Efficient Human-Robot Interaction for Robust Autonomy in Task Execution

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ABSTRACT

Robust autonomy can be achieved with learning frameworks that refine robot operating procedures through guidance from human domain experts. This work explores three capabilities required to implement efficient learning for robust autonomy: (1) identifying *when* to garner human input during task execution, (2) using active learning to curate *what* guidance is received, and (3) evaluating the tradeoff between operator availability and guidance fidelity when deciding *who* to enlist for guidance. We present results from completed work on interruptibility classification of collocated people that can be used to help in evaluating the tradeoff in (3).

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1 INTRODUCTION

Robots are increasingly deployed to domains where it is difficult to fully anticipate needs and operating conditions in advance. To ensure robust autonomy in such realms, it is advantageous to equip robots with learning frameworks that refine operating procedures from experience or through guidance from human domain experts [2]. However, it is also unreasonable to expect continuous monitoring and feedback from humans. This work aims to accomplish robust autonomy through human guidance, while reducing the expectations on a human's time and monitoring abilities. Specifically, we explore three capabilities: (1) regulating autonomy to identify safety-critical moments in a robot's task execution when assistance might be necessary (**when**), (2) using active learning to proactively sample demonstrations from humans in order to regain and improve autonomy (**what**), and (3) soliciting help from those humans that are likely to be available and provide the highest fidelity of guidance at the moment of need (**who**). We address *when* and *what* to improve robot autonomy over time by allowing robots to learn and refine its operating procedures. We tackle *what* and *who* to make the learning process efficient by asking the right questions to the right person at the right time.

*Regulating Autonomy (**When**).* Our goal is to equip robots with the ability to autonomously identify safety-critical task situations where it should seek human guidance under uncertainty. Concretely, assume a task plan that requires the press of a button and consider a situation where the robot is uncertain if it is in the state where the button should be pressed. In one scenario, if pressing the button initiates a dangerous mechanism, the robot should halt execution and seek guidance. However, in another scenario, if pressing the button kills a dangerous mechanism about to run wild, the robot should proceed even without guidance. Prior works address components of this problem with logic-based formulations [6] that provably halt and confidence-based formulations [3] that allow execution under uncertainty. We will explore the tradeoffs between such approaches when applied to the above situation (and others).

*Improving Autonomy (**What**).* Our goal is to gather information efficiently when refining the robot's task models from interaction with a human: a goal best accomplished through active learning. We plan to leverage extensive work on intrinsic motivation in robotics [5] and results from self-exploration for affordance learning [4] to tailor the content of each interaction to derive the most gains in task model refinement through guidance.

*Operator Selection(**Who**).* Our goal is to contact the right person at the right time. We assume that the robot can contact either remote users or collocated people, and that there are tradeoffs to encounters with each class of person. Specifically, we assume that remote humans are always available but provide low fidelity input, while collocated people are not always available but provide high fidelity input. Our goal, therefore, is to apply an arbitration mechanism to evaluate these tradeoffs when choosing the correct human for guidance at the time of need.

The work so far has been focused on operator selection for robots soliciting help. Such requests are likely to interrupt humans, causing a disturbance. These disturbances can be ameliorated with appropriate timing: a notion captured by *interruptibility* [9]. The interruptibility of a person is high if they might be amenable to an interruption, and low otherwise. By enabling robots to autonomously classify human interruptibility, we allow the creation of the mechanism of choosing **who** to seek for guidance.

2 INTERRUPTIBILITY

We first introduce a framework where we identified features that can be useful for interruptibility classification and a model that remained robust to noise in the features [1]. Then, we present evaluations of the framework in a user study designed to gauge the validity of the model's classification. We found that the robot using our framework interrupted humans at appropriate moments more often, which has implications on human task performance and subsequent human-robot interaction during the interruptions.

Features. Combining prior work on human engagement detection [7] with interruptibility research [9], we hypothesized that interruptibility can be estimated using features that describe the

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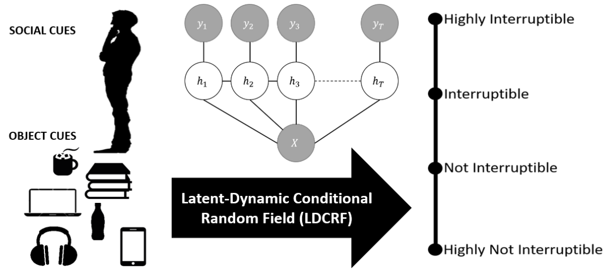

Figure 1: Interruptibility classification framework.

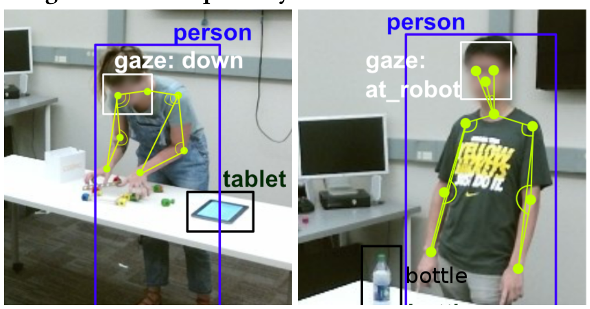

Figure 2: Visualization of our detected features

person state, and those that describe the *interruption context* (Fig. 1). We defined the person's state as their body position and orientation, their gaze, and their projected audible cues. Context has been defined to include the task, the environment, and the relationships between these [9]; we considered environment (or scene) context and proposed that the objects that a person is interacting with can serve as useful cues to the full interruption context. For example, an individual nursing a coffee mug in a lounge is more interruptible than an individual using a laptop in the same lounge. We focused on objects because object recognition is widely available on robots.

Model. We primarily considered temporal models for interruptibility classification[1]. We hypothesized, in particular, that the class of discriminative temporal models called Latent-Dynamic Conditional Random Fields (LDCRFs) [8] are well suited to the task.

Feature & Model Evaluation. We collected a dataset of scenes common to a kitchen area to test our three hypotheses. In the dataset, we constructed different sets of the social cue features such that the sets made a tradeoff between providing models with more information at the cost of more noise. We found that (1) the LDCRF consistently outperformed all other models and improved its classification accuracy with more social cue features despite the added noise, (2) the social cue features are relevant to interruptibility classification because the LDCRF achieved an average MCC[2] score of 0.9 when provided with all the social cues, and (3) adding context cues with objects greatly improved classification for the LDCRF, with average MCC scores increasing by 0.03 to 0.08 points.

Study Design. We designed a between-subjects user study where the robot interrupted participants in a mock manufacturing environment either randomly (RND) or intelligently using the classification framework (INT). Participants (14 Male, 14 Female, aged 22–29) were intermittently given build tasks through a tablet, but were free

[1]Non-temporal models such as Random Forests (RF), SVMs, kNN, and Multi-Layer Perceptrons (MLP) were also evaluated. We found that their consistency in classification across multiple timesteps was low, despite promising accuracies with RF & MLP.
[2]Matthew's Correlation Coefficient: ranges from -1 to 1; 1 as perfect & 0 as random.

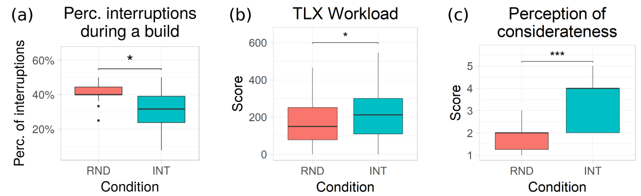

Figure 3: Results. Asterisks indicate level of statistical significance: $^{*}\ p \leq 0.05$, $^{**}\ p \leq 0.01$, $^{***}p \leq 0.001$.

otherwise. When interrupting, the robot requested assistance with its own build task, which the participants could choose to ignore. In the INT condition, we adapted our framework for autonomous interruptibility classification to use features from the output of five deep networks (Fig. 2). The LDCRF was then trained on annotated interruptibility labels of participants in pilot studies and in RND.

Study Results. We found that the framework significantly increased the likelihood of robot interruptions when participants were free (Fig. 3a). Additionally although we found that there were no significant differences in participant performance, participants surprisingly reported significantly more workload in INT than in RND (Fig. 3b). This result is likely because robot interruptions in INT gave participants less free time. Despite the higher workload, participants still reported the robot as more considerate in INT than in RND (Fig. 3c), with many in INT attributing considerateness to robot nonverbal behaviors, which were the same across conditions.

3 FUTURE WORK

We glean two insights from our results: (1) interruptibility classification is important not only for efficient learning, but equally so for improving the social aspects of interactions, and (2) our operator selection (**who**) mechanism might require more nuance than our naïve expectation of ideal interruptions during free time would have us believe. Future research will elaborate on this.

Meanwhile, we are also focused on researching different task representations to evaluate the regulation (**when**) and the improvement (**what**) of autonomy. We plan to explore algorithms for both capabilities in toy simulation domains before we present results by executing the developed algorithms on our mobile robot.

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