertia of the robots cannot be neglected. Additionally, the interaction with the environment, i.e. with objects or humans, cannot be handled appropriately. The dynamic decoupling control proposed in Musić et al. (2017) addresses these shortcomings. The allocation of responsibilities to the individual robots, according to the selected subtasks, and the role they have within the team is an important step and can be handled in various ways, see for example Gerkey and Matarić (2004) and Zhang, Xie, Yu, and Wang (2007).

2.2. Human behavior modeling

An appropriate human model can predict under which conditions the human exhibits good or bad performance and may be beneficial in the design of appropriate control sharing strategies. Generic human behavior models over all levels of abstractions - from reasoning and planning to motion - are very difficult to establish if not infeasible. Therefore, modeling ambitions focus on particular aspects of human behavior - typically distinguishing between high-level cognitive decision-making models and low-level interaction models. The modeling type is closely related to the human role and the level of abstraction in the interaction. Therefore, here we first extend the team control concept introduced in Section 2.1 to include the human by assigning him/her a role and a layer for the interaction with the robot team. Then we review selected human behavior models.

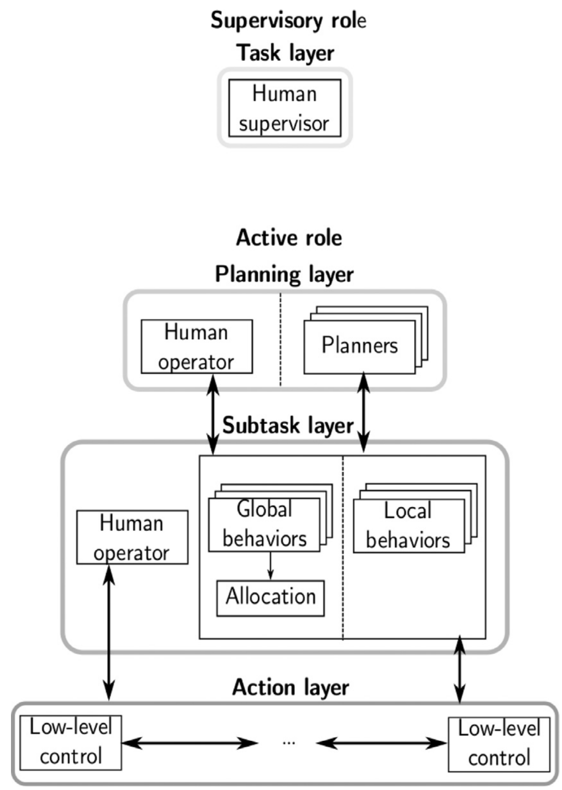

Fig. 3. Possible human roles within the robot team control architecture.

2.2.1. The human role

The literature distinguishes between a *supervisory* and an *active* human role (Chen & Barnes, 2014). A supervisory role brings human *on* the loop where the interaction with the robot team is typically symbolic (discrete). Matching this to the hierarchical team control architecture in Section 2.1.2, the human supervisor is typically located in the task or planning layer. In the task layer, the human supervisor is aware of the overall goal and is capable of modifying it. If the responsibilities of the human extend to selecting global and local behaviors and intervening when necessary, then he/she would be allocated in the planning layer as well. The remaining lower layers are opaque in the sense that they cannot be directly influenced by human control input, but only indirectly through the task and planning layer. The active role brings human *in* the control loop with the robot team, the interaction between human and robot team is typically continuous (in some applications even physical) (Lee & Spong, 2005). Matching this to the hierarchical team control architecture in Section 2.1.2, the human in the active role directly influences the lower layers, e.g. by providing control inputs to the subtask or action layer. The association of the human role to the layers in the hierarchical team control architecture is illustrated in Fig. 3 (for simplicity, only the "control" layers are shown and the supervisory role is depicted only in the task layer).

2.2.2. Human decision making models

In high-level interaction with the robot team, i.e. in the supervisory role, human cognitive decision-making models play an important role. In this context, results from cognitive psychology provide valuable insight. The scientific challenge is to transfer these insights into models suitable for systems and control analysis. In the following we will present some human decision-making modeling approaches for particular scenarios from the literature.

Very often the human in the supervisory role is modeled by a *Markov model*. In Sycara, Lebiere, Pei, Morrison, and Lewis (2015), a Markov model is obtained from the neurally inspired cognitive model and it predicts the human decision when choosing between two global behaviors of the swarm, Deploy (D) or Rendezvous (R). The probability of transition from one behavior to another is assumed to be

$$p_{s_i \to s_j} = \frac{c_{s_i \to s_j}}{\sum_{s_t \in \{D,R\}} c_{s_i \to s_j}}, \tag{8}$$

where s_i, $s_j \in \{D, R\}$ are two possibilities of the team behavior, and $c_{s_i \to s_j}$ is the number of transitions from s_i to s_j obtained during the training of the Markov model. The prediction of the next chosen behavior is obtained with

$$s_{i+1} = \underset{s \in \{D,R\}}{\operatorname{argmax}}\, p_{s_i \to s}. \tag{9}$$

Models that can capture the dynamics of the decision making are termed as *accumulator models* (Peters et al., 2015). Accumulator models are typically used for *two-alternative forced-choice tasks* (TAFCTs), i.e. tasks where the decision is between two discrete alternative choices. Because of the discrete nature of the choices, they are suitable for modeling the human decision-making behavior dynamics in the supervisory role.

The accumulator model proposed in Stewart, Cao, Nedic, Tomlin, and Leonard (2012) for human-robot team interaction uses a stochastic soft-max choice model that emerges from a *drift-diffusion* (DD) model. The probability that the human operator will choose option A is defined as a sigmoidal function

$$p_A(t+1) = \frac{1}{1 + e^{-\mu d(t)}}, \tag{10}$$

where μ represents the slope of the sigmoidal function and $d(t)$ is the subjective expected payoff. The probability (10) can be represented with a drift-diffusion model

$$dz = \lambda dt + \sigma dW, \quad z(0) = 0, \tag{11}$$

where z is the accumulated evidence in favor of a candidate choice, λ is a drift rate representing the signal intensity of the stimulus, and σW is Wiener process with standard deviation σ.

Gao and Lee (2006) present an alternative accumulator model and formulate an *extended decision field theory* (EDFT) model to represent multiple sequential decisions in human-automation interaction with the human in supervisory role. The preference in the TAFCT at time instant k is proposed as

$$P(k) = (1-\gamma)P(k-1) + \gamma d(k) + \epsilon(k), \tag{12}$$

where γ determines the influence of the previous preference state, $P(n-1)$, and ϵ is the residual (produced by fluctuations in attention). Apart from modeling human decision making between different action choices, this model is also used to model the *reliance* of the human on autonomy. The reliance is determined by *trust* of the human in the autonomy and by *self-confidence* of the human in his/her manual control. Here, the two alternatives are modeled as the human preference for *autonomous* or *manual* control. *Trust* in autonomy is the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty (Lee & See, 2004). *Overtrust* and *undertrust* in autonomy can cause overreliance (*misuse*) and underutilization (*disuse*), respectively (Parasuraman & Riley, 1997). For a review on human trust in autonomy the reader is referred to Lee and See (2004). Based on (12), trust and self-confidence are estimated as (Gao & Lee, 2006)

$$\begin{aligned} T(k) &= (1-\gamma)T(k-1) + \gamma d_{ca}(k) + \epsilon(k) \\ SC(k) &= (1-\gamma)SC(k-1) + \gamma d_{cm}(k) + \epsilon(k), \end{aligned} \tag{13}$$

where T and SC correspond to trust and self-confidence, while d_{ca} and d_{cm} are subjective expected payoffs if the task is automated and if it is manual, respectively. The reliance is computed as the preference $P(k) = T(k) - SC(k)$. Therefore, it depends on the dynamical interaction between the trust and the self-confidence.

Modeling the continuous interaction between a human and a robot (team) remains a largely open challenge. In classical teleoperation literature, control design commonly relies on the assumption that the *trained* human behaves passive (Hogan, 1989; Sirouspour, 2005). Hatanaka, Chopra, and Fujita (2015) use black-box methods to identify human decision-making behavior in the active role of commanding a robot swarm. The frequency analysis of the obtained linear time-invariant system, however, reveals that the human decision-making process violates the passivity condition in the high-frequency range. Accordingly, passivity-based models have their limitations and more research is needed in this area. Parametric models are also proposed but are very specific to particular tasks and individuals, see e.g. Gillespie and Cutkosky (1995).

2.2.3. Human behavior constraints

Another way of representing human behavior is through the characterization of its constraints. Important constraints that affect the human-robot team interaction are *human workload* and *situational awareness* (Chen & Barnes, 2014).

The *mental workload* is the extent to which a task places demands on the human's cognitive resources (Sheridan & Stassen, 1979). The workload increases significantly if the human operator interacts with the individual robots within the team (Chen, Barnes, & Harper-Sciarini, 2011), i.e. interacts on the action layer. The results in Goodrich, Quigley, and Cosenzo (2005) suggest that the maximum number of homogeneous and uncoupled robots a single human can manage is determined by the *fan out* (FO) expression

$$FO = \frac{NT}{IT} + 1, \tag{14}$$

where NT is the neglect time allowed and IT the interaction time required for each robot. The mental workload can be reduced by increasing the autonomous capabilities of the robot team, and by establishing the interaction through the subtask layer. However, with the increase of the robot team autonomy, *situational awareness* (SA) (Endsley, 1995) of the human degrades, reducing human apprehension of the robot team states. It has been shown that if the robot team is involved in the decision making, the situational awareness is negatively affected (Parasuraman, Barnes, Cosenzo, & Mulgund, 2007). Therefore, the higher the support from the robot team, the greater the risk from complacency, impaired situational awareness and skill degradation. True danger from these effects can occur when the automation fails and the human does not react, has a delayed response or does not have the skill to react properly (Onnasch, Wickens, Li, & Manzey, 2014). Transparency and observability properties are essential for a satisfactory situational awareness (Chen & Barnes, 2014) and can be improved by a suitable interface design.

3. Interaction in human-robot teams

In this section we discuss different interaction paradigms between a human and a robotic team in terms of levels of auton-

Table 1
10 levels of autonomy by Sheridan and Verplank (1978).

1	The human executes all actions.
2	The computer offers complete set of action alternatives.
3	The computer offers a selection of action alternatives.
4	The computer suggests one alternative.
5	The computer executes an action autonomously if the human approves.
6	The computer allows the human a restricted time to veto before automatic execution.
7	The computer executes an action and informs the human.
8	The computer executes an action and informs the human if asked.
9	The computer executes an action and informs the human if it decides to.
10	The computer executes all actions autonomously.

omy, allocation of responsibilities, and handling multiple subtasks. Furthermore, we provide a review of the interfaces used in these types of interaction.

3.1. Interaction paradigms

In Section 2.2 we started already to discuss interaction paradigms through the definition of a human role and the association to a layer for the interaction in the hierarchical team control architecture. Here, we approach the topic from the viewpoint of robot autonomy, i.e. the degree to which the robot team can perform functions autonomously. Obviously, the human role and the responsibilities are majorly influenced by the *levels of robot autonomy* (Hardin & Goodrich, 2009).

3.1.1. Levels of autonomy

The concept of *levels of autonomy* is introduced in the area of human-machine interaction (HMI) and defines which functions should be autonomous and which should be managed by the human (Sheridan & Verplank, 1978). Early research proposes a fixed number of discretized levels of autonomy between no autonomy and full autonomy. For example, Sheridan proposes ten levels of automation in Sheridan and Verplank (1978), see Table 1. This concept has been extended to the levels of autonomy for each information-processing system function: information acquisition, information analysis, decision and action selection, and action implementation. Parasuraman, Sheridan, and Wickens (2000) find that a high level of autonomy is desirable for information acquisition and information analysis functions, but not for decision making as it causes human skill degradation, complacency, and poor situational awareness.

Levels of autonomy have been considered for human-robot team interaction as well. In Coppin and Legras (2012) a concept of *autonomy spectrum* is proposed for human-robot team interaction using the ten levels of autonomy proposed in Sheridan and Verplank (1978). An example of the autonomy spectrum is depicted in Fig. 4. It is a graphical representation of operating modes (depicted by nodes), with levels of autonomy and functions to be executed along the vertical and horizontal graph axes, respectively. Additionally, the level of autonomy is also marked in the node. The approach allows to determine several operating modes for each function, and to combine them (depicted with lines). This method emphasizes the importance of having multiple operating modes during the task execution. Another important property that needs to be ensured for interaction modes is smooth and seamless transition, termed as *sliding scale autonomy* (Sellner, Heger, Hiatt, Simmons, & Singh, 2006). In Lin and Goodrich (2015) a sliding autonomy approach is proposed for robot swarms.

3.1.2. Subtask allocation in human-robot teams

In Musić and Hirche (2016) different interaction paradigms in the subtask layer are introduced for human-robot team interaction. The authors propose the subtask allocation to the human operator

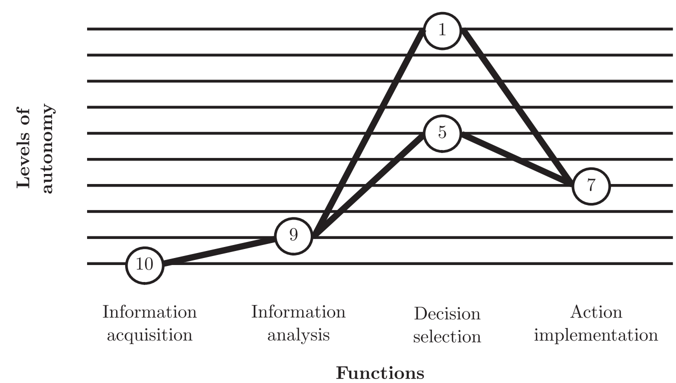

Fig. 4. An example representation of the autonomy spectrum as proposed in Coppin and Legras (2012).

and the autonomous controller of the robot team according to the available levels of autonomy. Three interaction paradigms are proposed: *direct*, *complementary* and *overlapping*. In the direct interaction paradigm the human provides commands for all the subtasks. In the complementary interaction paradigm the human provides input to a subset of subtasks, while the robot team executes the remaining subtasks autonomously. In the overlapping interaction paradigm the inputs from the human and the robot team autonomy are blended to perform a common subtask. A formal definition for these interaction paradigms in terms of relations between the set of all subtasks $\mathcal{S}$, subtasks allocated to the human $\mathcal{S}_h$, and to the robot team $\mathcal{S}_r$ along with interaction control concepts are provided in Table 2.

In many, especially in time-critical, applications it is necessary to allocate and prioritize subtasks according to availability of resources of the human and the robot team. Parasuraman et al. (2007) propose to design an *automation matrix* which contains weights (representing subtask importance, expected workload and other factors) that are used to prioritize subtasks and determine which of them should be automated. It can be used to allocate responsibility within the interaction and fuse control inputs from the human and the robot team. However, the priority between subtasks is, so far, determined in advance and cannot dynamically change during the task execution.

3.2. Interfaces for human-robot team interaction

The user interface builds the bridge between the human and robot team, and determines the command and feedback information for the human user and its representation. The design of the interface has a significant influence on the achievable performance in human-robot team interaction. According to Chen and Barnes (2014), the interface needs to ensure the human understands intentions and behaviors of the robots and the environment. Furthermore, it needs to appropriately allocate human attention to important events and ensure the decision authority of the human. Overall, the interface for human-automation interac-

Table 2
Properties of the interaction paradigms.

Interaction paradigms	Human responsibilities	Robot team responsibilities	Examples	
Direct	$\mathcal{S}_h = \mathcal{S}$	$\emptyset$	Teleoperation	
Complementary	$\mathcal{S}_h \subset \mathcal{S}$	$\mathcal{S}_a = \mathcal{S} \setminus \mathcal{S}_h$	Semi-autonomy	Autonomy
Overlapping	$\mathcal{S}_h \subset \mathcal{S}$	$\mathcal{S}_a \subset \mathcal{S}$, $\mathcal{S}_h \cap \mathcal{S}_a \neq \emptyset$, $\mathcal{S}_h \cup \mathcal{S}_a = \mathcal{S}$	pHRI	

tion needs to be determined by: *purpose* (degree to which the automation is used w.r.t. the designer intent), *process* (if the autonomy level is suitable for a given situation) and *performance* (reliability, predictability and capability) (Chen & Barnes, 2014). There is an enormous amount of literature on human-machine interface design, often for particular applications. It is beyond the scope of this article to perform an exhaustive review on the different technologies. In the following we will focus on selected aspects of user interfaces for human-robot team interaction.

3.2.1. Command interfaces

The command interface translates the human action to an appropriate control command for the robot team. In the supervisory role, the human typically interacts with the robot team via a *graphical user interface* (GUI) (e.g. touch screen (Bruemmer et al., 2005) or through voice (Jones, Berthouze, Bielski, & Julier, 2010)). The action of the human supervisor is mapped into high-level commands as for example setting goals for the robot team or individual robots, assigning levels of autonomy, or interfering in the case of events (McLurkin, Smith, Frankel, Sotkowitz, Blau, & Schmidt, 2006; Parasuraman, Galster, Squire, Furukawa, & Miller, 2005; Chen, Barnes, & Harper-Sciarini, 2011). In the active role, the human provides continuous commands, for example motion and/or force commands. This type of commands is typically conveyed through a motion-measuring device such as a touch screen (Hatanaka et al., 2015), vision-based system (Alonso-Mora, Lohaus, Leemann, Siegwart, & Beardsley, 2015; Sieber et al., 2015), or a haptic device (Lee & Spong, 2005; Musić et al., 2017).

Apart from the sensing technology, also the mapping from a measured command signal on a control command for a robot is part of the command interface. In this context we observe an *asymmetry* in the interaction between the human and the robot team: The robot team has a much higher number of degrees of freedom in comparison to the dimensionality of the human command signal. The key challenge is to find an *intuitive* mapping from the low dimensional human command signal to the control tasks in the robot team, which enables an efficient learning on how to interact for the human.

This challenge of intuitive interaction with highly redundant systems has been tackled for specific application examples only. For example, Alonso-Mora et al. (2015) and Diana, de la Croix, and Egerstedt (2013) consider the scenario of formation control. It is obvious that a single human is not able to simultaneously control the positions of an even moderately high number of robots in the team in order to keep the formation. So, instead of commanding relative distances between individual robots, the human operator commands the change of the formation shape using the concept of virtual deformable volumes. Similarly, in Musić et al. (2017) the formation of multiple robots grasping an object is controlled through a virtual sphere. The latter work makes use of a subtask-based control approach as described in Section 3.1.2 and suggests that the interaction with the robot team through global behaviors in the subtask layer of Fig. 2 provides a suitable paradigm for the interface in human-robot team interaction as well, as it implies a dimensionality reduction of command (and feedback) information.

From the control perspective, the investigation of *controllability* of the system can aid in the interface design (Musić & Hirche, 2016). Knowing the level of autonomy implies which states of the robot team should be controllable by the human. In order to ensure controllability of those states, it is necessary to provide sufficient number of command channels. This number conditions the command interface suitable for the interaction.

3.2.2. Feedback interfaces

The feedback interface translates the output of the robot team to appropriate feedback information for the human. In the literature on human-robot team interaction the feedback is often visual, in some cases additionally augmented by haptic feedback.

In the supervisory role, the human receives feedback via GUI and video. In Bruemmer et al. (2005) the authors show that if the roles of the human and the robot team are changing during the task execution, the interface should provide *dynamical feedback*. In Crandall, Cummings, Della Penna, and de Jong (2011) authors distinguish between GUI interfaces for visual representation, warning systems (visual, auditory and haptic) and suggestion systems which indicate where the attention should be allocated. The performance in managing multiple UAVs individually proved to be the best with suggestion systems.

In the active role, haptic feedback often augments visual feedback information. The haptic feedback channel may provide additional information about internal robot states, for example the distance to an obstacle (Rodríguez-Seda et al., 2010; Son et al., 2013), the internal force in cooperative manipulation (Griffin, Provancher, & Cutkosky, 2005; Musić et al., 2017) or the interaction with the environment (Franchi et al., 2012). The usefulness of the haptic feedback in human-robot team interaction has been also confirmed in Nunnally, Walker, Lewis, Chakraborty, and Sycara (2013). Analoguously to the supervisory role, the feedback of continuously changing states should be provided to the human in dynamical form. This conclusion has been made through experimental validation for the control of multiple UAVs in Donmez, Cummings, and Graham (2009) and Donmez, Graham, and Cummings (2008). In Alder, McDonald, Colton, and Goodrich (2015) the authors investigate haptic human-robot team interaction with variable formation. The haptic signal informs the human when the swarm is stretched, compressed or reshaped. Relative behavior of the individual robots in the team is a useful feedback information if robots establish multiple contacts with the environment, e.g. in cooperative manipulation tasks. It is shown that wearable haptic devices provide a suitable feedback interface technology in this case (Musić et al., 2017).

Note though that due to complexity of human-robot team interaction, it is no longer sufficient to provide only the feedback about the system states. It is necessary to represent activity of the automation as well (e.g. the change of the autonomy level) and sensitivity to future activities (e.g. warnings) (Woods, Tittle, Feil, & Roesler, 2004). The activity of automation of multiple UAVs is examined as a function of interfaces in Squire, Trafton, and Parasuraman (2006). The authors show that the interfaces which allow the human to select between different autonomy levels reduce switching costs.

In summary, the existing literature provides many individual studies on suitable interface design for specific examples of human-robot team interaction. However, a systematic control theoretical understanding of the closed-loop system performance and limitations given the properties of the command and feedback interfaces is still missing.

4. Shared control for human-robot teams

In human-robot team interaction, the responsibilities over the task execution are shared, which is accomplished by so-called *shared control* approaches. In this section, existing shared control concepts are reviewed. Control approaches from the broader area of human-robot interaction are also included in the discussion if they are deemed suitable for human-robot team interaction.

In Coppin and Legras (2012) the authors distinguish between *control by behavior*, where the human interacts with each robot in the team individually, and *control by policy*, where the human interacts with the complete robot team. In the context of the hierarchical team control concept in Fig. 3, control by behavior refers to the control of local behaviors by the human. In contrast, control by policy is interpreted as the control of global behaviors by the human and the autonomous execution of local behaviors. The comparison of these control approaches shows, that the limited interaction intervals in the case of control by behavior can cause inefficient interaction and, in worst case, failures (Goodrich, McLain, Anderson, Sun, & Crandall, 2007). The interaction of the human with individual robots limits the number of robots within the team as it imposes workload and time-related stress on the human operator (Mau & Dolan, 2007; Wang & Lewis, 2007). As an alternative the human interacts only through a single *leader* robot with the team reducing the human workload considerably (Setter et al., 2015). In this case the human is required to have a very good understanding of the autonomous team behavior in order to efficiently perform tasks. In general, for a large number of agents the control by policy appears more suitable (Goodrich et al., 2007).

The control by policy approach enables the human to operate on *higher levels of abstraction* (Crandall, Goodrich, Olsen, & Nielsen, 2005). They are termed as *attractors* in Brown, Kerman, and Goodrich (2014). They represent states of the collective team dynamics (or their subset). Attractors can be interpreted as *projections* of robots' states onto a lower-dimensional state space or as an abstraction from the individual to the collective behavior. They correspond to the introduced concept of global behaviors in Section 2.1.2. Brown, Kerman et al. (2014) additionally impose the stability on the global behaviors. This is an important requirement for the shared control design since the human does not need to stabilize the system. Furthermore, the control design on the level of global behaviors is easier in terms of dimensionality (Kolling, Walker, Chakraborty, Sycara, & Lewis, 2016). However, the human is a point of failure of such a system (Brown, Kerman et al., 2014). One solution to this problem is the interaction with a subset of robots in the team (Hatanaka et al., 2015).

4.1. Shared control for different interaction paradigms

In this subsection control approaches for human-robot team interaction are reviewed. So far, human-robot team interaction is often considered to be remote and most of the literature addresses shared control design for teleoperation scenarios. In the following, we review selected approaches for the complementary interaction paradigm and for overlapping interaction paradigm, see also Section 3.1.2.

4.1.1. Control for the complementary interaction paradigm

As discussed before, the human control of global behaviors is particularly promising for human-robot team interaction. In Sieber et al. (2015) the robot team is in charge of coordinating autonomously. Additionally, the robots within the team may perform the local subtask of collision avoidance, see e.g. Franchi et al. (2012) and Rodríguez-Seda et al. (2010). However, the authors do not consider that the desired commands for different behaviors may be in conflict. This causes unpredictable behaviors of the robot team. Such situations can be resolved by decoupling the dynamics of the overall robot team into the dynamics for the required behaviors. This is achieved by ensuring that the autonomous task is uncontrollable to the human, see e.g. Sieber et al. (2015) and Musić and Hirche (2016).

Since a robot team is inherently redundant, it can perform multiple subtasks simultaneously. In order to avoid conflicts of control inputs, a *null-space based behavioral control*, introduced in Section 2.1 can be applied to define, decouple and prioritize multiple subtasks. Using a double-integrator model of the robots within the team, Lin, Khong, and Liu (2015) assign the responsibility over a set of global behaviors of the team to the human operator. Those are termed as *teleoperated tasks* and include commanding the robot team mean pose and its variance

$$\begin{aligned} \boldsymbol{f}_m(\boldsymbol{x}) &= \frac{1}{N}\Sigma_{i=1}^{N}\boldsymbol{x}_i, \\ \boldsymbol{f}_v(\boldsymbol{x}) &= \frac{1}{N}\Sigma_{i=1}^{N}(\boldsymbol{x}_i - \boldsymbol{f}_m^2(\boldsymbol{x})), \end{aligned} \tag{15}$$

where $\boldsymbol{x}_i \in \mathbb{R}^n$ is the vector of generalized coordinates of the robot i, $\boldsymbol{f}_m(\boldsymbol{x})$ is the mean pose of the robot team, and $\boldsymbol{f}_v(\boldsymbol{x})$ its variance.

The subtasks performed by the robot team are dispersion, avoidance of obstacles and of other members of the team. Within the subtask layer, desired control inputs for the low-level controllers within the action layer are computed according to

$$\dot{\boldsymbol{x}}^d = \boldsymbol{J}_{s,t}^{+}\dot{\boldsymbol{x}}_{s,t} + \left(\boldsymbol{I}_{nN} - \boldsymbol{J}_{s,t}^{+}\boldsymbol{J}_{s,t}\right)\boldsymbol{\psi}_{s,a}, \tag{16}$$

where $\boldsymbol{J}_{s,t}$ is the partial derivative of one of the teleoperated subtasks, while $\boldsymbol{\psi}_{s,a}$ is the sum of partial derivatives of the autonomous subtasks. In this way it is ensured that the teleoperated and autonomous subtasks do not interfere if there are sufficient degrees of freedom. If they interfere, the teleoperated subtasks are of a higher priority over the autonomous subtasks. The priority is fixed which might not be suitable in the case of unpredictable events.

The intentional interaction and/or collision of the robotic team with the environment is not treated extensively in the literature. However, cooperative manipulation by the robot team in teleoperation scenarios provides some insights into the appropriate control approaches. In Lee and Spong (2005) energetic passivity is enforced via passivity-based control. Therefore, passivity of the overall system when interacting with a passive environment, and therefore stability, is guaranteed. Another approach uses impedance control to ensure passivity in interaction with environment, see e.g. Angerer, Musić, and Hirche (2017) and Musić et al. (2017). The block structure of the control loop for the example of human guided cooperative manipulation is depicted in Fig. 5.

The reviewed approaches are suitable for the active human role. In the supervisory role, the human typically behaves as a switch. There are also approaches in which the human performs both roles. For example, in Franchi et al. (2012) the human selects the mode of interaction while the team of UAVs autonomously controls its variable topology. The choice can be made between global intervention (steering the centroid of the formation to the goal) or local

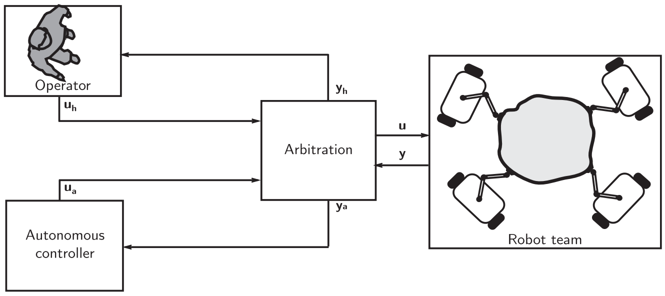

Fig. 5. Block scheme of the control loop for the human-robot team interaction in a cooperative manipulation task.

intervention (steering a single UAV). In Hatanaka et al. (2015) the human switches manually between two controllers: the control of the robot team position and the control of the robot team velocity, and provides the input commands to the chosen controller.

The drawback of the reviewed approaches is that the subtask distribution is constant during the task execution and the level of the robot team autonomy is fixed. This is problematic as it reduces the flexibility of the interaction. Furthermore, if multiple subtasks need to be executed, their prioritization is of fixed order. It would be beneficial to be able to dynamically change the priorities of the subtasks according to the stage of the task execution and to allocate the responsibilities of the subtasks online.

With increasing robot autonomy, the performance of the robot team does not necessarily improve with a persistent human command given the robot team knows the goal. Still, in open-ended missions (Chen & Barnes, 2014) control approaches that allow the human to be part of the control loop when necessary and to leave the loop when desired, appear very promising in long-term.

4.1.2. *Control for the overlapping interaction paradigm*

So far, we reviewed human-robot team interaction in which robot team autonomy complements human capabilities. Here we focus on shared control concepts, where the human and the robot team jointly perform a common task. Approaches where the human may interfere with the autonomous control command, are termed as *mixed-initiative*. This type of control approaches belongs to the overlapping interaction paradigm. The obtained control commands are a synthesis of the human command input and the input from an autonomous function.

Another example for control sharing within the overlapping interaction paradigm is provided in Chipalkatty et al. (2013). A model predictive control (MPC) scheme is employed to establish a mixed-initiative control of the helicopter robot team, partially teleoperated by the human operator. The autonomous controller has a built-in planner, i.e. the robot team is capable to reach a target autonomously. The human can inject input for the overall robot team behavior and, in this way, interfere with the input from the autonomous controller. The coordination between the robots within the team is handled autonomously. The stability of the global behavior commanded by the human operator is not guaranteed though. Instead, it is assumed that the human is capable of stabilizing the corresponding states. Other control sharing approaches within the overlapping interaction paradigm can be found in the broader area of human-robot interaction. Typically, they are obtained by blending human control inputs and autonomous control inputs. In the remainder we review blending approaches that appear also suitable for human-robot team interaction.

Blending mechanisms: Let us denote the human control input as $\boldsymbol{u}_h(t)$ and the autonomy control input as $\boldsymbol{u}_a(t)$. Their blending is often considered linear

$$\boldsymbol{u}(t) = \boldsymbol{K}_h \boldsymbol{u}_h(t) + \boldsymbol{K}_a \boldsymbol{u}_a(t), \quad \boldsymbol{K}_h + \boldsymbol{K}_a = \boldsymbol{I}, \tag{17}$$

where $\boldsymbol{u}(t)$ is the resulting control command, $\boldsymbol{K}_h$ and $\boldsymbol{K}_a$ are *arbitration* matrices, and $\boldsymbol{I}$ is the identity matrix. In general, $\boldsymbol{K}_a$ quantifies the level of autonomy of the robot team. There are many ways in which arbitration matrices can be selected. A simple approach is to assign fixed and constant values to the matrices (Evrard & Kheddar, 2009). In Trautman (2015) shared control is defined as a joint optimization between agreeability, safety, and efficiency of the interaction. A probabilistic shared control is proposed and linear blending is derived as a special case. It is further shown, that linear blending can generate unsafe sharing with safe human and safe autonomous input. Concretely, the shared control input is determined as (Trautman (2015))

$$\begin{aligned} &\boldsymbol{u}(t) = \boldsymbol{f}^{R*} \\ &\left(\boldsymbol{h}, \boldsymbol{f}^R, \boldsymbol{f}\right)^* = \underset{\boldsymbol{h}, \boldsymbol{f}^R, \boldsymbol{f}}{\operatorname{argmax}}\ p\left(\boldsymbol{h}, \boldsymbol{f}^R, \boldsymbol{f} \middle| \boldsymbol{z}^h_{1:t}, \boldsymbol{z}^R_{1:t}, \boldsymbol{z}^f_{1:t}\right), \end{aligned} \tag{18}$$

where $\boldsymbol{h}, \boldsymbol{f}^R, \boldsymbol{f}$ are human, robot, and dynamic obstacle trajectories, and $\boldsymbol{z}^h_{1:t}, \boldsymbol{z}^R_{1:t}, \boldsymbol{z}^f_{1:t}$ their corresponding measurements. The probability $p(\boldsymbol{h}, \boldsymbol{f}^R, \boldsymbol{f}|\boldsymbol{z}_{1:t})$ is determined as

$$p\left(\boldsymbol{h}, \boldsymbol{f}^R, \boldsymbol{f}|\boldsymbol{z}_{1:t}\right) = \psi\left(\boldsymbol{h}, \boldsymbol{f}^R\right) p\left(\boldsymbol{h}\middle|\boldsymbol{z}^h_{1:t}\right) p\left(\boldsymbol{f}^R, \boldsymbol{f}|\bar{\boldsymbol{z}}_{1:t}\right), \tag{19}$$

where $\psi(\boldsymbol{h}, \boldsymbol{f}^R) = \exp(-\frac{1}{2\kappa}(\boldsymbol{h} - \boldsymbol{f}^R)(\boldsymbol{h} - \boldsymbol{f}^R)^T)$ is the interaction function between the human and the robot with the coupling factor κ,$p(\boldsymbol{h}|\boldsymbol{z}^h_{1:t})$ the human behavior prediction function, and $p(\boldsymbol{f}^R, \boldsymbol{f}|\bar{\boldsymbol{z}}_{1:t})$ the dynamical prediction of the autonomy.

The arbitration of the human input and the robot team input can also be achieved using *game-theoretical* approaches, see e.g. Li et al. (2015). Recently, the arbitration based on the estimation of human trust and self-confidence has been validated. In Saeidi et al. (2016) a mixed-initiative bilateral teleoperation is proposed for the control of a single mobile robot. It uses trust models to scale the manual and the autonomous control inputs with a human-to-robot trust and to scale feedback with a robot-to-human trust. A passivity-based controller successfully manages the time-varying scales and communication time delays.

The arbitration can also be applied on the parameters of the low-level controller of the action layer. For example, in order to obtain safe and intuitive assistance, an approach to the allocation of control authority is achieved using a human-inspired decision-making model (10). Geravand, Werner, Hauer, and Peer (2016) treat the problem of shared control of a mobile assistive robot (MAR) by solving simultaneously three low level sub-tasks: follow a path, avoid collisions and mitigate human fatigue. For each subtask a drift-diffusion decision-making model is used for gain scheduling of the low-level control parameters of an admittance or impedance controller

$$c(t) = p_A(t+1)\underline{c} + (1 - p_A(t+1))\bar{c}, \tag{20}$$

where $\bar{c}$ and $\bar{c}$ represent the upper and lower bounds of the control parameter c. However, the authors disregard the problem of subtask conflicts. A similar approach is used in Corredor, Sofrony, and Peer (2016) for a single task and bilateral teleoperation scenario. Experimental results show that the employment of human decision-making models is promising for intuitive mixed-initiative interaction.

In mixed-initiative shared control, the modeling of the human is important, since it is necessary to determine the most appropriate autonomous control input based on the human behavior to accomplish a satisfactory assistance. In Dragan and Srinivasa (2013) the authors propose the linear arbitration with constant selection matrices, and with the autonomous control input that is based on the prediction of the human intent. This approach adapts to the robot confidence in itself, to the user confidence, and the user type. Furthermore, the authors argue that the learning process of the human can be facilitated by *task legibility*

Table 3
An overview of surveyed literature for control sharing in human-robot team interaction.

Topic	References
Supervisory role and human-on-the-loop	Cummings et al. (2012), Gao and Lee (2006), Chen et al. (2011), Peters et al. (2015), Ruff, Narayanan, and Draper (2002), Mau and Dolan (2007)
Active role and human-in-the-loop	Lee and Spong (2005), Malysz and Sirouspour (2011), Franchi et al. (2012), Sirouspour (2005) Hatanaka et al. (2015), Saeidi et al. (2016), Son et al. (2013), Lee et al. (2013), Chen and Barnes (2014), Lin et al. (2015), Liu (2015), Rodríguez-Seda et al. (2010), Sieber et al. (2015), Lee (2008), Lee (2010), Franchi, Giordano, Secchi, Son, and Bülthoff (2011), Corredor et al. (2016)
Human modeling (Section 2.2)	Chen et al. (2011), Goodrich et al. (2005) Endsley (1995), Lee and See (2004), Crandall et al. (2011), Cummings et al. (2012), Gao, Clare, Macbeth, and Cummings (2013), Gao and Lee (2006), Roe, Busemeyer, and Townsend (2001), Stewart et al. (2012), Onnasch et al. (2014), Peters et al. (2015), Hatanaka et al. (2015), Cao, Stewart, and Leonard (2008), Bruemmer et al. (2005), Schuster et al. (2011), Sycara et al. (2015)
Robot team control (Section 2.1)	Shim, Kim, and Sastry (2003), Murray (2007), Gazi and Fidan (2007), Sugar and Kumar (2002), Desai et al. (2001),Jin et al. (2003), McDowell, Chen, and Bourgeois (2002), Dunbar and Murray (2006), Michael, Zavlanos, Kumar, and Pappas (2008), Leonard and Fiorelli (2001), Swaroop and Hedrick (1996), Olfati-Saber and Murray (2004)
Robot team surveys (Section 2.1)	Murray (2007), Farinelli et al. (2004), Dudek et al. (2002), Cao, Fukunaga, and Kahng (1997), Gazi and Fidan (2007), Arai, Pagello, and Parker (2002)
Interaction paradigms (Section 3.1)	Sheridan and Verplank (1978), Onnasch et al. (2014), Parasuraman et al. (2000), Ruff et al. (2002), Baker and Yanco (2004), Desai and Yanco (2005), Beer, Fisk, and Rogers (2014), Coppin and Legras (2012), Walker, Nunnally, Lewis, Chakraborty, and Sycara (2013), Musić and Hirche (2016), Squire et al. (2006) Woods et al. (2004) Feth, Tran, Groten, Peer, and Buss (2009)
Interfaces (Section 3.2)	Chen et al. (2011), Goodrich et al. (2005), Bruemmer et al. (2005), Diana et al. (2013), Alder et al. (2015), Alonso-Mora et al. (2015), Donmez et al. (2008), Donmez et al. (2009), Griffin, Provancher, and Cutkosky (2005), Nunnally et al. (2013), Son et al. (2013), Setter et al. (2015), Squire et al. (2006), Nevatia et al. (2008), Boessenkool, Abbink, Heemskerk, van der Helm, and Wildenbeest (2013)
Adjustable control (Section 4)	Franchi et al. (2012), Chiou et al. (2016), Hatanaka et al. (2015) Miller, Funk, Goldman, Meisner, and Wu (2005)
Mixed-initiative control (Section 4)	Marble, Bruemmer, and Few (2003), Hardin and Goodrich (2009), Baker and Yanco (2004), Brown, Jung, and Goodrich (2014), Saeidi et al. (2016), Geravand et al. (2016), Chipalkatty et al. (2013), Wang and Lewis (2007), Roth, Hanson, Hopkins, Mancuso, and Zacharias (2004), Bruemmer et al. (2005), Kortenkamp et al. (1997), Corredor et al. (2016), Li et al. (2015), Dragan and Srinivasa (2013), Trautman (2015), Loizou and Kumar (2007) Brookshire, Singh, and Simmons (2004)

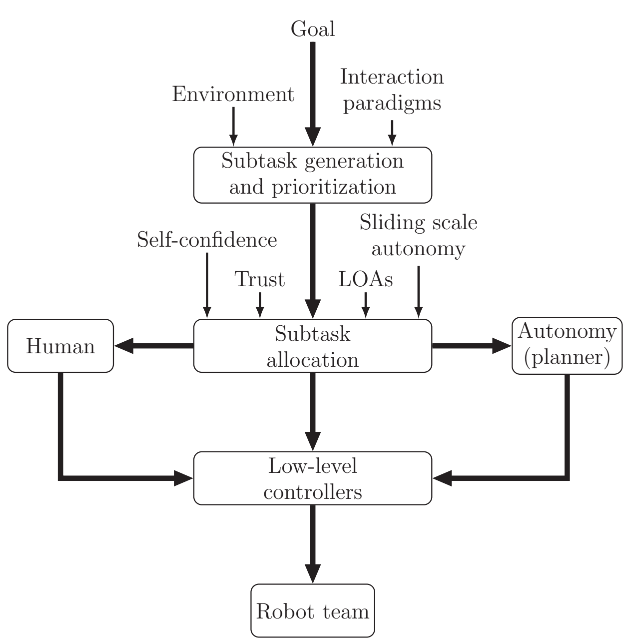

Fig. 6. Block structure of the general hierarchical shared control architecture for human-robot team interaction. Based on a desired *goal* of the interaction and the *environment state* subtasks are generated and prioritized. Allocation of subtasks to the human and the robot team is dynamical and determined depending on the available *levels of autonomy*, current *self-confidence* of the human and its *trust in automation*. Low-level controllers receive desired control inputs either from human or from the built-in robot team planners.

which refers to the robot capability to convey an intent to the human (Dragan, Lee, & Srinivasa, 2013).

We can conclude that tasks should be decomposed into multiple subtasks represented by stable global and local behaviors. Furthermore, these subtasks should be prioritized according to the current state of the environment, decoupled to avoid interference, and preferably allocated dynamically to the human and/or the autonomous controller of the robot team as depicted in Fig. 6.

The dynamical distribution of subtasks among the human and the robot team is termed as *trading control* (Hayati & Venkataraman, 1989; Kortenkamp, Bonasso, Ryan, & Schreckenghost, 1997). To the best of the authors knowledge, this has not been investigated so far for human-robot team interaction.

5. Conclusion

In this survey we have reviewed key concepts and selected approaches for control sharing in human-robot team interaction. Important aspects concern the modeling of human behavior and the robot team, the interface, interaction and shared control. The following conclusions are derived based on the reviewed literature:

- With the increase of autonomous capabilities of robots, the role of the human in the interaction is not reduced. On the contrary, the human gains more high-level responsibilities; the complexity of the interaction tasks increases. Therefore, it is important to consider the human in the control loop as a decision-making dynamical system.
- The autonomous capabilities of robot teams are suitably described by the autonomy spectrum, which includes levels of autonomy assigned to each subtask that the robot team can perform. Combinations of levels of autonomy define interaction paradigms between the human and the robot team including the human role. These paradigms represent the design aspects of the interaction and indicate shared control requirements.
- The interaction of the human with the robot team on subtask level by managing its global behaviors appears most promising for the current state of robot autonomy. The asymmetry in the interaction in terms of the low-dimensional human command channel vs. the high degree of freedom of the robot team, is implicitly addressed.
- Intuitive interfaces (including subtask decompositions) is a largely open research question and requires more research.
- Mixed-initiative shared control approaches enable both human and robot team to make decisions and can benefit from the human behavior modeling.
- Despite preliminary attempts, the systematic understanding of the interaction behavior under the different interaction

paradigms including performance and stability guarantees is a largely open research challenge. We believe that the control community may significantly contribute to this. Human behavior models will play a significant role here.

An overview of the reviewed literature is sorted in Table 3 with respect to the elements of the shared control loop and the taxonomy for human-robot team interaction.

6. Future work

The review of the available literature indicates the need to explicitly consider the decision-making dynamics of the human. There are a number of research challenges within the area of human-robot team interaction; we highlight some of them:

- Models of the human cognitive process are necessary within the control theoretical context. Therefore, decision-making dynamical models from cognitive psychology might provide a useful construct.
- Developing a control architecture which tunes the autonomous functions of the robot team based on the monitored workload and situational awareness can enable human and robots to function as a team. Therefore, mixed-initiative shared control is a promising control concept for further research.
- Another important aspect is how to effectively and appropriately choose suitable level of autonomy. A lot of potential lies in approaches that optimize level of autonomy with respect to the human confidence in performing certain task, i.e. by modeling trust in automation and human self-confidence.
- A major challenge is to design appropriate one-to-many mappings between the human and the robot team from the control theoretical perspective in order to be able to formally analyze interaction and closed-loop system properties.
- Robot teams as redundant systems can perform multiple subtasks simultaneously. A major challenge is to design, prioritize, and distribute the subtasks among the human and the robot team autonomy dynamically. This largely depends on the state of the environment and the available levels of autonomy.
- If multiple subtasks are considered, the control loop needs to handle multitasking situations from the human and control perspective. Therefore, incorporating multitasking decision-making models into control loop would be a challenging research goal.

Overall, sophisticated shared control strategies that rely on mixed-initiative interaction, multitasking capabilities, dynamical prioritization and distribution of subtasks will bring us closer to *intuitive and efficient* human-robot team interaction.

Acknowledgments

This research is partly supported by the ERC Starting Grant Control based on Human Models (con-humo) under grant agreement 337654 and by the European Union Seventh Framework Programme FP7/2007-2013 under grant agreement no. 601165 of the project “WEARHAP - Wearable Haptics for Humans and Robots”.

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