A Taxonomy for Characterizing Modes of Interactions in Goal-driven, Human-robot Teams

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***Abstract*— To rewrite!**

I. INTRODUCTION

This paper is motivated by the changing nature of co-operative and collaborative interactions in HRI. During the 1990s and early 2000s human and robots were teaming up with each other across several domains, namely under-sea operations [46, 55], automated manufacturing, and even docents in museums [50, 5]. These robots were either deployed in controlled environment or made for a closed set of functionality. However, true collaboration with elements of cognitive inter-dependency, physical-coupling, adaptivity and elevated levels of communication for more efficient interaction came into play in the later decade [49]. The field has made numerous attempts to categorize and characterize the research space of HRI as a field but the rapid evolution of technology and spreading ubiquitousness of robots in every application domains warrants another inspection at how interaction itself has evolved during this time.

The applicability of robots is extending beyond situations involving a single autonomous agent interacting with a single human to scenarios involving larger heterogeneous teams of multiple autonomous agents and humans working together [33, 25]. Additionally, interaction between humans and autonomous agents has transformed from simple tasks in controlled environments to more complex domains characterized by unmapped and dynamic environments [11, 7], novel and unmodeled tasks [21, 23, 8, 9, 22], and unstructured human and agent populations within teams [50, 5, 40, 44]. These domains require new informational abstractions and representations to support information sharing and collaborative decision-making.

We aim to understand how to characterize needs for information sharing and interaction within heterogeneous teams in complex scenarios and to highlight areas for further research. Specifically, we focus on interactions in a heterogeneous team, where human(s) and robot(s) are involved in a shared activity. The activity must have a shared task workflow or shared goal. That said, we do not include interactions which are solely afforded due to interfaces or concentrate only on coexistence in a social context. The differentiator here is the notion of pre-meditated "intention" over the human-robot interaction. As a first step, we systematically review taxonomies already proposed over HRI problems and create an upper ontology which highlights the relevant features as seen from different perspectives. Additionally, we aim to identify the factors which affect the different levels of information awareness in the interactants, and the basic dimensions which can be used to delineate these states. We want to use these insights to develop a quantifiable scale for awareness and investigate how can interaction help fill the relative information gap.

Outline of the paper.

II. Operational Contexts for Collaborative HRI of the Future

In this section we present brief overviews of the contextual setup and communication requirements of different operational contexts. The purpose of this is to highlight the variety of system-level variables as well as the specific challenges that mixed-team interaction designers needs to consider.

- **Urban search and rescue (USAR).** USAR is an especially difficult use case for the robot operator in terms of the cognitive load [7] as well as the risky environment conditions [23]. The interaction risk of this context is considered high as human lives are at stake. The environment is usually unmapped with difficult terrain [11]. Additionally since most of the robotic teams are not a pre-existing part of the disaster management sub-group, there is also a gap between perceived and actual *task-model* [11].
- **Interactive Learners and Museum Docents.** This sub-section includes two supervisor-follower cases at the polar ends of the *task-model* and *teammate-knowledge* dimension. In the former scenario the human is the expert and influences the robot [13, 21], while in the latter the robot is the expert influencing the museum experience of the human crowd [50, 5, 6]. A typical interactive learner scenario does not always require social skills, but on the other hand a docent deals with robot-novice crowds [6] and requires functional social skills. In terms of the *environment*, both of these contexts assume a priori knowledge of physical space and use execution models designed to handle partial observability as they interact with unmodeled teammates in a dynamic environment. An interactive learner scenario relies on demonstrations and corrections [23, 8], kinesthetic as well as verbal [51, 21]. A museum

docent on the other hand is endowed with much more natural means of communication [47, 4].

- **Military Building Breach Operation** One example of a domain that demonstrates complexity in all dimensions, *environment*, *task*, and *team*, is a military building breach operation. Such an operation involves a *heterogeneous* team of human soldiers, unmanned aerial vehicles, unmanned ground vehicles, and autonomous computer aids working together to navigate an urban environment and breach a building. The task is complex and multi-stage requiring different abilities and resources for different stages. Planning stage requires team to plan for safely scouting the area and accessing the building while avoiding enemy forces, a scouting stage in which the team checks if the area is clear of enemy forces, a troop movement stage in which the team approaches the building, and finally the building breach. The *environment* is largely unmapped and dynamic since enemy forces might be encountered, and the team hierarchy is fluid, allowing for changing of roles depending upon arising contingencies and abilities of the teammates.

In summary, some of the important dimensions that kept cropping up through our operational context analysis were: 1) risk-level 2) environment knowledge 3) knowledge of task-model, and 4) modeling of teammates.

III. An Overview of Existent Taxonomies in HRI

To present the reader with an orderly review of the taxonomies, we have categorized them under the following major categories:

- **Human-Animal Analogy.** A quick review of how behavioral scientists categorize cooperative human-animal relationships and its effects on the HRI community.
- **Contextual taxonomies.** Here we focus on delineating the independent dimensions which are characteristic of a task and environmental configuration in an HRI problem.
- **Social Taxonomies.** This category consists of taxonomies identifying the social skills that an agent needs to afford for interacting with a human.
- **Information: Function and Types.** An outline of surveys from HRI as well as behavioral sciences describing various models used for generating the content of an interaction.

A. Human-Animal Analogy

Naderi et al. [38] identify three main features to describe co-operative interactions between guide-dog and human pairings: *action congruity*, *execution synchrony* and their *spatial relationship*. Similarly, Topál, Miklósi, and Csányi [51] looked at dogs' behavior in a problem-solving setting. They observed that pets who were considered to be work-dogs engaged more with the task, while dogs considered family-members were dependent on the owners to initiate the problem solving. This seems to suggest that the expertise of a dog and/or the perceived role by owner affected the way the interactions are shaped.

The HRI community has also studied these interactions to develop guidelines [43] and descriptive categorizations for future human-robot team-tasks [42]. [43] looks at a simple scale of categorizing whether human-animal teams employ the animal in a more "tool-like" or more of a team-mate context by assessing interactions over task interdependence and amount of communication. [42] refines this scale further by breaking task interdependence into: *pooled*, i.e. parallel, *sequential* or *reciprocal*, i.e. dialog-like modes; whereas communication is characterized by *directionality* and the *modality* of information. They also provide a scale for characterizing which type of cooperative or collaborative activity the team is performing. The scale ranks each activity as an extension, augmentation or replacement of physical, emotional or cognitive ability of the human. The relevant dimensions found from this space are summarized in figure 1.

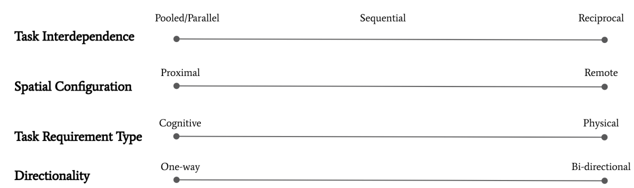

Fig. 1. Relevant dimensions used to characterize interactions in human-animal collaboration

B. Contextual Taxonomies

Beer et al. [3] have conducted a work addressing similar concerns as us, but at a more fine-grain level of how prototypical classes of tasks affect human-robot interaction. Firstly, they divide up the context into three main dimensions: *task focus*, *constraints* and *team capabilities*. Next, they perform a clustering over the kinds of missions undertaken in collaborative HRI problems and come up with six main focus types for multi-robot tasks as expanded in section V. Similarly, they cite *environment*, *communication* and *mission requirements* as the main indicators of constraints. Yanco and Drury [58, 57] provide an exhaustive meta-survey identifying all the domain-independent, dominant axes which could be important to an interaction as per the community. Important factors like *criticality* of the task, *roles* of the human [45], and *autonomy level* are identified. One of their valuable contributions is in defining the different grouping combinations possible for mixed human-robot teams focusing on whether command consensus in multi-agent teams is centralized or decentralized. This grouping instantiates the more general workflows of parallel, sequential and reciprocal as defined in [38].

If the task and environmental makeup constitute the problem-context specification of an HRI instance, then the collective configuration should count as the solution-context specification. A *collective* here means a heterogeneous team of humans and robots, where the team hierarchy could be flat or not, and the robotic agents can also be heterogeneous in capabilities. Balch in [1] presents a taxonomy for categorizing a collective into different bins with an eye for reward-based learning by scrutinizing how does the motion-plan and the task-execution affect reward-input. Dudek, Jenkin, and Milios [17, 16] and Cao, Fukunaga, and Kahng [10] present a more exhaustive (and neutral) taxonomy over collective design motivations and configurations respectively. Together they highlight two important high-level dimensions of *communication constraints*, and *group architecture*. Communication constraints are characterized by bandwidth, range, and hardware among others. Group or collective architecture is an umbrella term for specifications like size of the collective, composition, i.e. level of heterogeneity, reactive versus deliberative processing models, communication protocols, and modeling methods for other agents.

Beer, Fisk, and Rogers [2] provide an exhaustive overview of the automation taxonomies produced by the computing community, dating back to the human-machine interaction days [46, 18]. They impose a deliberative definition over the concept of autonomy: "The extent to which a robot can *sense* its environment, *plan* based on that environment, and *act* upon that environment with the intent of reaching some task-specific goal (either given to or created by the robot) without external control." This results in the delineation of 10 different autonomy modes (table **??**) with human and the agent *sharing or solo-owning responsibilities* for different parts of the sense-plan-act [37] cycle. The basis for autonomy-selection lies on three main aspects: task criticality, task accountability and environmental complexity. Jiang and Arkin [32] view the autonomy topic as a problem about when and how to seize and relinquish initiative in a heterogeneous team. They identify factors like *goal-set-overlap*, mode of seizing/relinquishing of the initiative (reactive/deliberative/hybrid) and whether the trading of initiatives is opportunistic or handed-off in a cooperative way. This results in a descriptive taxonomy of literature highlighting the techniques which support the required modes and trade-off philosophies.

Gerkey and Matarić [26] present a taxonomy for task-allocation based on the context of task type, robot capability and allocation method. Korsah, Stentz, and Dias [35] update this taxonomy to include task decomposition complexities and inter-task dependencies. While not directly conceptualized with an interaction lens, the concept of inter-task dependency relates back to the concept of responsibility sharing in [2], goal-set-overlap in [32] and group dependencies from [42].

C. Social Taxonomies

One of the most important factors shaping human-robot interaction, which we have implicitly mentioned multiple times, is the role of the human. Scholtz [45] used Norman's seven-stage model of interaction design [39] to reflect on the failure/assistance required by the intermediate layers of intention, action and perception in the agent, figure **??**. This lead to formulation of the 5 archetypal roles humans can play while interacting with the robot. Interestingly, Norman used his model for conceptualizing human-centric designs, however [45] flips the model to come up with a robot-centric view of usefulness of human knowledge such that the human-robot system is usable. It warrants mention that since robotic technology is increasingly ubiquitous in the human-occupied world, there is a space for conception of additional collaborative human-robot roles. This role-call was last updated in 2007 [28] with the addition of two new entries(*), one of which is specifically robot-centric: 1) Supervisor, 2) Operator, 3) Mechanic, 4) Peer, 5) Bystander, 6) Mentor* (robot-centric role), and 7) Information Consumer*

Most of the taxonomies in this category focus on robots for which interaction plays a key role [24]. This is important to consider, as the taxonomies seen in contextual and computational sections take more of an interaction-for-command view. Fong, Nourbakhsh, and Dautenhahn [24] discuss the various functional designs that support the interactive requirements of social robots. They also present a taxonomy identifying the basic components of a robotic system which affect human-robot social interactions: embodiment, emotion, dialog, personality, human-oriented perception, user modeling, socially situated learning, and intentionality. Feil-Seifer and Mataric [20] extend this taxonomy to include domain-dependent user context, type of task (tutoring, daily life assistance, etc.), role of the robot and sophistication of interaction.

Dautenhahn [14] steps back and takes a holistic look at the human-robot interaction field, and asks the question that in order to make robots more useful what value does development of social skills for robots hold? They use 4 major axes for evaluating HRI application areas, namely: contact with humans, robot functionalities, role of the robot, and necessity for social skills. They present two different user studies and describe the two major paradigms emerging in the socially assistive landscape - humans as caretaker [34] and robot as companion [15]. The assistant paradigm is the one more relevant to our definition of interaction in this paper, and [14] highlights that this is more of a peer-to-peer than a supervisor-subordinate relationship. They echo the need for user-based adaptation, and social skills as a necessity.

D. Information: Function and Types

We must first analyze the question of *what* is the role of this information and *why* must it be disseminated at all? Endsley [19] provides a framework defining the concept of "situational awareness" grounded in the processing mechanisms, design and knowledge of a dynamic system. It is recognized for the delineation of information into three progressively complex levels of situational awareness (SA). Chen et al. [12] ground this model into mission description of a multi-agent interactive task and incorporate information at different levels of plan abstraction for elevated transparency between a robotic agent and the operator. The following describes this Situation Awareness-Based Agent Transparency (SAT) model with the italicized phrasing describing the level of SA as defined by Endsley.

- **Level 1.** *Perception of elements in the environment.* - Current goal, short-term plan, agent status and state.
- **Level 2.** *Comprehension of the current situation.* - [7] adds another dimension of subjectivity to this level asserting that comprehension can be of two kinds namely, identification and interpretation with respect to the current situation. [12] ascribes all processes illuminating agent reasoning methods and relevant constraints from environmental and other agents' state to this level.
- **Level 3.** *Projection of future states* - Projection of finish-time, cost, uncertainities, etc. towards future states and goal status.

While classifying modalities is not a part of the scope for current paper, we want to highlight that for successful interaction the right type of information needs to be supported by the right way of exchanging information. Goodrich and Schultz [28] split up the way information is exchanged into two components. "the communication medium and the format of the communication". They enlist the following as the major communication formats in HRI:

- Visual Displays
- Gestures - Including hand and arm movements, as well as facial indicators
- Speech and natural language
- Non-verbal signalling
- Physical interactions and haptics

IV. Analysis

Roles have been given an important place in HRI literature due to the quantity of information each label conveys. Each human-robot relationship has a different knowledge-gap with respect to task expertise, environment expertise, and knowledge of agent's form and function. In collaborative activities, the aim is to use the a priori knowledge about agent to convey the required information about task and environment such that expertise of each role can be leveraged in the right context. Each label represents different prior experience, and therefore different informational requirements during execution.

Therefore, we carve out an additional category of **a priori situational awareness** which helps us to describe the prior experiences of the role taken on by the human or the agent. This is motivated by the SA coding scheme in [7] which includes the preexisting environmental knowledge and knowledge about the task plan and strategy for describing the content of the in-team interactions. This category consists of sub-categories relating to preexisting knowledge about the:

- Task
- Environment
- Other Interactant

The last axis is agent/human because one of the roles is actually robot-centric, i.e. the "Mentor" which is uniquely applicable to the application area of museum docents, guides and tutors.

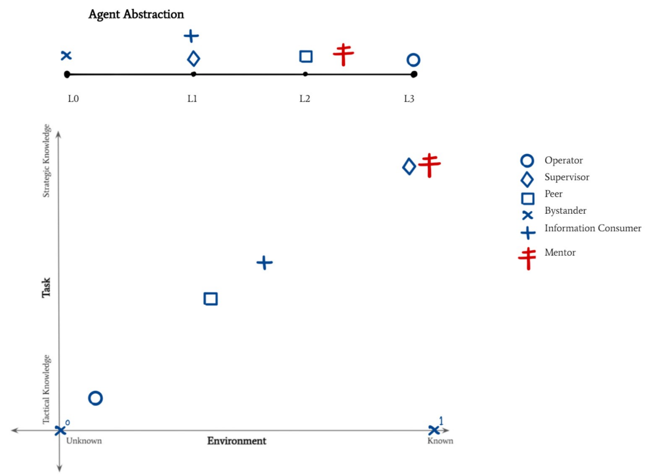

Fig. 2. Roles sorted on the dimensions of a priori knowledge of: (a) Agent abstraction, (b) Task and (c) Environment

A. Quantifying A priori Situational Awareness

The three categories proposed in the previous section have different functions. Task and environment subcategories denote the expected expertise of a role in these aspects. However, the *other interactant* subcategory denotes the knowledge both interactants have about others behavior and reasoning model. This operates as a primary guideline for the question, which level of information should I exchange? In order to make these relations more tangible, we first ascribe levels to these subcategories grounded in the contextual factors identified.

- *Task axis* – A scale from tactical knowledge to strategic. Tactical knowledge here means the knowledge of next milestone in the plan which helps with immediate action and strategic knowledge denotes understanding the goals, constraints and priorities of the mission which helps in better long-term planning.
- *Environment Axis* – A scale from knowing the exact environment to having past experience with the environmental context and finally to being immersed in a novel context.

Next we want to quantize the levels of abstractions of a human or autonomous agent which can be expected to be understood by different roles:

- L3 - Internal – Knowledge of how the physical behaviors, interactions and commands affect the internal state and vice versa
- L2 - Physical – Knowledge of how the physical behaviors and reasoning manifests to fulfill functionality
- L1 - Functional – Knowledge of the physical and reasoning capabilities and limitations of the system
- L0 - None – The only knowledge is conditioned on the form of the robot

B. Informational Role Profiling

Figure 2 summarizes this distinction between roles based on the dimensions of a priori SA in task, environment and level of abstraction of robot.

V. An Overarching Taxonomic Characterization of HRI Problems

If we did a principle component analysis over the dimensions presented across various taxonomies in the last section, we can divide the dimensions into three primary classes with four underlying *traits*. We identified dimensions related to *task*, *team* (which includes users in a one-on-one system), and *environment* as major discriminators for contextualizing the analysis. At one level deeper, this context is then used to identify *type or function* of the interaction, *constraints* over system and interaction, and *observability* and a priori *modeling* of the entities. Additionally, some of the taxonomies have analyzed interactions via lens of higher-level complex phenomena like levels of robot autonomy, task or goal inter-dependency, planning philosophy, composition of team, team roles, the spatial relationship between agents, and social protocols. We include these concepts as dimensions in their own right and introduce an informed breakdown for each as gleaned from the various papers surveyed in the preceding section. This section will categorize these aspects to the three overarching contextual categories and analyze how they affect the identified traits of an interaction. Finally, we add guidelines how these traits affect the quality and abstraction of information that is to be shared between the agents.

A. CONTEXT

Variables that fall under the context category function as independent variables for a given situation. They are the factors inherent to the task, environment, and team that are taken as inputs to the problem.

1) **MODELING.** The modeling aspect of task, environment, and team context describes what information about each of the three is available to the team a priori, before task execution. The modeling of relevant features available before the task is executed drives interaction in that it determines what information will need to be sensed, communicated, or inferred online in order for the team to have the full information necessary for task execution. It should be noted that every team member does not need all state information in most cases, and as will be discussed in the section regarding dynamics, roles assumed by each teammate and task allocation contribute to defining which state information is relevant to the task at hand for each team member. For each of task, environment, and team, we categorize modeling along a spectrum of partial to full availability of relevant state information a priori.

   a) *Task.* Modeling of the task refers to what is known about the task a priori, or the task specification. The two sub-categorizations then correspond to situations in which a full or a partial task specification is provided. In much of the literature on interaction in human-agent teams, the full task specification is known [add citations here]. However, in some cases, some aspects of the task specification may not be provided outright, such as constraints or the objective function. This is particularly the case when constraints or objective functions are complex and difficult to specify [literature here or in the observation section?].

   b) *Environment.* We split environment modeling into two primary categories: semantic (structure) and physical (mapping). Whether a partial or full model of the environment is available is determined only over state variables in the environment that are relevant to task execution and interaction.

      i) *Structure* This property encapsulates whether the operational environment has a known underlying semantic structure or if it is largely unknown. We assign it three tiers of values: A) *Structured*, e.g. an industrial workplace, B) *Partially structured*, e.g. an office setting and C) *Unstructured*, e.g. domestic setting or USAR scenario.

      ii) *Mapping* Mapping captures whether physical mapping of the environment in which the task will be executed is available before execution time. There are three categories of mapping: A) *Mapped* in which a full map of the environment is available. B) *Partially Mapped* in which some information is available, but the rest will need to be learned as the environment is encountered, and finally C) *Unmapped* in which no information about the environment is available a priori.

   c) *Team.* also look at [10] "Modeling of other agents". Team modeling describes what a priori information each teammate has about other teammates that they interact with during task execution. This could include, for instance, a policy that a teammate is using to decide on actions to take. We split team modeling into two categories: partial and full model. Partial or full modeling can be defined over interaction with another individual or over the whole team. For example, before execution, a teammate might have partial or full information about factors influencing another individuals behavior and also might have partial or full information about team behavior overall.

2) **OBSERVABILITY.** As compared to task modeling which demonstrates where a priori gaps in knowledge of task, environment, or team exist and what information would ideally be acquired through interaction during task execution, observability considers what information is possible to sense, communicate, or infer during task execution and consequently which gaps are possible to close. Similar to modeling, observability is categorized along a spectrum of partial to full observability for task, environment, and team.

   a) *Task.* Partial and full task observability describe which unknown aspects of a task specification can be observed online during task execution. Unknown aspects of task specifications might include constraints or objectives of the task that might inform how teammates approach a task and share information. In some circumstances, certain unknown aspects of task specification may be unobservable in that they are too difficult to specify in a useful and intelligible way. For instance, Gombolay et al. [27] explain that domain experts often have difficulty describing their decision-making processes, causing the codification of the relevant objectives in these problems to be difficult. Instead of aiming to observe objectives directly, they capture domain expert heuristics to guide task execution. In such cases, proxies such as policies can be used, but the direct objective function is effectively unobservable.

b) *Environment.* Partial and full observability of the environment describe whether some or all states relevant to task execution in the environment can be observed by teammates performing a task. Task planning and execution with both partial and full observability of the environment are well-studied concepts in the literature [cite MDP, POMDP papers here].

c) *Team.* When considering observation in terms of the team and its individual members, we consider both observability of teammates and the dual of this concept, defined as the observation ability of the team. Observability of teammates parallels observability of task and environment and can be categorized as either partial or full observability. Partial observability of teammates arises when there are latent states impacting a teammate's actions that cannot be known directly [54].

   As with observability, observation ability of the team can either be partial or full, meaning the team can either observe all possibly accessible state information relevant to task execution in the environment or a subset of the available information given its sensing and reasoning capabilities. It should be noted that both observability of the team and observation ability of the team can be defined for interactions between one to two teammates or over the whole team.

3) **TYPE.** Each major class in the contextual ontology is ascribed a stereotypical set of properties which help encapsulate the expectations agents should have from a task, environment or team-formation. This also helps in typifying the complexity of the context that the agents are situated in such that system designers can localize the challenges to be prioritized.

   a) *Task.* This category explicitly borrows from the taxonomies introduced in [38, 3] for the kinds of missions/tasks that humans and robots participate in. This is divided into two levels as follows:

      i) *Level 1.* The top-level is divided into three categories: A) *Physical*, B) *Cognitive*, and C) *Social*. This categorization sets the expectations for the kind of resources and information that the interactants will be exchanging.

      ii) *Level 2.* Our second level absorbs the "mission focus" categories from [3] and we add a new entry to this list (marked with *) to incorporate the training and learning phase of interactions

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      . Types of tasks most found in literature are missions involving: A) transit, B) area coverage, C) resource management, D) target search, E) construction, F) assistance, and G) *learning of task [23, 21, 22, 8, 9] or environment [36, 53, 52, 41].

   b) *Environment.* This categorization focuses on capturing environmental macro-complexities by the way of following:

      i) *Expected Dynamics.* This sub-category signifies the amount of expected activity in an environment.

         A) LOW

         examples and citations for low, med, high dynamics

         B) MEDIUM

         C) HIGH

      ii) *Hazard-level.* For differentiation between contexts with conditions harmful for human survival with other everyday human-inhabited environments. This affects latent variables like interaction design and team formation for safeguarding operators, after-hours management of harmful or harmed robot parts, logistics compensating for probable destruction of robots and allocation of duties between robot and humans. This is a binary property with assignments: *TRUE* and *FALSE*.

      iii) *Interactivity.* This sub-category describes the level of interactivity to be expected from an environment. Illustrative examples are semi-autonomous driving in traffic and docent in a crowded museum. Former has high interaction but under structured traffic protocols, while the latter has to contend with unstructured social interactions. Our taxonomy divides this sub-category into the following tiers:

         A) *NONE* - Agent will only interact with known teammates

         B) *STRUCTURED* - Agent will have to interact with bystanders but using a structured protocol

         C) *SOCIAL* - Agent needs to interact with bystanders in a social manner

   c) *Team.* We typify different kinds of team-formations through two broad categories:

      i) *Composition.* Borrowing from [16, 10] we ascribe the following three possible values to team composition:

         A) *IDENTICAL*

B) *HOMOGENEOUS* - Not identical, but same physical and cognitive properties

C) *HETEROGENEOUS* - Interactants are physically and cognitively disparate

This composition is not applied to the whole team but rather to the sub-team of interactants being scrutinized for system design under this taxonomy.

ii) *Cardinality.* This property differentiates if the interaction is between individuals or groups. It can take the following four values: A) *One–to-One*, B) *One-to-Many*, C) *Many-to-One*, and D) *Many-to-Many*. Cardinality of the interactants directly affects interface design as well as algorithm selection for aggregating and disbursing team information.

4) **CONSTRAINTS**

This trait consists of latent aspects of the three major classes which affect interaction as well as other important lateral properties which are indirectly affected by the complexity.

a) *Task.* One of the major latent aspects of a task is its criticality specially when the success of the larger mission or safety of other humans depends on it. Our ontology addresses this aspect at the macro-level, but note that detailed frameworks exist

insert risk assessment citations

for a finer context-sensitive assessment. This is typified in [2] which we extend by adding the following tiers to the originally proposed aspect of:

i) *Criticality.* We divide this aspect into two dimensions: criticality towards mission success, and criticality towards human-safety. Under the current state of robotic abilities and intelligence, the human-safety axis should have precedence over the task-critical axis when deciding for trade-offs between multiple action options. We suggest the following breakdown:

A) *LOW* - Task is neither mission-critical, nor affects human-safety.

B) *MEDIUM* - Task is mission-critical but does not affect human-safety.

C) *HIGH* - Task is critical to human-safety.

D) *SEVERE* - Task is mission as well as safety critical.

b) *Team.*

i) *Interaction Protocol.* Depending upon the context of the team (e.g. civil or military) the interaction protocol can vary dramatically (e.g. social or structured-jargon respectively). We introduce the following tiers going from most complex to most structured:

A) *Unstructured interaction* -

@Priyam add interaction protocol citations and examples

Examples where agents use natural language and can encounter highly unmodeled conversations, requests and protocols.

B) *Structured at mission/task level* - Could be in a social or structured setting but the modality for inputting information and commands, and eliciting information is constrained so the task description or questions are structured. However the field is still open for using unmodeled gestures, expressions and social cues.

C) *Structured at tactical/action level* - Highly structured team where every level of information, command and actions is encoded into an existing structure, which is shared by every agent. Example, military, naval, air traffic-control, etc.

ii) *Spatial Relationship.* We mainly use this subcategory to denote the distance relationship between the interactants, i.e. *PROXIMAL* or *REMOTE*. Although we do not include social proxemics [30] explicitly in our taxonomy, it is worth mentioning that while looking at social interactions this axis should also be considered. Distances help in modeling not only the social relationship but also the available information about the other agents' behavior from the environment.

B. DYNAMICS

As compared to context variables, dynamics variables are factors regarding team and task structure that can be set given the inputted context. Decisions on dyanmics-related factors impact how effectively a team can execute a task given the constraints imposed by contextual factors.

1) Task

a) Planning

Task planning is classified as either online in which subtasks are assigned and executed immediately as the high level task is being executed, or offline in which which task planning occurs in advance and teammates adhere to schedules assigned to them. Online and offline planning mirror the instantaneous assignment (IA) and time-extended assignment (TA) categorizations proposed in Gerkey and Matarić [26], which are also adopted by Korsah, Stentz, and Dias [35].

b) Task Dependencies

Our definition of task interdependence is based on the iTax classifications posed by Korsah, Stentz, and Dias [35]. While [35] focuses primarily on algorithmic solutions to task decomposition and task allocation, the categories proposed also apply to interaction. The task allocation within the team and the interdependence between the tasks that teammates are assigned in pursuit of the joint goal drives what information needs to be shared between them. We adopt the four primary categories proposed in [35] for task schedule dependencies as they relate to task decompositions: No Dependence, In-Schedule Dependencies, Cross-Schedule Dependencies, and Complex Dependencies.

c) Goal Dependencies
For classification of goal dependencies, we use the categorizations proposed by Beer, Fisk, and Rogers [2] to distinguish three general goals that contribute to achievement of any task: sensing, planning, and acting. Given a task decomposition and allocation to team members, one or more teammates may share in the sensing, planning, or acting aspects of working towards a shared task. We further classify each of the three goals as either joint in which two or more teammates work together, or individual in which a single teammate works towards the specified goal.

2) Team

a) *Roles.* Following from our discussion in the last section needs reference we break-down the concept of roles along the dimensions of: A priori task knowledge, environment knowledge and level of familiarity with the other agent. Since we are trying to form taxonomies over the relevant parts of an interaction, the above three subcategories of a priori situational awareness make for perfect dimensions for sorting the social roles in HRI.

- **Operator** – An operator is ideally supposed to understand the agent at the highest, i.e. internal level. On the other hand, as far as mission is concerned the operator has high expertise in tactical control once a milestone is known, but does not have stake in the strategy. Based on our insights from the user-studies in section II, unless specifically trained they almost always operate in a novel environment.
- **Supervisor** – A supervisor, by designation, supervises the actions and plans of the autonomous agent which indicates they have a functional knowledge of the agent, the lowest. This is contrary to their place in the team, where supervisors are usually the ones with field and strategic expertise.
- **Mentor** – A mentor robot can be programmed with algorithms like theory of mind, empathetic projections, etc. [24, 14]. However, we assert that it has a physical knowledge of the humans, since this is the most robust level robots have usually functioned at. Again, by designation, the mentor is expected to be a task and field expert.
- **Peer** – There are few examples in literature where peers are not collocated with the agent, and almost always have a line-of-sight observation of the autonomous agent. Therefore we can assume that generally peers have a physical knowledge (L2) of the agent. Human peers are expected to have tactical expertise and moderate experience with different kinds of environments.
- **Bystander** – A bystander sometimes does not even have a functional knowledge of the autonomous agent, we place them at L0 abstraction. Additionally, they are not interested in the task and can have none to expert knowledge of the environment. They are a non-deterministic element since the agent would not know if they have the directions until asked.
- **Information Consumer** – Information consumers are usually invested in the mutual task and can be expected to have substantial knowledge of the goals and priorities. They usually have a functional knowledge of the autonomous agent but need up to L3 environmental SA during execution so that they can project task status based on their own logic. We assume that since they are not experts, they have moderate knowledge of the environment.

b) *Expertise Hierarchy.* Roles of agents can signify much information about the informational requirements of the interactants, however one should note that roles are not always fixed properties [38]. To capture this phenomenon in our taxonomy we divide expertise hierarchy into the following two dimensions:

i) *Reconfigurability.* Borrowing from spatial reconfigurability in [16, 10], we ascribe a similar characteristic to the role hierarchy. Hierarchy can either remain *FIXED* (as in military operations) or be *FLUID* (domestic peer-to-peer assistance)

add citations for fixed/fluid team hierarchy

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ii) *Decision-making Protocol.* Depending upon the methods employed by the team the decision consensus can be either: *CENTRALIZED* or *DISTRIBUTED* [16, 10]. This affects if the information sources should periodically interact with the centralized decision-maker or opportunistically distribute updates wherever and whenever possible.

c) *Communication.* The communication model of the team as well as the capabilities of the individual interactants directly constrain information exchange [48, 10, 16]. Our taxonomy uses the following tiers to incorporate the referenced taxonomies:

descriptions of comm categorizations

i) *None or Environment-based* [10, 48] - There is no direct communication between the interactants, the agents are limited to observing the changes in environment or a connecting physical medium to infer other agents' actions and state.

ii) *Sensing-based* [10] - The interactants can only communicate by directly sensing the teammate and observing the actions and state.

iii) *Direct-Partial* [10, 16] - The interactants have a communication channel but are limited by range-of-communication.

iv) *Direct-Full* [10, 48, 16] - Interactants can communicate with any teammate, anywhere within the known environment.

C. EFFECTS

Effects are resultant factors driven by the operational context of a team and the chosen dynamics for achieving the joint goal. Given the task and team dynamics under our taxonomy, the level of autonomy of each teammate and the level of information abstraction for communicating with them should be set accordingly.

1) *Level of Autonomy.* We adopt the levels of automation defined by Beer, Fisk, and Rogers [2]. In [2], levels of automation are determined in three modes of operation: sense, plan, and act. Ten levels are delineated, assigning the sense, plan, and act modes of operation to the human, the robot, or both the human and the robot together. In this upper ontology, and as we move into a world in which autonomous agents have capabilities that extend beyond traditional robot roles, we expand the designation of human and robot roles in this classification of levels of automation to include any two teammates or sub-teams interacting within the larger team.

   Decision of level of autonomy is based on what role a given teammate has assumed and in what context. For example, an operator executing a task in a fully-observable and fully-modeled context might operate at a higher level of automation than an operator executing the same task with a partial model or partial observability. In the latter case, the operator might rely more heavily on teammates to gather and communicate the necessary information and provide instruction.

2) *Level of Information Abstraction.* Choosing the right level is information abstraction is an important part of designing functional interactions which provide information without cognitively overloading an interactant [56]. Grices maxims [29] provide succinct guidelines for designing cooperative communication. Grice introduces four maxims for shaping information exchange, we wish to highlight two of these:

   - **Maxim of Quantity** – Be as informative as you can, and no more.
   - **Maxim of Relation** – Be relevant to the discussion.

   These guidelines hint at a strong inter-dependence between information abstraction, “issue” being discussed and required situated awareness for better decision-making or discussion. Assuming agents interact rationally and discuss “issues” with the agents with the right expertise, then under our taxonomy we can use the stereotypical profiling of team-roles to provide us with the missing information. The a priori expertise of various teammates can be used to identify the right interactant for discussing issues related to strategic plans, tactical moves, and environmental uncertainties. Similarly, their expected level of information about agent’s model can be used to provide agent’s state and status information such that the exchange makes sense to either interactant.

   Following the thread of situational awareness, it is also important to know how much the interactants knows about current state and status of each other. If the spatial relationship is proximal then they have direct access to physical situatedness, however is the relationship is remote in nature then the interactants are charged with exchanging the cognitive as well as physical situatedness. By physical situatedness we mean state of the environment, agent’s situatedness in the environment and by cognitive situatedness we mean current state of plan and mission goals, and the agent’s place in this schema.

   Finally, the level of information abstraction also depends on the relevance of the state of either interactant to the other. This relationship can be assessed along the dimensions of goal and task dependency, outlined in our dynamics taxonomy. More the inter-dependency, higher the frequency of updates should be, conditioned on the fact that the updates should contribute to that dependency in a positive or negative way. Similarly, depending upon if the interactants have same or different goal the level of task abstraction should be adjusted such that the interactants share more granular or higher-level of task information, respectively.

VI. DISCUSSION

In this paper, we proposed an upper ontology for characterizing interaction for heterogeneous teams working in novel and complex domains. One of the objectives of this work was to lay the groundwork from which the community can identify where gaps in the literature exist, but we see a few initial key areas for further research. First, solidifying the relation of the level of autonomy and level of information effects to the context and dynamics of a given scenario would be of benefit. While we provide general categorizations as a starting point, specific mappings of appropriate level of autonomy or level of information for each teammate in their given context is an important area for future work. Second, this and other gaps in the literature would be supported by additional observational studies to better characterize interaction in large heterogeneous teams. Finally, while the subject of much of the literature in this space has thus far dealt with interaction in teams of two to a few, interaction in larger heterogeneous swarms is a nascent and less-studied area. We therefore recommend using the factors outlined here to study interaction in larger teams.

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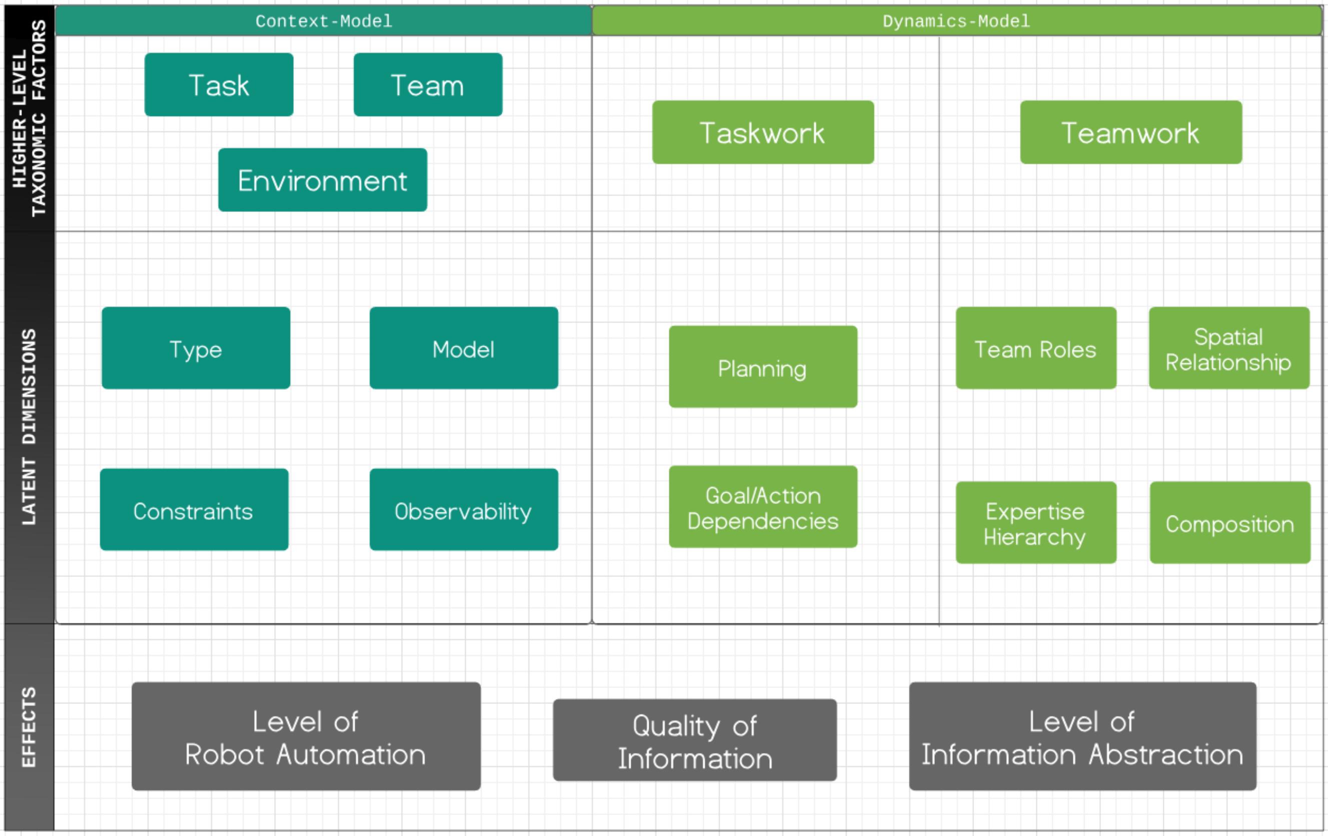

Fig. 3. Alternative Visualization for the Upper Ontology.

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