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

Thesis proposal

Deepak Edakkattil Gopinath
Department of Mechanical Engineering
Northwestern University
deepakgopinath@u.northwestern.edu

December 5, 2018

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*..

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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), entertainment (musical robots) and home robotics **R**.

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 **R**. 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 **R**.

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 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**.

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. According to them the computational level describes the high-level primary function of the agent, that is the model's primary job is to describe *what* the agent is doing [1]. On the other hand, algorithmic models focus on *how* a particular function is carried out by the agent and the representations that it depends on. Lastly, implementational level models are concerned with the physical realization of the procedures and representations on the hardware.

[1] The word 'agent' is used in order to refer to any information processing system. In this context we are interested in modeling human behavior. Human partners might also maintain similar models for their robotic counterparts.

Hiatt et al. goes on to claim that categorization of human models according to Marr's level of analysis 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. **incorporate implicit assumotion of distance based cost function in intent disambiguation work.** 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**.

WORK IN PROGRESS - REST OF IT Reference to Koopman operators for data driven models of human

How to handle noise and systematic errors in human behavior. Are the models learned directly from data or hand coded.

Models for intent inference. Reference to my work on DFT Models for updating trust. Models for human preference.

Algorthmic level models using MDP, POMDP. Autonomy maintains these models to predict human actions and integrates the predictions within its own decision making. David Hsu, Javdani et al.

MODELS FOR AUTONOMOUS POLICY GENERATION Models for autonomous policy generation We need models for how autonomy should be generating the control commands. Learning autonomous policies. That match human motion. That improves legibility and predictability. Risk-aware motion planning. Safety aware motion planning.

Models for autonomous policy? NN models that learns to take 'actions' conditioned on the current state.

LfD techniques. DMPs. Potential Fields. RL techniques to learn policies. Riemannian Motion policies. Planning based techniques.

potential fields - My work uses those.

Optimal control ideas (similar to POMDP).

MODELS FOR ASSISTANCE

What is the form of assistance and the math behind it. What kind of assistance? Navigation? Mode Switching?

MODELS FOR ENVIRONMENT?

Perception Models. Recognizing objects and affordances. Recognizing grasp poses. Recognizing Obstacles for safe navigations.

MODELS FOR SHARED CONTROL.

We need mathematical models that deal with how control should be arbitrated. Linear blending (My work), probabilistic shared control. Maxwell Demon's approach. Game Theoretic approaches. Shared control vs. traded control? Models for shared control optimizing for safety. For enhancing trust.

Linear Blending - My works uses those. Policy Blending Approach Trautman Hauser? Optimal Control and Maxwell's Demon. USer as POMDP. Shared control - Blending based, Maxwell's Demon, Joint Cost minimization, Heirarchical (Check out review paper)

References