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

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***Abstract*— To rewrite!**

I. INTRODUCTION

The applicability of robots is extending beyond a single autonomous agent interacting with a single human to scenarios involving larger heterogeneous teams of multiple, functionally-different autonomous agents and humans working together [5]. Additionally, interaction between humans and autonomous agents has transformed from simple tasks in human-engineered environments to more complex domains characterized by partially-known and dynamic environments [8, 5], novel and unmodeled tasks [16, 6], and unstructured human and agent populations within teams [45, 3, 38]. These domains require new informational abstractions and representations to support information sharing and collaborative decision-making.

While there is a wealth of literature exploring one-to-one human-agent interaction in structured domains, as autonomous agents are incorporated into larger heterogeneous teams in unstructured environments, it becomes increasingly important to define how information will be shared between teammates and sub-teams in pursuit of shared goals in these novel domains [26, 9, 29]. To this end, in this paper we characterize needs for information sharing and interaction within heterogeneous teams in complex scenarios by surveying the literature and defining an upper ontology that details important factors impacting interaction in these domains. We ground factors driving interaction in the concept of situational awareness (SA) introduced by **endsley1998design** [**endsley1998design**]. For our analysis, we analyzed existing taxonomies studying interactions in human-robot teams and literature studying interactions as a means to an end. This body of literature drew from works exploring interaction in the behavioral sciences [9, 14, 33] and social contexts [18, 20] and algorithmic techniques driving interaction in human-robot teams [29, 2].

[50] define a taxonomy for human-robot interaction that incorporates aspects of task structure and team composition, including robot features and roles of the human with respect to the robot(s) in the team. Additionally, [2] explores a framework for multi-human multi-robot interaction that takes into consideration the team, task, and environment structures for a given scenario and the corresponding goals and constraints within the given context. While we see valuable insights in these works and build on the structures they propose, these works and others largely assume static roles for humans and autonomous agents operating in teams. As capabilities of autonomous agents are extended and teams are consequently afforded greater flexibility in pursuit of shared goals, a framework that defines interaction requirements in terms of roles within the team, agnostic as to whether the role is filled by a human or an autonomous agent, is necessary. The primary aim of this paper, therefore, is to propose an upper ontology over existing taxonomies and literature that extends existing structures in a way that allows for definition of human-autonomous agent interaction in these increasingly complex scenarios characterized by greater flexibility.

II. Operational Contexts for Collaborative HRI with Mobile Robots

While reviewing different operational contexts, as described in [4], four macro-themes were observed which complicated the scenario and its interactions, namely: 1) *environmental* complexity, 2) knowledge of task goals and priorities or the *task model*, 3) differing nature of other agents or the *team model*, and 4) level of *risk* to humans and autonomous agents. Following scenarios are chosen to highlight the variety of challenges along the above dimensions.

- **Interactive Learners and Museum Docents.** This is an example of scenarios with *structured environment*, and the complexity arises from the problem of how to inform other agents to enhance their knowledge of underlying *task model* and how to adapt this information to different types of *team models*? We outline two predominantly social scenarios where one interactant assumes the expert role and supervises the other into conducting interactions with the environment which in turn enhance their knowledge about the task being executed. Interactive learner scenario is where a human acts as a task expert and influences robot's interactions with the environment [16] to help it learn an optimal cost function representing the goals and constraints of the given task [10]. In this space, algorithms are developed for robot-novice users such that they can train robots via natural means, therefore this requires the robot to be capable of supporting natural language and non-verbal gestures [27]. In the museum docent scenario, a domain-expert robot guides and informs museum-goers such that they can experience the space with a deeper understanding of artifacts exhibited [45, 3, 4]. This also requires support for natural means of communication and is made even more challenging since the human audience is not only robot-novice, but also *multiple* in count.

- **Urban search and rescue (USAR).** This is a typical search and rescue scenario, except instead of using specialized dogs or hard-to-maneuver tube cameras a human remotely operates a robot into physically challenging spaces to search for trapped humans in need of rescue [8]. The robot here is used as an easily controllable, physically compact extension of human operator's cognitive capabilities. This context is complex in terms of *environment* as the areas being scouted are largely *unknown*, *unstructured*, usually dimly lit which makes perception hard and *dynamic* since debris can move anytime. The risk is high as the environmental elements can harm the robots but also the unaware human operators while operation since all their attention is fixed on the robot and not on their own surroundings [5, 26]. 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* priorities [8].
- **Military Building Breach Operation.** Like USAR this context also has unmapped, unstructure and dynamic environment to contend with but the complexity increases as the team is required to navigate a multi-stage task and there is an added potential for agents to encounter other *unmodeled adversarial agents*. Such missions require physical assistance as well as cognitive support through out the varying stages of the task. Scenario involves a mixed team of human soldiers, heterogeneous variety of autonomous agents, and autonomous computer aids working together to navigate an urban environment and breach a building. This further adds to the problem of formulating specific informational abstractions which can function independently of the differing abilities of the team-members. The multi-stage task requires different abilities and resources like, planning stage requiring plan for safe scouting, building access and enemy avoidance, scouting stage specifically focusing on monitoring of adversarial troops followed by troop movement stage and finally the building breach. Moreover, the team hierarchy is fluid, allowing for changing of roles depending upon arising contingencies and abilities of the teammates, and the overall risk is high.

III. An Overview of Existent Taxonomies in HRI

Apart from identifying specific dimensions and their effect on interactions, we also found overarching themes over the surveyed taxonomies which influence the structure of the upper ontology proposed in this paper. For instance, all the taxonomies are built to scrutinize a different part of the cooperative system, not only does this differ over lateral components like task context [2] and team configuration [12, 7], but also over different levels of depth, i.e. from macro-*context* [50] to local complexities or *dynamics* of a specific task instantiation [29]. Furthermore since each taxonomy describes interactions within a smaller context, we did not find an explicit characterization of *environment* context which we portrayed as instrumental to the challenges of a cooperative mission during our analysis of operational contexts. Additionally, we found multiple taxonomies presenting a discussion over similar topics like *task interdependency* and *level of robot autonomy* (LoRA) under different names and from different investigational perspectives. In our new taxonomy we include the insights from these taxonomies to break-down these concepts further along these varying dimensions. We present the surveyed taxonomies categorized under a similar structure as they have imparted to our formulated taxonomy.[1]

A. Context-driven Taxonomies

We briefly define contextual taxonomies as those describing the "problem" context and "solution" context of an HRI application. Here the kind of task being undertaken and the complexity of operational environment forms the problem part, while the configuration of the team deployed is identified as the solution.

1) Task and Environment as the Problem: Yanco and Drury [50] provide an exhaustive meta-survey identifying important factors which are critical to our definition of interaction context. However, the paper itself does not impose any logical structure over these dimensions even though they significantly differ in their level of assessment of a system, e.g. while task type is a context-sensitive variable, centralized versus decentralized mode of command consensus is local to the particular role the interactants play in a team hierarchy. More recently [2] have conducted a work addressing the problem of classifying mixed-team HRI task contexts and the effects on inter-team interactions, but specific to military and commercial operations. Our upper ontology is influenced by their highest-level of distinction which explains context along the dimensions of: *task focus*, *constraints* and *team configurations*. Note that while there is an explicit division between task and team-model, environment is relegated to the second-level of categorization used for producing constraints due to the narrow scope of relevant operational contexts. Apart from enlisting environment as a constraint they also mention that the kind of mission can impose specific constraints on the objective as well, e.g. need for stealth, or speed. However since there is not a structured framework guiding specific kinds of constraints this serves as more of a guideline than a taxonomic differentiation. More importantly, [2] identifies six main task focuses of missions undertaken in military and commercial HRI problems, which we have extended and incorporated in our own upper ontology in section V.

From the social robotics perspective, Dautenhahn [11] steps back and asks the question of how can we evaluate

[1] Readers should note that some taxonomies present variables for local dynamics along-side contextual variables so we have divided the discussion for those papers over two different sections.

criticality of robots to different domains such that social skill development in HRI is justified. They use four major axes for evaluating HRI application areas, and we have included three of those as important dimensions in our taxonomy as a way of typifying the contextual challenges that mixed teams should expect from different operational environments. [40] taking inspiration from human-animal cooperation characterize the type of activity as: *physical* , emotional or more generally *social*, and *cognitive*. This axis directly maps with the kinds of interactions occurring in outlined contexts of building breach, museum docents and USAR respectively.

2) Collective or Solution 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. The team context specifies macro-dimensions like the size and composition of the group [2], and communication constraints imposed by system design [12, 7]. Another important aspect is the a priori modeling of teammates to better understand their needs during execution. [7] employ a belief-desire-intention model to describe agents, while [44] define heterogeneous agents by their goals, actions and knowledge structures.

B. Cooperation-driven Taxonomies

In an attempt to understand natural cooperation better, the HRI community has studied human-animal interactions to develop guidelines [41] and descriptive categorizations for future human-robot team-tasks [40]. [41, 40] identify the frequency of communication and task-flow interdependency between two interactants as critical to characterizing the level of cooperation between them. [40] breaks task-interdependence into three modes which specify parallel, sequential and dialog-like modes of working on a task. This dimension of interdependence is echoed in [19, 29] from the perspective of task allocation. They divide task interdependence over two major dimensions of inter-agent task labor division and the scheduling constraints between the allocated sub-tasks. This presents a more systematic breakdown than [40] and is included in our taxonomy. In similar vein, [1, 25] illustrate a strong link between the projected criticality of a task, in terms of life-risk and importance to mission success, and the chosen levels of robot autonomy for a mixed system. Both [1, 25] define level of robot autonomy as a spectrum of responsibility or initiative overlap over the different task-stages and goal milestones, respectively. [1] outlines 10 specific configurations of these possible responsibility overlaps during task execution by deconstructing the task as a sense-plan-act cycle [35].

One of the most important behavioral factors shaping human-robot interaction, which we have implicitly mentioned multiple times, is the role of the human. Scholtz [42] used Norman's seven-stage model of interaction design [37] to reflect on the failure of robots and typify related assistance required by the intermediate layers of intention, action and perception in the agent. This led to formulation of the 5 archetypal roles humans can play to help the robot. Interestingly, Norman used his model for conceptualizing human-centric designs, however [42] flips the model to come up with a robot-centric view of usefulness of human knowledge such that the combined 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 [20] with the addition of two new entries(*), one of which is specifically robot-centric. The papers do a good job of explaining "why" such roles are needed to make a system usable and presents a detailed synopsis of "what" information the system designers should focus on while designing a human-robot interface for these roles. However, as we move towards a more cooperative landscape of HRI we will need the autonomous agents to fluidly move through a team hierarchy and wear different hats during different contexts, just as we expect from a collaborative team of humans. This entails that the expectations of expertise and knowledge from these roles need to be quantified by grounding it within the mission context of a mixed team's knowledge structures. This way an autonomous agent can better validate and support their move from one kind of role to the other.

With a critical eye towards contexts where social interactions are inter-woven with functionality of a team, as compared to being used as a means to another end, [18, 15, 11] present a taxonomy identifying the basic components of a robotic system which affect human-robot social interactions. Focusing on these dimensions from our more generic lens, we found that there is a need for inclusion of training phase of interactions [18] in the task taxonomies of the past, and we merge this additional aspect with the *task focus* list in [2] for our taxonomy. Furthermore, there is additional support to be found for explicitly modeling types of users and the need for a deeper discussion on types of role the human and robot can take in a context where the team hierarchy is more *fluid* [15, 11].

1) Information requirements for cooperation: To study information exchange in interactions we must analyze the question of *what* is the role of this information and *why* must it be disseminated at all? Endsley [13] 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. [9] 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.* - Current goal, short-term plan, agent status and state.

- **Level 2.** *Comprehension.*[2] - Reasoning aspects like belief and purpose in terms of the plan, environment and other constraints.
- **Level 3.** *Projection.* - Projection of finish-time, cost, and uncertainties over future states and goal status.

IV. Gap Analysis

Our last section identified the need for better understanding of the following aspects of characterization going forward:

- A better structure which can encompass the *macro-context* as well as the *local dynamics* while preserving the differentiation between them.
- A combined synthesis of dimensions like *task interdependence* and *LOA* which includes the differing perspectives of the surveyed taxonomies.
- A need for quantifiable reformulation of roles grounded within the shared knowledge structures of a collective such that they can be used an online framework to assess and validate the informational requirements at different levels.

We address the first two issues by proposing a reformulated upper ontology over the surveyed taxonomies in the next section. Specifically, we include context-driven dimensions from last section to the major category of context further sub-divided into three major classes of: task, team and environment. These three classes are the result of our analysis of varying operational contexts (section II) and identified dimensions from [50, 2, 1, 12, 7]. The environment category has been promoted to a major class even though none of the taxonomies explicitly describe it because our analysis of operational contexts highlights this as an important discriminator across different civil, social, military and commercial contexts. The cooperation-driven taxonomic dimensions are included within the major category of *local dynamics* which is further broken into *task-work* and *team-work dynamics*. This is inspired by the team-work and task-work model used by behavioral scientists to study the cooperative behaviors of a team [33]. The second issue is also addressed within the taxonomy by including task interdependence as an important part of task-work dynamics and breaking it down over the identified axes.

The rest of this section introduces a new quantified knowledge structure which can be used for: 1) grounding all the shared information of a team, and 2) to associate specific levels of information expertise and a priori knowledge to the roles defined in [42, 20] and motivated in [18, 11, 15].

A. Task, Team and Environment Knowledge Levels

In order to make the expectations from and typification of roles more tangible, we break down the three major classes of contextual factors into varying levels of domain knowledge.

- *Task axis* – A scale from tactical knowledge to strategic. Borrowed from [43] the terms are defined generically as follows: 1) tactical - short-term knowledge, e.g. next milestone or next immediate action, 2) operational - knowledge about abilities of the team and short-term task priorities such that communication and priorities can be managed, and finally 3) strategic - understanding of long-term goals, constraints and priorities of the mission.
- *Environment Axis* – A scale from knowing the exact environment to having past experience with similar environmental context and finally to being immersed in a novel environment.

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 and cognitive behaviors, interactions and commands affect the internal state and vice versa
- L2 - Behavioral – 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. A priori Situational Awareness

Scholtz [42] not only conceptualizes the roles of humans in an HRI system but also provides a detailed description of how their functions are tightly coupled with their situated awareness of the event context. However, this is done from the perspective of understanding at the end of HRI system designers rather than as a framework to be used by autonomous agents for embodying these roles online. Some key things to remember are that 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. 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 in part by the coding scheme in [5] which includes the preexisting environmental knowledge and knowledge about the task plan and strategy as a part of the overall SA of an interactant. A priori SA consists of sub-categories relating to preexisting knowledge about the:

- Task
- Environment
- Other Interactant

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 is critical to pay attention to before

[2] [5] adds that comprehension can be of two kinds namely: identification of elements, and interpretation of events under the current situation.

sharing the current state of an agent with other interactants. These axes together provide guiding functions to the questions of whom to address a task, team or environment-centric issue to, what level of guidance to expect in return and at what level should the current state of the interactant be transformed to so that it makes sense to both of them? Using these axes now we can create a stereotypical profile of each role conditioned on their expertise and a priori knowledge:

- **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** – We assert that a mentor robot has a behavioral 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 behavioral-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 their environment expertise unless they interacted.
- **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.

Figure 1 summarizes this distinction between roles based on the dimensions of a priori SA in task, environment and level of abstraction of the other agent.

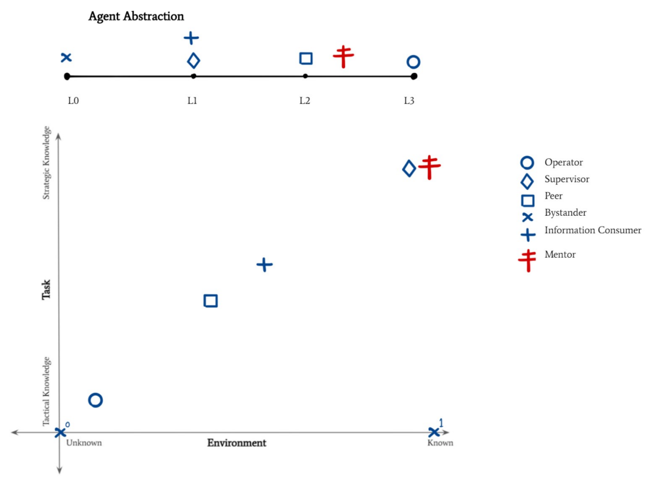

Fig. 1. Roles sorted on the dimensions of a priori knowledge of: (a) Agent abstraction, (b) Task and (c) Environment

V. A Reformed Upper Ontology for Analyzing HRI Problems

introduction to taxonomy

A. *SYSTEM CONTEXT*

Variables that fall under the context category function as independent variables for a given situation taken as inputs to the HRI problem.

Factor	Modeling	Observability	Type	Constraints
Task	[7, 12]	[7]	[40, 2]	[1, 20, 50]
Environment	Novel	Novel	[11, 50]	N/A
Team	Novel	Novel	[7, 12, 50]	[20, 50]

TABLE I
Motivating Taxonomies for Contextual Factors

1) **TYPE.** Each major class in the contextual ontology is ascribed a stereotypical set of properties which help encapsulate the expected complexities the agents face from their task, environment or team-formation.
   a) *Task.* Builds on task type taxonomies introduced in [40, 2].
      i) *Requirement Type.* [40] - A) *Physical*, B) *Cognitive*, and C) *Social*.
      ii) *Task Focus.* [1] - We add a new entry to this list (*) to incorporate the training and learning phase of interactions as seen in domestic and other social domains. A) transit, B) area coverage, C) resource management, D) target search, E) construction, F) assistance, and G) *learning of task [17, 16, 6] or environment [30, 47, 46, 39].
   b) *Environment.* Focuses on capturing environmental macro-complexities by the way of following:
      i) *Expected Dynamics.* [11, 4] - Motivated by discussion of contexts in [4]and “contact with humans” dimension in [11].

A) LOW - [49]
B) FREQUENT - [8]
C) HIGH - [45, 3, 38].

ii) *Hazard-level.* A new categorization motivated by different application contexts defined in [4], with conditions harmful for human survival versus other everyday human-inhabited environments. A binary property with assignments: *TRUE* and *FALSE*.

c) *Team.*

i) *Composition.* [12, 7] -

A) *HOMOGENEOUS* [28]
B) *HETEROGENEOUS* [26, 16]

This composition is applied to the sub-team of interactants being scrutinized under this taxonomy.

ii) *Cardinality.* Motivated by survey of operational contexts and size dimension in [12, 7]. A) *One–to-One* [16], B) *One-to-Many* [45, 3], C) *Many–to-One*, [31] and D) *Many-to-Many*.

2) **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, i.e. before task execution. This helps in anticipating the information gap during execution and guides sensing, communication, and inference actions online.[3]

a) *Task.* Motivated by our analysis of operational contexts with varying understanding of task models. Can take the following values: *FULL* [45] or *PARTIAL* [16, 8].

b) *Environment.* Motivated by [4], encapsulates whether the operational environment has a known underlying semantic structure or not, and whether the physical map is known a priori or not.

i) *Structure* (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* (A) *Mapped* in which a full map of the environment is available. (B) *Partially Mapped* in which some information is available, but the current state might have changed requiring adaptability, and finally (C) *Unmapped* in which no information about the environment is available a priori.

c) *Team.* [44, 7, 9] -

i) Shared-knowledge structures [44]
ii) Decision functions [44, 9]
iii) Action repertoire [7, 44, 9]
iv) Capabilities - Sensors, and effectors [7, 44]

3) **OBSERVABILITY.** As compared to task modeling which demonstrates where a priori gaps lie in knowledge and what information would be required 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.

a) *Task. PARTIAL* and *FULL* observability of task refer to whether unknown aspects of a task specification, such as constraints or objectives, can be observed online during task execution. This categorization is motivated by the military building breach and interactive learners/museum docents operational contexts in which task specifications are not fully known a priori and must be learned online. [7] reviews work in a 'learning' dimension which discusses reinforcement learning techniques for ascertaining unknown aspects of task, but formal dimensions are not provided.

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 agents performing a task.

i) Partial [22]
ii) Full [36]

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. Both of these categorizations are motivated by the operational contexts in which relevant factors driving decision-making of team members are not fully known and in which team members do not have full observation capabilities of relevant contextual factors.

i) Observability

Observability of teammates parallels observability of task and environment and can be categorized as either *PARTIAL* or *FULL* observability.

ii) Observation Ability

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.

4) **CONSTRAINTS.** This trait consists of latent aspects of a class as well as effect of type-complexity on other lateral factors which affect interaction.

a) *Task.*

i) *Criticality.*[4] [1, 50] - 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

[3]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 local dynamics.

[4]Our ontology addresses this aspect at the macro-level, but note that detailed frameworks exist [32] for a finer context-sensitive assessment.

suggest the following breakdown:

A) *LOW* - Neither mission-critical, nor affects human-safety.
B) *MEDIUM* - Mission-critical, does not affect human-safety.
C) *HIGH* - Critical to human-safety.
D) *SEVERE* - Mission as well as safety critical.

b) *Team.*

i) *Interaction Protocol.* [11] - Motivated from "requirement of social skills" aspect in [11] and our observations from study of operational contexts where either structured or social communication is strongly preferred.

A) *Social protocols* [45, 3, 6, 16, 27]
B) *Structured protocols* [43, 24].

ii) *Spatial Relationship.* [50, 20, 18] - We assign two high-level values to this aspect, i.e. *PROXIMAL* or *REMOTE*.[5]

B. LOCAL DYNAMICS

As compared to context variables, local dynamics variables are factors regarding team-work and task-work structure [33] which impact how effectively a team can execute a task given the constraints imposed by contextual factors.

1) Task

Factor	Planning	Task Dependencies	Goal Dependencies
Task	[19, 29]	[1, 25, 40, 41, 29, 19]	[25, 2]

TABLE II
MOTIVATING TAXONOMIES FOR TASK-RELATED DYNAMICS FACTORS

a) *Planning.* [29, 19] - We reformulate the instantaneous (IA) and time-extended (TA) task-assignment categorizations proposed in Gerkey and Matarić, Korsah, Stentz, and Dias [19, 29] as more generic online and offline task planning, respectively.

b) *Task Dependencies.*
Our definition of task interdependence is based on review of taxonomies classifying properties of task allocation and interdependence [29, 19, 40, 41]. We adopt the four iTax classifications as defined by Korsah, Stentz, and Dias [29]:

i) No Dependencies
ii) In-Schedule Dependencies
iii) Cross-Schedule Dependencies
iv) Complex Dependencies

c) *Goal Dependencies.* We For classification of goal dependencies, we use the categorizations proposed by Beer, Fisk, and Rogers [1] to distinguish three general goals that contribute to achievement of any task: *SENSE*, *PLAN*, and *ACT*.
Each of these three goals can be filled by two or more teammates, classified as a *JOINT* approach, or by a single teammate, classified as *INDIVIDUAL*. These categorizations are adopted from Jiang and Arkin [25].

[5]Although we do not include social proxemics [23] explicitly in our taxonomy, it is worth mentioning that while looking at social interactions this axis should also be considered.

2) Team

Factor	Roles	Expertise Hierarchy	Communication
Team	[20]	[7, 12, 50]	[7, 44, 12]

TABLE III
MOTIVATING TAXONOMIES FOR TEAM-RELATED DYNAMICS FACTORS

a) *Roles.* Following from our discussion in the last section IV we break-down the concept of roles along the dimensions of:

i) A priori Task Knowledge,
ii) A priori Environment Knowledge,
iii) A priori Level of familiarity with other agents

Refer to sub-section IV-B for a detailed breakdown of every role along these axes.

b) *Expertise Hierarchy.* [11] - As seen in [11] roles are not always fixed properties. To capture this phenomenon in our taxonomy we divide expertise hierarchy into the following two dimensions:

i) *Reconfigurability.* Motivated from spatial reconfigurability of teams in [12, 7]. Hierarchies can either remain *FIXED* [8, 45] or be *FLUID* [34].
ii) *Decision-making Protocol.* [50, 12, 7] - The decision consensus protocol can be either: *CENTRALIZED* or *DISTRIBUTED*.

c) *Communication.* The communication model of the team as well as the capabilities of the individual interactants directly constrain information exchange [44, 7, 12].

i) *None or Environment-based* [7, 44] - 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* [7] - The interactants can only communicate by directly sensing the teammate and observing the actions and state.
iii) *Direct-Partial* [7, 12] - The interactants have a communication channel but are limited by range-of-communication.
iv) *Direct-Full* [7, 44, 12] - 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 context, and 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 [1]. In [1], 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 just enough information without cognitively overloading an interactant [48]. Grices maxims [21] 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 *a priori level of familiarity with an agent’s model* can be used to provide agent’s state and status information at the right abstraction level.

Following the thread of situational awareness [13, 14], 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 level 1 aspects of [9] and by cognitive situatedness we mean the level 2 and level 3 aspects from the same paper.

Finally, the level of information abstraction also depends on the relevance of the state of either interactant to the other [25, 1]. This relationship can be assessed along the dimensions of *goal and task dependency*, outlined in our dynamics taxonomy. Our guidelines ate that more the inter-dependency, higher the frequency of updates should be, conditioned on the fact that the updates should contribute to the constraints of 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 tactical and operational or strategic task information, respectively.

VI. Discussion

In this paper, we proposed an upper ontology for characterizing interaction within heterogeneous teams in complex scenarios and introduced an a-priori-situation awareness framework to support it. This upper ontology builds on existing taxonomies by organizing existing categorizations from these works and defines new categorizations to classify problems involving task-, environment-, and team-related complexity.

The need to define a new upper ontology over existing taxonomies is demonstrated by the operational contexts discussed in section II. In the museum docents and interactive learners context, while the environment is known, the task model is incomplete and there are numerous unmodeled interactants. In the USAR scenario, complexity arises from the lack of known structure and full mapping of the environment in addition the non-static assignment of roles to teammates. Finally in the military building breach scenario, teammates are operating in an unknown environment, the task is only partially modeled, and there exists a fluid team hierarchy. These operational contexts motivate the need for categories considering a priori modeling and online observability and also the need to classify level of automation and level of information as effects rather than static artifacts of a given context.

The structure of the upper ontology developed in this work has highlighted some areas of interest for future work. First, for categorizations not delineated by existing taxonomies, more research is needed to examine the impact of these factors on interaction. These categories primarily include modeling and observability in the task, team, and environment contexts and a particular exploration of these ideas as they relate to large, heterogeneous teams. Additionally, further research is needed to explore the optimal relations between the context and dynamics variables and effects. Developing a full mapping between given context and dynamics variables and the recommended levels of automation associated with each role and subsequent levels of information necessary for each role is an open area for further research.

Todo list

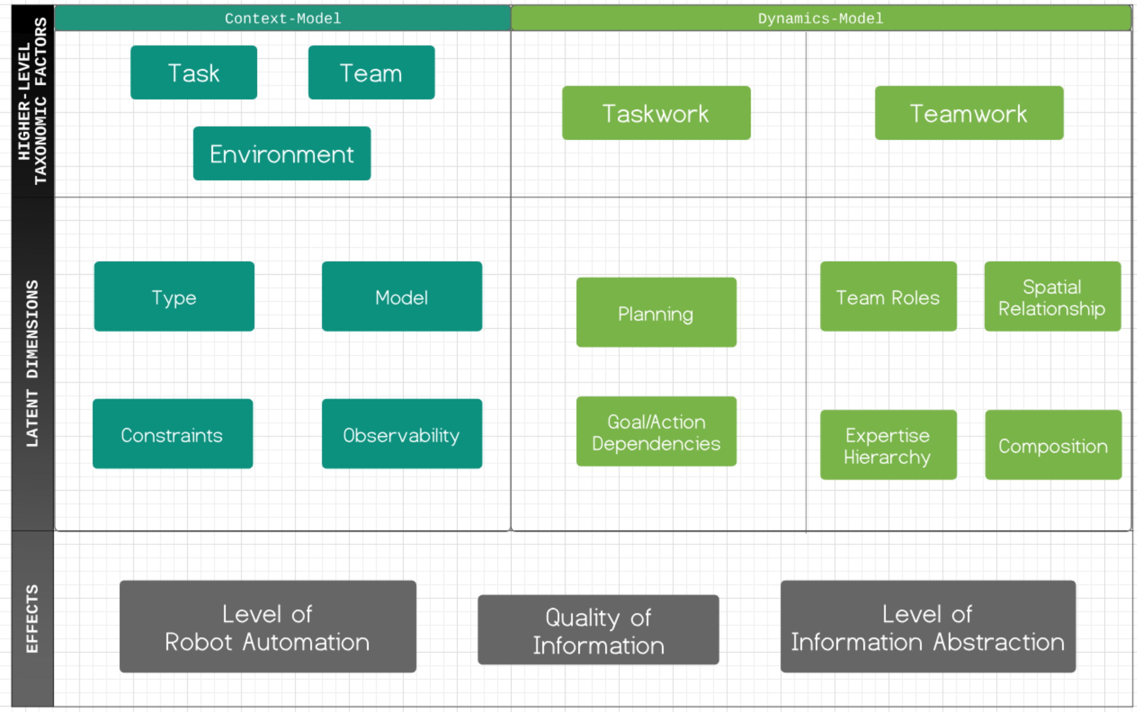

Fig. 2. Alternative Visualization for the Upper Ontology.

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