Towards an Information Theoretic Analysis of Human-Robot Interaction in Shared Autonomy

Thesis proposal

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Abstract

Human-Robot Interaction (HRI) in the context of shared autonomy is a rich and complex phenomena. The effectiveness and usefulness of shared-control human-machine systems critically depends on the fluency and efficacy of human-robot interaction. Efficient HRI can lead to an improvement in joint task performance with higher user satisfaction and enhanced trust, all of which are desired characteristics of a joint human-machine system. From an engineer/systems designer's perspective, in order to achieve optimal performance the design of autonomy should adequately taken into account the richness, subtleties and complexity of the interaction between the human and the machine.

In this thesis proposal, I plan to propose a mathematical framework for human-robot interaction in the context of shared autonomy utilizing ideas from probabilistic graphical models and information theory. More specifically, the interaction between human and autonomy will be modeled as coupled perception-action loops unfolding in time using *causal Bayesian Networks*. Within this framework of causal Bayesian Networks, design of autonomy can be thought of as appropriately timed *interventions* at specific parts of model, with an intention to alter the bi-directional information flow between the human and machine. Using the proposed mathematical model, I will research three important problems that arise in HRI within shared autonomy, namely, a) learning b) inference and c) joint task performance. More specifically, I will focus on information theoretic analysis of how each of the above mentioned phenomena unfolds during task execution. The eventual goal is to utlize the proposed mathematical framework to inform the design of autonomy that will help *facilitate human learning*, *improve inference accuracy* and *enhance task performance*..

Contents

1 Introduction

Robots are ubiquitous in the modern-day society and have revolutionized the relationship between man and machine. Compared to a few decades ago, in the present day, robots have transitioned out of the rigid, structured and specialized industrial environments to the more rich, complex and unpredictable day-to-day human environments and have impacted diverse domains of human endeavor such as healthcare (medical, assistive and rehabilitation robotics) [7], entertainment (musical robots) [5] and home robotics [2].

The impact is even more significant in the domain of assistive and rehabilitation robotics in which the potential to drastically enhance the quality of life for people suffering from motor impairments as a result of spinal cord or brain injuries is immense [9]. Devices such as smart wheelchairs, exoskeletons and assistive robotic arms can help to promote independence, boost self-esteem and help to extend mobility and manipulation capabilities of motor-impaired individuals and can revolutionize how they interact with society [8].

The standard usage of these assistive machines, however, still relies on manual teleoperation by the human typically enacted through a control interface such as a joystick or a switch-based headarray **R**; that is, in such scenarios robots are not endowed with any intelligence and can be thought of as *passive* machines that function as extensions of human motor abilities. However, one of the most difficult conundrums is that greater the motor impairment of the user, the more limited the interfaces that are available for them to use. As a result, control of these machines can become extremely difficult due to the low dimensionality, sparsity and bandwidth of the control interfaces and are further exacerbated by the inherent complexity in robot dynamics and the physical limitations of the users **R**. In such cases, *robot autonomy*, the ability of robots to accomplish a task independently without requiring explicit instructions from a human, holds considerable promise as a tool to offset (and in some cases restore) the above-mentioned limitations. Advances in the fields of machine learning and artificial intelligence have helped to endow these assistive machines with better decision making and prediction capabilities while interacting with humans in real-world scenarios **R**. However, in literature there is a growing consensus that users of assistive technologies *do not* prefer to cede full control authority to the robotic partner during task execution **R**. Users, in general, like to have a more active role when interacting with an assistive robot **R**. In such cases, the introduction of *shared autonomy* seeks to find a middle ground between full teleoperation and autonomy by offloading only some aspects of task execution to the autonomy **R**.

In a shared autonomy system, the task responsibility is split between the user and autonomy with the aim of reducing human effort in accomplishing a task. Human-Robot Interaction (HRI) in the context of shared autonomy is a rich and complex phenomena **R**. The effectiveness and usefulness of shared-control human-machine systems critically depends on the quality and efficiency of human-robot interaction. That is, for robots and humans to work side-by-side and achieve joint goals and accomplish various tasks in a coordinated and cooperative manner, it is imperative that both parties understand each other, communicate and infer internal desires and intentions efficiently **R**. From an engineering perspective, design of appropriate kinds of autonomous behaviors for a shared-control system, therefore, needs to take into account the dynamics of human-robot interaction during the course of task execution **R**. This points to the need for rich mathematical frameworks that will model all the relevant variables and their interactions **R**.

Current research approaches for design of shared autonomy systems rely on various types of mathematical models and heuristics to solve different aspects of the problem independently and therefore suffer from generalizability across tasks, robotic platforms and various types of users. For my thesis proposal, I am motivated by the desire to develop a *unified* mathematical framework to analyze different aspects of human-robot interaction under a common umbrella in an attempt to shed light on the more *fundamental* and *low-level* descriptors.

To that end, I plan to propose a mathematical framework that models human-robot interaction in the context of shared autonomy, utilizing ideas from *probabilistic graphical models***R** and *information theory***R**. More specifically, the interaction will be modeled as coupled perception-action loops unfolding in time using *causal Bayesian Networks* **R**. The nodes in the network will represent the different variables (both latent and observed) that are relevant for the model and the edges represent the probabilistic influence they have on each other**R**. In an attempt to quantify the fluency, transparency and cooperation of human-robot interaction heavy emphasis will be placed on analyzing the *information flow* between the nodes in the network. Within this proposed framework of causal Bayesian networks, design of autonomy can be thought of as appropriately timed *interventions***R** that has the potential to alter bidirectional information flow between human and autonomy. Our hypothesis is that *information flow* is a more fundamental and low-level descriptor of joint system performance that system designers should focus on when designing autonomous behaviors. Using the proposed model, I propose to address three main subproblems relevant to shared autonomy namely, *learning*, *inference* and *task performance*.

The first research question (**RQ1**) that I will address in my work is *how can autonomy help humans learn robot dynamics better*. When a human and machine interact in a shared autonomy setting, both parties are continually learning about each other**R**. For example, for novice users, with practice their familiarity with the device increases and they learn about the dynamics of the control interface and the robot**R**. The initial forward (and inverse) dynamics model that the user maintains internally during task execution might be drastically different from the true dynamics**R**. Due to learning effects, the internal model will tend towards the true model. However, the learning strategies that humans adopt need not always be optimal, for example, users might not sample the state and action space in an efficient and exhaustive manner and therefore can erroneously extrapolate dynamics between different regions of the workspace**R**. Therefore, autonomy can play the role of a *teacher* and help the human in skill acquisition and provide appropriate guidance during the learning process**R**.

Inherent limitations of the control interface and motor impairments, however, can possibly put an upper bound to skill level that can be acquired. In such scenarios, the need for autonomy becomes inevitable. However, any successful assistive robotic system needs to have a good idea of the user's needs and intentions. That is, *user intent inference* is a necessary and crucial component to ensure proper assistance**R**. Therefore, the second research question (**RQ2**) that I will address in my thesis is *how can autonomy be designed so that inference becomes more accurate*. Typically, the user's internal state (desires, goals and intentions) is latent (if not fully, partially) from autonomy's perspective**R**. It has to be noted that inference is not a unidirectional phenomena. For example, from the users' perspective the internal logic with which autonomy helps them is not always explicitly known and therefore needs to be inferred as well. User satisfaction and acceptance heavily depends on the user's understanding of how the autonomy works**R**. In this thesis, I plan to utilize the proposed mathematical model to reason about and shape the information flow from the user's internal state to autonomy to improve the inference accuracy.

In addition to facilitating learning (**RQ1**), and improving inference accuracy (**RQ2**), autonomy has to work in conjunction with the human to perform the task optimally. Therefore, the third and final research question (**RQ3**) that I hope to tackle in this thesis is *how to design autonomy to ensure optimal task performance* **R**. Typically, both subjective (user satisfaction, acceptance, trust) and objective metrics (task completion time, number of mode switches) equally inform the optimality criteria **R**. Rather than focusing on the above-mentioned metrics independently, in this work we will focus on optimal bidirectional information flow between the human and autonomy. Our hypothesis is that optimization of information flow between the autonomy and human will result in better communication of latent states. This will likely lead to enhanced cooperation and mutual understanding as a result of which the desired outcomes (better task performance, improved user satisfaction) will naturally emerge.

In summary, in this proposed thesis I intend to develop a mathematical framework to model human-robot interaction in shared autonomy and plan to research solutions to the questions presented above (RQ1, RQ2 and RQ3). I am motivated by the need to develop a unified theoretical framework for shared autonomy. This work will be the first to treat information content and flow as the key components to understand the dynamics of interaction between human and autonomy in a shared autonomy setting. More importantly, this work proposes a fundamentally different way of thinking about autonomy; one in which *autonomy is a exogenous intervention that alters the information flow in a coupled perception-action loop to bring about desired outcomes*.

2 Human-Robot Interaction in Shared Autonomy

In this chapter I present a discussion of existing mathematical approaches adopted by researchers for modeling different aspects of a shared autonomy system. I also briefly discuss how research into softer aspects of HRI such as legibility, transparency, cooperation, attention and coordination guide the design of effective shared autonomy systems.

2.1 Mathematical Models for Shared Autonomy

In shared autonomy, complementary abilities of humans and robots are leveraged to jointly accomplish various tasks such that the joint system is typically more capable than either the human or the the machine on their own. However, there is no one singular definition of what constitutes shared autonomy or shared control. In a recent survey paper on shared control **R** Abbink et al. defines shared control as one in which '*...human(s) and robot(s) are interacting congruently in a perception-action cycle to perform a dynamic task, that either the human or the robot could execute individually under ideal circumstances*'. More importantly, they also propose that in a shared autonomy system, the human and robot actions should be linked by combining them into a final control action and that each agent should directly perceive how its intent is influenced by the actions of other agent(s). Clearly, human-robot interaction in this context is a rich and complex phenomena and for robots to function properly alongside humans, it becomes imperative that they have the capability to predict their partners actions and intentions effectively using mathematical models.

Researchers develop mathematical models for various purposes, for example, to model human behavior, to learn autonomous policies from human demonstrations that generate the robot control commands, to recognize objects in the environment and generate waypoints for navigation and grasp poses for manipulation, to model control allocation and decide how the human and autonomy control commands should be arbitrated to produce the final control command for a shared controlled system **R for each example**.

2.1.1 Models for Human Behavior

Teamwork in a shared autonomy system is enhanced when the team members understand each other's intentions, desires and goals **R**. This has been well established in the domain of human-human interaction in various domains **R**. However, there are particular challenges that arise in human-robot interaction due to the differences in the mental and physical capabilities of humans and robots**c**. Robots can deal with such challenges by maintaining models of human cognition and behavior**R** spanning different timescales and levels. These models endow robots with an ability to predict and therefore plan actions accordingly for the future.

Hiatt et al. **R** relies of 'Marr's levels of analysis **R**' to categorize models for human behavior into three distinct categories namely: computational, algorithmic and implementational. They go on to claim that categorization of human models according to Marr's level of analysis **R** provides a useful framework as it clarifies what aspects of human behavior is being modeled. Computational level techniques, are ideal for scenarios that benefit from the knowledge of normative behavior that humans are ought to exhibit. These models typically rely on simplistic assumption of perfectly rational behavior and treat human idiosyncrasies and deviations from the norm as observational noise. Algorithmic level analysis seeks to delve into the processing constraints that agents have and how they lead to systematic errors thereby providing better insight into why agents deviate from normative behavior. However, the algorithmic models typically work well over shorter timescales and therefore are not suited for modeling human behavior that last over longer timescales.

Within the computational category, one of the most common methodologies is to adopt simple probabilistic models that attempt to model very low-level short time horizon behaviors (such as reaching motions performed by humans during a manipulation task). For example, Dragan et al. **R** assumes a framework in which the human is treated as a optimal agent that noisily optimizes a goal-dependent cost function. This model is used by the robot to infer user's intent in which the predicted goal is the one with lowest cost given the user's control input. Optimality principles are particularly attractive because of their success in the domain of motor control**R** and also because they provide a principled approach to how agents ought to behave. The framework, however, requires well-defined cost functions that provide succinct description of the task at hand. Cost functions can either be hard-coded under assumptions of rationality or expertise within the domain (for example, minimization of distance to goal) or can be learned from human demonstrations using techniques such as inverse reinforcement learning **R's**. In our work on human-driven customization of shared autonomy levels **R**, we have modeled humans utilizing ideas from optimal control theory in which we assume that humans are acting optimal with respect to an unknown cost function. We make no assumptions regarding the nature of cost function but instead provides the human the capability to customize/optimize the control allocation parameters directly. Similarly, our work on mode switch assistance for intent disambiguation implicitly assumes that the model for human teleoperation of the robot is one in which the human is optimizing for shortest path to goal.

Data-driven approaches utilizing conventional machine learning algorithms, for example GMMs, SVMs, MLPs **R** have also been successfully used to recognize human behavior in a wide variety of domains such as social robotics**R**, assistive robotics**R** and learning from demonstrations**R**. However, most of the machine learning approaches are extremely data hungry**R** and suffer from generalization issues to cases outside of examples seen in the training set**R**. More recently, data-driven approaches based on Koopman operators have also been utilized to learn models of joint human-machine systems **R**. Koopman operator based approaches scale well to high-dimensional spaces as the computational complexity does not grow with the number of data points. As a result, model training is extremely efficient and fast **R**.

In general, computational approaches are well suited for situations in which one is primarily concerned about what the human is doing without necessarily reasoning about the underlying causes for the behavior.

In the algorithmic category, Hidden Markov Models (HMMs) and other Markov-based approaches are common choices for modeling human behavior**R**. HMMs in particular are well suited for behaviors that have rigid temporal structure**R**. HMMs are powerful due to their ability to express latent variables and can be used for efficient online inference of hidden states given a set of observations. An extension of HMMs that can be useful for modeling human-robot collaboration is the Partially Observable Markov Decision Process (POMDP)**R**. Solving a POMDP amounts to the computation of the optimal policy (probability distribution over actions given state) executed by the agent**R**. POMDP based models can be used by autonomy in which the human intent or actions are treated as hidden states. By performing online inference on human intent and actions, autonomy will be equipped to plan better by taking into consideration the human as well**R**. For example, POMDP based models are used for assessing the human's trust**R** in the autonomous partner and to incorporate human preferences into autonomous planning**R**. In general, inference over latent variables in a POMDP framework is performed via Bayesian methods in which a prior distribution over the variables is updated via Bayes Theorem upon receiving new evidence. The choice of likelihood function, typically encodes, the human's actions/preferences give a state (policy)**R**. In our work, we have relied on heuristic approaches**R** based on simple directedness and proximity based confidence functions to estimate reaching intent in a table-top manipulation tasks. In order to incorporate information from past states, in my previous work, I have also developed a framework for intent recognition based on ideas from *Dynamic Field Theory***R** in which the time-evolution of the probability distribution over intent is specified as a constrained dynamical system**R**. The activation function that drives the dynamical system plays a role akin to that of the likelihood function in Bayesian approaches in that it encodes the human's preferences. Additionally, in the domain of autonomous driving, I have developed a framework to learn agent models from partial observations that will help to predict their actions from noisy observations and deduce missing information about their environment. The probabilistic models for partially observed agents are learned via IRL techniques**R** through which we recover the agent's policy and reward structure. Within the model, efficient inference of latent states and actions is made possible by learning specific proposal distributions**R** to be used within an Reversible Jump Markov Chain Monte Carlo process**R**.

A generalization of HMMs, known as Dynamic Bayesian Networks (DBNs) are also used successfully to model human robot collaboration. DBNs are attractive due to their ability to handle multi-variate, mixed-observability variables and to represent the interdependencies between them at same as well as different time slices**R**. DBNs have been successfully utilized to model human beliefs, desires and learning **R** which can then be used for intent prediction and understanding cognitive phenomena such as concept learning**R**. However, structure of DBNs need to pre-specified by a domain expert and learning the parameters requires large amounts of data**R**.

2.1.2 Models for Policy Generation

Mathematical models are widely used for generating/learning policies for how autonomy should be controlling the robot. In addition to accomplishing the task at hand, users would likely require the autonomous partners actions to be legible, natural, and safe. Learning from Demonstration (LfD) [1] provides a framework to learn autonomous policies directly from user-provided demonstration data. Within this framework various types of approaches are utilized. For example, in imitation learning (IL) deep neural network based models can be used to learn direct mapping from states to actions. A more generalizable approach is to cast the problem as an inverse reinforcement learning problem in which the task is to recover the reward function of the user. Encoding tasks as reward functions and then deriving policies that optimize long-term return (solution of the forward RL problem) improves the robustness and generalization capabilities of the autonomous partner. Closely related to the RL approach is to utilize standard control theoretic framework to derive optimal policies for a given task. Standard optimal control theory techniques presume the existence of a dynamics model and solves for the optimal policy given a pre-specified cost function. State-of-the-art RL techniques, on the other hand, can be model-free and can resort to sampling-based techniques to derive optimal policies.

Planning-based approaches such as probabilistic road maps (PRMs) and RRTs are also widely used for generating motion plans (for both manipulators as well as mobile robots). In addition to task accomplishment, for enhanced user experience robot motion plans typically also need to possess various other desired characteristics. Human robot interaction in shared autonomy can become more seamless if the robot is able to make its intentions legible to the user and to that end researchers have attempted to mathematically define legibility and predictability of motion. By explicitly incorporating the legibility metric into the motion optimization procedure. Similarly, safety is a of paramount importance when robots work in close proximity to humans. Therefore, behaviors such as obstacle avoidance are incorporated into motion plans. To this end, the on-board perception system typically relies on object detection and recognition models to identify objects of interest and obstacles thereby characterizing favorable and unfavorable parts of the state space of the robot. In my work, I have utilized potential fields defined in the full 6DoF Cartesian space (task space) to generate the robot control commands. Obstacle avoidance is implemented using velocity-dependent repellers and the intended goal is modeled as the sole attractor. Potential fields are computationally lightweight and produces more intuitive trajectories that correspond to straight line paths in Euclidean space. More recent work from Ratcliff et al, treats obstacles as local deformation in the geometry of the workspace and aims to derive motion policies directly in a curved Riemannian workspace. The effect of the obstacle is to curve the geodesics (straight line paths) around itself as determined by the local curvature induced by the obstacle.

2.1.3 Models for Control Allocation

In a shared control setting task responsibility is shared between the human and autonomy. Therefore, control allocation, that is, how exactly should control be arbitrated between the human and autonomous partner, needs to appropriately implemented for desired outcomes. Different approaches exist for sharing control between the human and autonomy that depend on the application domain, user preferences and robot platform. Broadly speaking, shared control approaches can be broadly classified into three categories: hierarchical, blending-based and control partition based approaches.

In the hierarchical paradigm, control allocation typically occurs at the task level in which higher level task goals are entrusted with the human and the autonomy takes care of the low-level control of the robot. For example, in the assistive domain smart wheelchair users can use a click-based interface to a select a desired destination in the world or a laser pointer to point to a desired goal and the autonomy can generate the global as well as local plans utilizing any state-of-the-art motion planners. In the domain of table-top manipulation users can use natural language based interfaces to specify the desired grasp or reach target which then combined with a object recognition and motion planning modules can result in a desired robot trajectory.

Blending-based approaches seek to arbitrate between human and autonomy actions at the control signal level (or the policy level) directly. Dragan et al. introduced the policy blending formalism for shared control in which they propose that “arbitration should be contextual and the should depend on the robot’s confidence in itself and in the user, as well as on the particulars of the user”. A commonly used arbitration scheme is one in which the final control command issued to the robot is a linear blend of human and autonomy control commands. The blending parameter can be fixed or can be a parameterized function of the context and the autonomy’s confidence in its prediction of the user’s intent. In our work on human-in-the-loop customization of control allocation parameters we have utilized a blending-based shared control in which the linear blending factor is a function of the probability of the predicted goal (agnostic to the kind of intent inference algorithm used). We assumed a piecewise-linear function and under the assumption that the human is optimizing an unknown cost function, we developed an iterative procedure with which the user is able to tune the arbitration function parameters to the users' satisfaction and preference [4]. By casting shared control allocation in a broader theoretical framework, Trautman has also proposed a mathematical model for probabilistic shared control in complex dynamic environment. In this work, the interactive relationship between the human, autonomy and the environment is modeled as a undirected graphical model. The paper also introduces the notion of an *interaction* function between the operator and the autonomy that captures the "agreeability" between the human and autonomy. For specific forms of the interaction function, Trautman is able to recover linear blending as a special case of the more general framework and shows that in general, linear blending is suboptimal with respect to the joint metric of agreeability, safety and efficiency.

In the domain of assistive robotics, there exists yet another particularly challenging problem. The standard usage of these assistive machines relies on manual teleoperation typically enacted through a control interface such as a joystick. However, the greater the motor impairment of the user, the more limited are the interfaces available for them to use. These interfaces (for example, sip-and-puffs and switch-based head arrays) are low-dimensional, discrete interfaces that can only operate in subsets of the entire control space (referred to as *control modes*). The dimensionality mismatch between the interface and the robot's controllable degrees-of-freedom (DoF) necessitates the user to switch between control modes during teleoperation and has been shown to add to the cognitive and physical burden and affects task performance negatively [10]. In order to offset the drop in performance due to shifting focus (also known as task switching) from the task at hand due to switching between different control modes different mode switch assistance paradigms have been proposed. A simple time-optimal mode switching scheme has shown to improve task performance [6]. Machine learning techniques have been utilized to learn mappings from robot state to control modes preferred by human users**R**. Robot operation in certain control modes can also help the autonomy to infer the user's intent more accurately and confidently, especially in scenarios where autonomy's inference of user intent is exclusively informed by human's control commands issued via the control interface. To that end, in our work, on mode switch assistance for intent disambiguation we developed a disambiguation metric to characterize the intent disambiguation capabilities of a control dimension of control mode. By having the user operate the robot in the disambiguating control mode, the control commands become more *intent-expressive* and as a result autonomy is able to step in and provide appropriate assistance. In this work, we also introduce the notion of *inverse legibility*, in which the roles are switched and the human-generated actions *help the robot* to infer human intent confidently and accurately [3].

2.2 Desired Characteristics of HRI

Humans are highly adept at working together in teams and are able to effectively coordinate and cooperate with another human in a seamless, natural and fluid manner in a joint task setting. How exactly are humans able to interact efficiently in a team setting? And what do humans prioritize, besides successful task accomplishment, when working alongside others? Researchers in the fields of cognitive psychology philosophy have been long interested in these questions. Human-robot interaction researchers and roboticists will likely benefit from insights that psychologists and philosophers have had with respect to what constitutes successful interaction between partners in a shared setting.

Need for efficient communication and information exchange and transparency

Need for fluency?

Shared Mental Models
Joint Attention
User-centric system development.

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