Designing Robot Behavior in Human-Robot Interactions

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Preface

Human-robot interactions (HRI) have been recognized to be a key element of future robots in many application domains such as manufacturing and transportation, which have huge social and economic impacts. Future robots are envisioned to be acting like humans, which are independent entities that make decisions for themselves; intelligent actuators that interact with the physical world; and involved observers that have rich senses and critical judgements. Most importantly, they are entitled social attributions to build relationships with humans. We call them co-robots.

Technically, it is challenging to design the behavior of co-robots. Unlike traditional robots which work in structured and deterministic environments, co-robots need to operate in highly unstructured and stochastic environments. The book is dedicated to study the methodologies to ensure that co-robots operate efficiently and safely in dynamic uncertain environments.

This book sets up a unified analytical framework for various human-robot systems, which involve peer-peer interactions or hierarchical interactions. Various methods to design robot behavior through control, planning, decision, and learning are proposed. In particular, the following topics are discussed: **safety** during human robot interactions, **efficiency** in real-time robot motion planning, **imitation** of human behaviors by robot, **dexterity** of robots to adapt to different environments and tasks, **cooperation** among robots and humans and conflict resolution. The proposed methods have been applied on various scenarios, such as human-robot collaborative assembly, robot skill learning from human demonstration, interaction between autonomous and human-driven vehicles, etc.

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Nomenclature

x	state
u	control
y	measurement
π	historical data (combination of all measurements)
t	time
k	time step
t_s	sampling time
g	logic function (from measurement to control)
f	dynamic function (from control to state)
h	measurement function (from state to measurement)
$\mathcal{J}$	cost
$\mathcal{M}$	model
$\mathcal{B}$	behavior system (including knowledge, logic, and learning)
$\mathcal{X}$	state space
$\mathcal{C}$	configuration space
Ω	constraint on control space
Γ	constraint on state space
$\mathcal{I}$	constraint for interaction
ϕ	safety index
$\mathbb{E}$	expectation
$\mathbb{P}$	probability
$\mathcal{N}$	normal distribution
κ	curvature
$\hat{\cdot}$	estimate
$\tilde{\cdot}$	estimation error
X	mean squared estimation error
$\mathbf{I}_n$	$n \times n$ identity matrix
w	contact wrench
K	controller gain
$\emptyset$	empty set
σ	covariance
Σ	covariance matrix
$\mathcal{T}$	registration function
$\mathcal{O}$	complexity
$\cdot^T$	matrix transform
$\cdot$	registration point

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Part I

Introduction

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1 Introduction

1.1 HUMAN-ROBOT INTERACTIONS: AN OVERVIEW

Human-robot interactions (HRI) have been recognized to be a key element of future robots in many application domains such as manufacturing, transportation, service, and entertainment. In factories, robots are expected to collaborate with human workers [109]. Manufacturers are interested in combining human's flexibility and robot's productivity in flexible production lines [102]. In transportation systems, autonomous vehicles are expected to interact with various road participants, including human-driven vehicles and pedestrians. In hospitals, medical robots are expected to help doctors to perform surgeries on patients. Exoskeleton robots are expected to assist stroke patients to walk [100]. Nursing robots [169] are expected to take care of patients. Robot guide dogs [203] are expected to help blind people.

These applications entail huge social and economic impacts [52, 34]. Future robots are envisioned to be acting like humans, which are independent entities that make decisions for themselves; intelligent actuators that interact with the physical world; and involved observers that have rich senses and critical judgements. Most importantly, they are entitled social attributions to build relationships with humans [63]. We call these robots co-robots.

Technically, it is a challenge to design the behavior of co-robots. Unlike conventional robots that work in structured and deterministic environments, co-robots need to operate in highly unstructured and stochastic environments. The skill sets that have been developed for conventional robots can no longer meet the needs of co-robots. This book explores methodologies to equip co-robots with desired skill sets, in order to enable wide adoption of co-robots in various interactive environments, as mentioned earlier. The fundamental research question to address in this book is *how to ensure that co-robots operate efficiently and safely in dynamic uncertain environments*. Regarding broadness and complexity of HRI [52], the following four aspects of the fundamental question are considered:

Diverse modes of interactions

The potential applications of co-robots lie in various domains, with different modes of interactions [167, 111, 55]. For example, humans and robots can be collaborators in factories, while automated vehicles and vehicles driven by human drivers are competitors for limited road resources on public roads. Different modes of interactions imply different system dynamics as well as diverse performance requirements for the robot. Moreover, the relationship that a robot builds with a human may be dynamic, i.e., the mode of interaction may change over time. A unified model for various HRI

applications is needed in order to provide a comprehensive understanding of HRI, guide the design of the robot behavior, and serve as an analytical framework for performance evaluation of the human-robot systems.

Design of the robot behaviors

Behavior is the way in which one acts or conducts oneself, especially towards others. Action can be taken in multiple ways. For a humanoid robot, it can be physical movement, gesture, facial expression, language, etc. For an automated vehicle, it can be physical movements, turning on lights, honking, etc. We study the methodology of behavior design, i.e., how to realize the design goal (to ensure that co-robots operate efficiently and safely in dynamic uncertain environments) within the design scope (the inputs and outputs of the robotic system). This book mainly considers physical movements of co-robots.

Software embodiment of the behavior and its computation efficiency

The designed behavior is embodied as robot software. The complexity of the software will increase dramatically when the environment or the task becomes more complex. To ensure timely responses to environmental changes and guarantee safety during operation, real-time computation and actuation is crucial. Efficient algorithms are highly demanded.

Analysis, synthesis and evaluation of complex human-robot systems

The effectiveness of the designed robot behavior needs to be evaluated in human-robot systems. The evaluation can be performed theoretically as well as experimentally. The challenge in theoretical analysis is the complication of interweaving software modules. The difficulty in conducting experiments is that the tolerance of failure is extremely low when human subjects are in the loop, i.e., human safety is critical. Moreover, it is difficult to repeat some human-in-the-loop experiments due to the stochasticity of human behaviors. It is important to develop effective evaluation platforms for human-robot systems.

The focus of this book is to (1) set up a unified analytical framework for various human-robot systems; (2) establish methodologies to design robot behaviors under the framework that address the fundamental question. The considerations in the above four aspects will be elaborated in the following sections.

1.2 MODES OF INTERACTIONS

Interaction between a human and a robot may have various modes. We divide it into two kinds of relationships: *parallel relationships* and *hierarchical relationships*.

Figure 1.1: Various modes of human-robot interactions.

Color version at the end of the book

Parallel HRI

In a parallel relationship, a human and a robot are two independent entities who make their own decisions. In literature, parallel interaction is also called peer-peer interaction [55]. Typical examples of parallel relationships are (1) the interaction between an automated vehicle and a human-driven vehicle and (2) the interaction between an industrial co-robot and a human worker in production lines. In either case, the robot (the automated vehicle or the industrial co-robot) and the human (the human-driven vehicle or the human worker) are peers as opposed to hierarchical relationships. In the parallel relationships shown in Fig. 1.1a, the actions of the human and the robot either need to be synchronized (e.g., when the human and the robot are moving one workpiece cooperatively) or need to be asynchronized (e.g., two vehicles cannot occupy the conflict zone at the same time when they are crossing an intersection). We call the synchronized actions *collaboration* and the asynchronized actions *competition* (since there will always be a vehicle that passes the conflict zone first). Competition is the most common interaction mode. For instance, if a human and a robot are competing for space, the competition can be understood as collision avoidance.

Hierarchical HRI

In hierarchical relationships, either the human or the robot transfers the responsibility of making decisions to the other, completely or partially. Typical examples in hierarchical relationships are listed below, which is also shown in Fig. 1.1b.

1. The interaction between an automated vehicle and a passenger inside a vehicle, where the human passenger allows the vehicle to make driving decisions.¹
2. The interaction between a robot nurse and a patient, where the robot decides the moving trajectory for the patient.²
3. The interaction between a human and a human-assistive device such as an exoskeleton. The human can be guided by the robot, but can also “fight” against the robot.
4. The interaction between a human driver and a driver-assistance system.³ The driver-assistance system can serve as a guardian angel [89] that allows the driver to decide in safe situations and takes over during an emergency, or as an assistant that takes charge in safe situations and asks the human to take charge of emergencies.⁴
5. The interaction between a human and a robot when the human teaches the robot a skill by kinesthetic teaching. In this case, the robot is following the moving trajectory taught by the human.
6. The interaction between a human tele-operator and a tele-operated robot, where the robot purely follows the command from the human.⁵

As discussed in the above examples, the allocation of responsibilities varies for different hierarchical interactions. The robot purely follows the human’s command in one extreme, while the human purely follows the robot’s motion in another extreme. When human dominates the decision process, it is called supervisory interaction [153] in literature. Allocation of responsibility can change throughout time as discussed in the guardian angel case for driver-assistance systems.

The modes of interactions among multiple humans and robots can be built from those basic interaction modes between one human and one robot. A multi-agent framework will be proposed in Chapter 2 to provide a unified framework to analyze various kinds of interactions, where every intelligent entity (human or robot) is viewed as one agent. For simplicity, we do not distinguish between a robot and a co-robot literally in the following discussion.

¹Online figure: <http://www.autonews.com/article/20160111/OEM06/301119965/autonomous-vehicle-architects-begin-to-contemplate-the-human-inside>.

²Online figure: <http://newatlas.com/riba-robot-nurse/12693/>.

³Online figure: <http://editorial.autowebs.com/autowebs-guide-to-adaptive-cruise-control/>.

⁴The level of autonomy of an intelligent vehicle is divided into six categories in the SAE International’s new standard J3016 [6], which ranges between the two extremes: either the human driver makes all the decisions or the automated vehicle makes all the decisions.

⁵Online figure: <http://www.telepresenceoptions.com/2014/08/r/>.

1.3 ROBOT BEHAVIOR SYSTEM

This book focuses on behavior design of a robot from the perspective of physical movement, e.g., how to generate safe and efficient motions during interactions.

1.3.1 OVERVIEW

Three components

To generate desired robot behavior, we need to

1. encode correct knowledge in the robot;
2. design a correct logic to let the robot turn the knowledge into desired actions;
3. design a learning process to update the knowledge and the logic, in order to make the robot adaptable to unforeseen environments.

Knowledge, logic, and learning are the major components of a behavior system, as shown in Fig. 1.2a. In the diagram, the robot obtains measurement π from the human-involved environment and generates its action u according to the logic.

(a) Components of a behavior system.

(b) The life-cycle of a behavior system.

Figure 1.2: Behavior systems.

Knowledge and logic can be considered in both the model-based framework or the model-free framework. Model-free knowledge consists of a set of data points

(π, u) , which implicitly encodes the relationship between measurement and action. The corresponding logic is a model-free logic that acts according to the implicit mapping from π to u observed in the data points. Model-based knowledge consists of *cost* that describes task requirements and *model* that describes the dynamics of the environment. The corresponding logic $g(\pi|\mathcal{J}, \mathcal{M})$ ⁶ is a mapping from measurement to action that depends on its knowledge: the cost $\mathcal{J}$ and the model $\mathcal{M}$.

The learning process updates the knowledge and the logic based on the data π , which is necessary since (1) the designed knowledge may not cover all possible scenarios and (2) the environment may be time varying. The mathematical formulation will be further explained in Chapter 2.

Robot lifetime

The lifetime of a robot is divided into three phases: the design phase, the training phase and the execution phase, as shown in Fig. 1.2b. We call the first two phases offline process and the third online process. In the design phase, the human designers specify the three components in Fig. 1.2a for the robot. In the training phase, the robot can learn knowledge from experience or from human demonstration. The difference between the knowledge learned from human demonstration and the knowledge designed by human is that the former does not require the human to have a mathematical or quantitative representation of the knowledge. In many cases, such mathematical representations are hard to obtain and unintuitive for the human. For example, it is easier for a human to gesture a motion trajectory than to come up with a mathematical function of the trajectory. In the execution phase, the robot performs its task and interacts with the environment. While performing the tasks, the robot can update the knowledge or the logic through online learning. However, due to limitations in computation power, online learning is restricted to small-scale parametric adaptation. Structural changes such as learning a new skill from scratch are performed by offline learning in the training phase. The training phase and the execution phase can be performed iteratively in a lifelong learning system [212]. It is also possible that the robot goes directly from the design phase to the online execution phase without going through the training phase.

Nature vs. nurture

Knowledge is the key content of a behavioral system. How much it should be designed (nature) and how much it should be learned (nurture) still remains arguable [51].

Although knowledge can be learned, the two other components, logic and learning, are essentially algorithms to be designed. There are three ways to obtain logic g as illustrated in Fig. 1.3. The contours in the figures represent the internal cost $\mathcal{J}(u, \pi)$. The darker the color, the higher the cost. Logic g is a mapping from π to u , and can be obtained using the following three methods. The first two methods

⁶The function g is also called a control law in classic control theory or a control policy in decision theory.

Figure 1.3: Classification of behavior systems.

are model-based, which assume explicit $\mathcal{J}$ and $\mathcal{M}$. The last method is model-free, which only requires (π, u) data points.

1. Model-based explicit policy.

We can explicitly solve the optimization $\min_u \mathcal{J}(u, \pi)$ given $\mathcal{M}$ in the design phase (offline). In this way, we obtain a model-based *explicit policy* $g : \pi \mapsto u$ which solves the optimization, i.e., $g(\pi) := \min_u \mathcal{J}(u, \pi)$, as shown in the thick curve in Fig. 1.3a. The function g may be discontinuous, when the cost $\mathcal{J}$ is non-convex.

2. Model-based implicit policy.

The optimization can also be solved online in the execution phase. An algorithm (e.g., gradient descent) needs to be designed such that given any

observation π , a desired control input u can be computed. This provides a model-based *implicit policy*, as shown in Fig. 1.3b. When the cost $\mathcal{J}$ is non-convex, the control input u computed online may only be a local optimum. The computation of u is only initiated when π is obtained in the execution phase, which is different from an explicit policy that computes u for all possible π in the design phase.

3. Model-free policy.

We can also approximate the policy using parametric functions (e.g., neural networks) in the training phase. Given model-free knowledge which consists of a set of data points (π, u) , the function g can be approximated from the data as shown in Fig. 1.3c. Since no explicit cost or model is extracted from the data, this is a model-free logic.⁷

The three-component behavior system represents a variety of existing methods. We summarize the methods into the following three categories ranging from nature-oriented design to nurture-oriented design, as shown in Fig. 1.3d.

1. Category 1: Pure Nature

The designer specifies the cost and the model and designs model-based logics to solve the optimization without any learning process. Representative methods are (1) classic control methods and Markov decision processes (MDPs) where explicit policies are obtained in the design phase (e.g., in the control of flexible robot joints [100, 214], or in safety critical situations [80, 228]), and (2) model predictive control (MPC) methods where the optimization is computed in the execution phase [146, 46, 122].

2. Category 2: Nature + Nurture

In one case, the designer specifies the cost, designs the logic explicitly, and defers to the learning process to identify the models. Classic adaptive control and adaptive MPC belong to this category. Application of this approach in human-robot interactions can be found in [185, 131, 76, 152]. The advantage of this method is that it can account for time varying environmental changes, especially when humans are in the loop, while the designer still has control over the task performance through explicit design of the knowledge and the logic.

Another case is that the designer only designs the logic and the learning process explicitly. The knowledge is obtained in the training phase by either trial-and-error or expert demonstration. Representative methods are model-based reinforcement learning and inverse reinforcement learning such as apprentice learning [8, 15, 70]. The learning object can either be the cost

⁷Though a model-free policy can well approximate the true policy in data-rich regions, it may not generalize to regions with few data. Moreover, it is hard for model-free methods to infer hard constraints from the data. In Fig. 1.3c, the model-free policy (thick curve) deviates from the exact policy in regions with few data and even violates the hard constraint (shaded infeasible set).

(if the task is very complicated) or the model (if the dynamics are complicated) or both (as in cost-model coupled Q -learning). Application of this approach in human-robot interactions can be found in [211, 11, 162]. The advantage of this method is that mathematical modeling of the task and the environment is no longer required in the design phase.

3. Category 3: Pure Nurture

The designer designs the learning process explicitly, obtains model-free knowledge in the training phase, and approximates the logic using a model-free policy, which is usually represented by a neural network. In contrast to knowledge learning in Category 2, the knowledge in this category is not explicitly learned, but implicitly encoded in the data points and in the neural network. Representative methods are model-free reinforcement learning such as deep reinforcement learning [156] and imitation learning [104]. In addition to human subjects, the object to be imitated may be a behavior system in Category 1 and Category 2 [200]. This method is good for problems where (1) the task and the environment are extremely hard to model, (2) the state space is too large and (3) real-time computation is critical.

This classification may not be exhaustive. This book considers methods in Category 2 and Category 3. The existing methods in designing the three components will be reviewed in the following sections.

1.3.2 KNOWLEDGE

As illustrated in Fig. 1.2a, knowledge may contain both raw data (e.g., measurement-action pairs (π, u)) and the system principles extracted from raw data (e.g., the cost $\mathcal{J}$ and the model $\mathcal{M}$). The former is also called model-free knowledge, while the latter is called model-based knowledge. For model-free knowledge, the measurement in the raw data may contain (1) system states and (2) the instant cost evaluation on current states and actions. In the following discussion, we call (π, u) the state-action-cost pair, since it is a collection of system states, the corresponding desired actions demonstrated by human or calculated by a solver, and the instant cost evaluated on current states and actions. For model-based knowledge, the cost $\mathcal{J}$ provides incentives for the robot to finish the desired task efficiently as well as to interact safely with other agents in the system, while the model $\mathcal{M}$ should be designed in order to match the ground truth behavior of the environment. The cost $\mathcal{J}$ is a function that assigns values to all measurement-action pairs, while the instant cost in raw data is just a “point-wise” run-time measurement.

State-action-cost pairs

“All models are wrong, but some are useful.”

George E. P. Box

Because of the complexity of the real world, a manual-designed model is usually a subjective simplification of the actual system. On the other hand, raw data is an objective observation of the world, which usually contains more comprehensive information than a simplified extracted model. Recently, many data mining methods have been developed, trying to recover useful information from raw measurement data. Naturally, the first and critical step for data mining is to construct a database as comprehensive as possible to fully embed the system property.

In robotics, the state-action-cost pairs provide a straightforward encoding of cluttered data. These pairs describe the evolutionary system dynamics, the desired policy principle and the hidden cost mechanism implicitly. The state variables are the smallest possible subset of system variables that can represent the entire system condition at any given time. The action is the control command that can be applied on the system to influence the evolution of the system. The instant cost is a quantitative description of the goodness or badness of the current state and action. For a rational agent, it is supposed to be an optimizer which tends to achieve the highest rewards or the lowest costs by taking appropriate actions.

These data, i.e., the state-action-cost pairs, can be acquired by human demonstration or by robot self-exploration. In the demonstration approach, a human operator demonstrates the desired action w.r.t. a specific state, and labels the current condition with a corresponding cost value. In the exploration approach, the robot autonomously explores the state space by following some heuristic rules. The former approach collects more biased samples which contain human intention of optimality. This sampling bias might concentrate the learning in a limited region and boost the learning convergence. The latter approach, on the other hand, involves more randomness and explores broader regions. It provides more implementation flexibility since no human demonstration is required.

Cost

Cost $\mathcal{J}$ is a function on the state and action of the robot, which encodes a form of internal incentives for the robot to finish certain tasks. A rational robot always seeks to minimize the cost. The cost can either be a *static cost* or a *dynamic cost*. Static cost is a function on current state and action, which can be measured as the instant cost in the raw data discussed earlier. Dynamic cost is a function on a trajectory, i.e., a sequence of future states and actions, which is a discounted sum of all static costs

along the trajectory.⁸ Static cost includes runtime cost (e.g., the cost incurred before the completion of the task) and terminal cost (e.g., the cost related to the completion of the task). If the process never ends, there can be no terminal cost. For example, there is no terminal cost during lane following for automated vehicles. Dynamic cost can be summed either for a fixed time horizon (finite time or infinite time) or for a fixed task cycle. Fixed time horizon is adopted in linear quadratic regulator, preview control and receding horizon control. Fixed task cycle optimization is also called “minimum time problem” as the terminal time is treated as a decision variable. Fixed task cycle optimization is usually adopted in trajectory planning with fixed targets. The cost $\mathcal{J}$ will refer to the dynamic cost in the following discussion.

For model-based methods, the cost can either be designed or learned, with different levels of details. In Category 1, the cost is explicitly specified by a designer to achieve certain design objectives. However, for complicated tasks, it is hard for a human designer to construct desired cost functions, while it is easier to let the robot learn from experience or learn from others. In Category 2, the cost is obtained from data, i.e., the state-action-cost pairs discussed above. In particular, model-based reinforcement learning allows the robots to learn static cost from past experience, which can then be combined to formulate dynamic cost. Inverse reinforcement learning allows the robot to infer the cost $\mathcal{J}$ from some observed policy $\hat{g}(\cdot|\mathcal{J}, \mathcal{M})$, e.g., from an expert. The design of $\mathcal{J}$ will be discussed in the following chapters w.r.t. specific applications.

Model

Since the robot model is usually known in advance, we focus on the models of other intelligent entities in the environment, especially humans. As pointed out in [43], the biggest challenge in human-robot collaboration comes from human factors. To make co-robots human-friendly, human behavior needs to be modeled, learned, and predicted [14, 32, 176, 230]. The following three kinds of models are frequently used to describe human behaviors.

1. Reactive model.

Under a reactive model, human dynamics are described using ordinary differential or difference equations. The inputs to the model are the identified features that affect human behaviors [191], while the output is the human motion.

2. Rational model.

Under a rational model, a human is treated as a cost minimizer [160, 217], whose cost function depends on both his or her behavior and the robot’s behavior. The human will reason his or her best action given his or her belief in the robot’s behavior.

⁸In the MDP context, the static cost is equivalent to the reward function and the dynamic cost is equivalent to the value function or the Q function.

3. Bayesian model.

Under a Bayesian model, a human is treated as a stochastic agent [215]. A Bayesian network [170, 179] is associated with his or her decisions, i.e., the human's motion follows a probabilistic distribution conditioned on the robot's behavior.

It is usually hard to obtain the cost function or probability distribution that precisely describes human behavior in sophisticated problems. Moreover, it is dangerous to assume that a human will always adapt his or her motion to a robot's motion, as it intrinsically implies that the robot can "control" the human [20]. Since no universal model exists that can precisely describe human behavior, learning of human behaviors is necessary.

1.3.3 LOGIC

As discussed in [section 1.3.1](#) and illustrated in [Fig. 1.3](#), there are two kinds of logic, i.e., model-based logic and model-free logic. The model-based logic assumes that the system follows some hidden deterministic rules. One deterministic rule can be that agents are rational. Under the rationality assumption, the control policy is designed to be an optimizer which explicitly calculates optimal actions for the robot to achieve optimal performance. The optimal performance is described by minimal cost in this book. The cost metric as a part of knowledge needs delicate design as discussed in [section 1.3.2](#). In contrast, the model-free logic regards the system as a stochastic process, where the control policy is nothing but a regression function between inputs (states) and outputs (actions). This regression function can be approximated purely by data mining, or modeled partly by system analysis. This section discusses methods to design model-based logic. Learning of model-free logic will be discussed in [section 1.3.4](#).

The fundamental problem of a model-based logic is to find the minimum in the cost $\mathcal{J}$, given the data π and the model $\mathcal{M}$. In engineering applications, as the problems are complicated and in large scale, minimum seeking is non-trivial and various levels of approximations are needed. A model-based explicit policy is suitable for well-defined tasks and environments, however, hard to cover a variety of complicated scenarios that co-robots may face. This book focuses on model-based implicit policies which require online optimization. As we focus on physical movements in robot behaviors, the behavior design problem is essentially a motion planning problem. Depending on the look-ahead horizon of the dynamic cost, there are two kinds of motion planners, i.e., global planner (or long-term planner) and local planner (or short-term planner).

Global planner

A global planner evaluates the dynamic cost in a relatively long time horizon. The horizon may go to infinity. A comprehensive model of the environment is needed.

The existing global motion planning methods fall into two categories: planning by construction and planning by modification. Planning by construction refers to methods that extend a trajectory by attaching new points to it until the target point is reached. Search-based methods such as A* or D* search [195] and sampling-based methods such as rapidly-exploring random tree [105, 108] are typical planning-by-construction methods. Planning by modification refers to methods that perturb an existing trajectory so that the desired property is obtained. Optimization-based motion planning methods belong to this category. Gradient descent performs the perturbation or modification of the trajectory when solving the optimization [90, 189, 56]. Every type of methods has pros and cons. The trajectories planned by construction are more feasible than trajectories planned by modification. However, as the space is usually discretized during trajectory construction, the constructed trajectories are not as smooth as the trajectories planned by modification. This book focuses on optimization-based methods. If the environment is perfectly known without any uncertainty in advance, the global planner is capable of finding the global optimal trajectory. However, in practice, it is computationally expensive to build the model of the environment given the limited sensing ability and computational resource.

Local planner

A local planner tries to only plan a few steps ahead based on the limited knowledge of the environment obtained by current sensory data. Such planners require less computation power, and are good choices for robots with limited sensing abilities. An extreme case of a local planner is the reactive controller where the planning horizon reduces to one. There are usually closed-form solutions for reactive controllers. A closed-form solution of reactive control is a direct mapping from the sensory data to the control, which can greatly relieve the computation burden.⁹ Existing reactive methods include potential field method [95], barrier certificate [12], sliding mode method [74], and a family of biologically inspired methods [23]. However, as it only regulates the motion locally, a local planner is sensitive to local optima. It is possible for the robot to get stuck in some location and cannot reach the target. Thus, the global convergence to the target needs to be addressed when designing a local planner. In general, it is very hard to guarantee global convergence for local planners, as the system under consideration is nonlinear (as the robot motion is nonholonomic), time-varying (as the obstacles in the system are moving and deforming), and stochastic (as the information about the environment is limited).

To leverage the advantages of different planners, a global planner and a local planner can be combined in parallel, which will be discussed in Chapter 2.

⁹ A reactive control policy is similar to an explicit policy in Fig. 1.3a in that they are both direct mapping from the sensory data to the control. However, only local information is considered in the reactive control policy, while global information is encoded in the explicit policy when it is computed in the design phase.

1.3.4 LEARNING PROCESS

Learning process updates the knowledge or the logic according to the observed data. The ultimate goal of learning is to derive a better logic from the updates. As mentioned in [section 1.3.1](#), there are model-based and model-free logics. In model-based approaches, learning process directly updates the knowledge, so that the logic can be updated based on physical principles and deductions [16]. In model-free approaches, the learning process directly updates the logic.

Updating knowledge

In a model-based approach, both the cost and the model can be updated. This book considers the learning on the model, which is a *cognition skill*. In particular, interpretation and prediction of human motions are considered. Learning on the model can be done both offline (in the training phase) and online (in the execution phase). Offline learning is usually used to classify human behaviors and to identify models that describe human behaviors as discussed in [19, 64, 178]. On the other hand, online learning is capable of adapting the offline learned models to humans' time-varying behaviors online as discussed in [72, 185]. Methods to learn human model will be discussed in Chapter 5.

Updating logic

In model-based approaches, the logic is indirectly updated when the knowledge is updated. Such an approach is good for system transparency and interpretability, which is critical in many application domains, especially for industrial applications.

However, as robots are deployed to more sophisticated tasks, such as grasping dexterous objects and manipulating deformable objects, a pure model-based learning approach runs into its bottleneck. In these scenarios, either the system complexity goes beyond our capability to model, or the existing models cannot introduce satisfying results. On the other hand, along with the development of machine learning methods, especially the breakthrough of deep learning in recent years [110], people realize that: although human cognition process is complicated to model, it could be alternatively regressed by high dimensional parametric functions given a large amount of training data [157]. With this observation, many model-free learning approaches have been proposed recently, trying to teach robots new skills from data, instead of modeling those skills from principles. In the training stage, thousands or even millions of demonstration data is collected either by offline expert demonstration (imitation learning [24, 8], learning from demonstration [15, 17]), or by online trial and error (model-free reinforcement learning [155, 194]). The collected samples are then utilized to fit an optimal control policy g such that $u = g(\pi)$. These model-free learning approaches have universal structure and common training process, which can be quickly deployed to various scenarios. However, many of them

are working in a black box manner. As a consequence, it can be hard to interpret the outcomes of model-free learning. The stability of the learning system is also difficult to evaluate. Therefore, model-free learning are usually deployed for high-level tasks (e.g., vision detection), while the low-level implementation (e.g., motor servoing) is still based on model-based learning approaches. This hierarchical structure achieves a balance between performance and stability of the overall system. It is notable that for non-safety-critical scenarios, end-to-end learning [113, 31] is favored, where the hierarchical structures of systems are embedded in a single framework of deep neural networks, and thus the maximum potential of neural networks is exploited.

The model-free learning approaches, together with the model-based learning approaches which need online system identification, are called data-driven approaches in general. The learning methods will be discussed in Chapters 5 and 6.

1.4 DESIGN OBJECTIVES

Intelligent robots are multi-purposed complex entities. Their behavior systems (introduced earlier in [section 1.3](#)) need to be designed such that the robots are safe during human-robot interactions, efficient in task performance, able to imitate behaviors of other intelligent entities, dexterous to adapt to different environments and tasks, and cooperative with other intelligent entities. This book studies methodologies to achieve these five design objectives in Part II. The challenges and existing solutions to address these design objectives are discussed below.

1.4.1 SAFETY

Human safety is one of the biggest concerns in HRI [204]. Robots should be both intrinsically safe, e.g., minimizing impact if collision happens [79], and interactively safe, e.g., avoiding collision at the first place [216]. Interactive safety needs to be addressed in the context of decision making, motion planning and control of the robot during HRI.

The difficulty of designing safe robot behavior comes from (1) sophistication of human motion and (2) real-time implementation of the algorithm. Control theory offers plenty of methods to deal with disturbances. However, when humans are in the loop, the disturbances introduced by human motions are much more complicated. They are time varying with unknown models. Moreover, it seems counterproductive to view human motions as disturbances in the robot control, as the system should be human-oriented. Learning of human behaviors is needed to make robots compliant. Even with robots learning human behaviors, another concern is that a complex control algorithm may not be executed fast enough to ensure quick responses of robots in emergencies.

Conventional approach to address the interactive safety is conservative, which slows down the robot when humans are nearby, hence sacrifices productivity for the sake of safety. Less conservative methods in the context of obstacle avoidance have

also been used to address safety in HRI, e.g., potential field methods [168, 95], sliding mode methods [74]. These two methods result in closed-form analytical control laws, but are not optimal. Some authors formulate the problem as an optimization or optimal control problem with hard constraints to represent the safety requirements [56]. Unfortunately, these non-convex optimization problems are generally hard to solve analytically [86]. Different approximations and numerical methods are used to obtain solutions [189, 195]. However, these numerical methods may not be executed fast enough for timely responses in emergency situations.

Chapter 3 discusses the approaches that we developed for safe human-robot interaction. The problem is formulated as an optimization with hard safety constraints, which is non-convex. We then transform the non-convex state space constraint into a convex control space constraint using the idea of invariant set. In this way, the problem is transformed to a convex problem which can be solved efficiently online. This method can also take the uncertainty in the human behavior into account. It has been shown that the safety constraint will never be violated using the safe control method if the human behavior satisfies certain assumptions.

1.4.2 EFFICIENCY

Robot efficiency is essential to maximize task performance. Robots should understand the current situation, then plan and execute the proper actions to complete the task in minimum time. In human-involved dynamic environments, robot motion needs frequent replanning to cope with time-varying tasks. Hence, computation efficiency of the motion planning algorithms is critical to ensure real-time response of the robot.

The challenge of efficient motion planning results from the complexity of the planning problem, which may be highly nonlinear due to the dynamic constraints, and highly non-convex due to the constraints for obstacle avoidance. It is hard to solve the planning problem in real time.

This book focuses on optimization-based motion planning. There are various methods developed to deal with the non-linearity and non-convexity [163, 199] in optimization-based motion planning. One popular way is through convexification [210], e.g., transforming the non-convex problem into a convex one. Some authors tried to transform the non-convex problem to semidefinite programming [58]. Some authors proposed to introduce lossless convexification by augmenting the space [9, 83], and some authors proposed successive linear approximation to remove non-convex constraints [141, 142]. However, the first method requires the cost function to be quadratic. The second approach depends highly on the linearity of the system and may not be able to handle various obstacles. Finally, the third approach may not generalize to non-differentiable problems. One of the most popular convexification methods is the sequential quadratic programming (SQP) [198, 213], which approximates the non-convex problem as a sequence of quadratic programming problems and solves them iteratively. The method has been successfully applied to offline robot motion planning [91, 189]. However, as SQP is a generic algorithm, the unique

structure of the motion planning problems is neglected, which usually results in failure to meet the real-time requirement in engineering applications.

Chapter 4 discusses the approaches that we developed to ensure efficient robot motion planning during human-robot interactions. In practice, the cost function for motion planning is designed to be convex [221, 177], while the non-convexity mainly comes from the physical constraints, e.g., robot dynamics and collision avoidance. By exploiting the geometric structure of the problems, we propose the convex feasible set algorithm [127] and the slack convex feasible set algorithm [136] to handle motion planning problems with convex objective functions and non-convex constraints. It will be shown that these methods perform better than generic methods in robot motion planning in terms of efficiency.

1.4.3 IMITATION

Imitation is the ability of robots to reproduce human-like movements. On the one hand, by learning to mimic human behavior, robots can better predict human's future motion through mental simulation. Better prediction of human motion can lead to smoother human-robot interaction. On the other hand, robots can physically behave more like humans, so as to accomplish dexterous tasks which usually require human skills.

Take robotic precision assembly as an example. Tuning an appropriate force controller for a robot is usually a non-trivial task. In contrast, humans can accomplish assembly tasks compliantly with much less time and fewer trials. Human's inherent assembly skill is achieved by a form of internal control, which has been well tuned through our daily operation and experience. It is more intuitive and efficient to teach robots insertion skill by mimicking human's compliant motions, compared to designing a new controller from scratch [206, 114, 44, 101].

In general, the challenges for robots to mimic human behavior come from two aspects. First, it is difficult to select the proper variables to sufficiently and efficiently depict human behavior, while those variables should be observable and measurable by available sensors. Second, it is difficult to properly encode the measured human behaviors, and to reproduce human-like motions in novel scenarios. There are specific challenges associated with imitation for prediction [201, 224] and imitation for action [39, 40, 187]. Regarding imitation for prediction, the major problem is homogeneity of the learned models, which ignores individual differences. Hence, to make accurate "personalized" predictions, online adaptation of those models are necessary. Regarding imitation for action (or skill learning), few of those existing methods are implementable on industrial robots. Unlike collaborative robots, industrial robots are highly rigid because of large gear reduction ratio on the drive train. For assembly tasks, it implies that there is no compliance on the industrial robot's mechanism to assist assembly. Besides, the clearance requirement for industrial assembly is much more strict. Therefore, new schemes which are implementable on industrial robots need to be developed to support imitation learning.

Chapter 5 discusses methods to (1) learn individualized human behavior models so as to make better predictions; and (2) teach industrial robots assembly skills from human demonstration with varying admittance. For prediction, we introduce online learning. For skill learning, we introduce a model-free framework with guaranteed stability from Lyapunov analysis.

1.4.4 DEXTERITY

Dexterity is the ability of robots to change its nominal motion patterns to adapt to the change of its surrounding environment or task requirements.

Although there are numerous approaches for robot learning, most of them follow a similar pipeline: learning the logic in the training stage, and then applying the learned logic in new scenarios. It is implicitly assumed that the learned logic is universally applicable. However, it remains challenging to verify that the learned logic is truly universal and dexterous. To make robots dexterous, it will be beneficial to first understand the dexterity of human and then equip robots with the same ability.

Many studies in cognitive science shows that humans can make dexterous decisions w.r.t. various scenarios through analogical reasoning [42, 164, 116]. Given a new scenario, humans will try to find its correlation with past scenarios, and transfer previous problem-solving actions to the new situation. With this analogy approach, the problem can be solved without understanding the universal policy or causality behind the system. This analogy approach also enables humans to learn efficiently from small data samples.

Chapter 6 discusses an analogy-based learning approach to make robots dexterous. Unlike traditional model-based or model-free approaches, which try to formulate control policies, this new approach focuses on finding correlations among scenarios. This approach has two stages: the reminding stage and the transferring stage. During the reminding stage, the similarity between the past scenarios and the current scenario will be calculated. The most similar pair will be selected and a mapping function between the two scenarios will be constructed by non-rigid registration. During the transferring stage, the past actions will be transformed by the mapping function to generate new actions in the current situation. This approach is plausible for applications which are hard to model or to collect data from. More properties and advantages of analogy-based learning will be introduced in details in Chapter 6.

1.4.5 COOPERATION

Cooperation is the ability of robots to achieve a mutual goal together with other intelligent entities (e.g., humans or other robots) without centralized coordinations.

Cooperation is hard to achieve mainly due to information asymmetry [175], i.e., the parameter in the behavior system of one agent is unknown to another agent. Information asymmetry is common in HRI. From the agent perspective, most learning and control strategies follow a centralized design philosophy, which adjusts the

agent's estimation if its observation deviates from its prediction. This strategy is suitable in the single agent case, since the deviation can only be caused by the agent's wrong estimation. However, in a multi-agent system, where each agent acts on its estimation of the unknowns, the gap between an agent's observation and prediction is not only caused by the agent's wrong estimation (wrong prediction), but also other agents' wrong estimations and subsequent improper actions (deviated observations). Interactions and other agents' sub-optimality need to be considered explicitly in agent behavior design.

Conventionally, to compensate information asymmetry during online execution, distributed control laws are designed for each robot agent [180]. Following the control laws specified by the intelligent designer, who has an omniscient perspective, the agents do not need much intelligence. Although it is not explicitly stated that the control laws are globally known, the effectiveness of the controllers is based on the confidence that the designed control laws are perfectly followed by all agents. In this case, an agent just needs to follow its own control law, while other agents will take care of everything else by following their designed control laws. This strategy usually works well on problems with predefined environment and interaction patterns, but has limited extendability, as it is hard to design a universal control law that leads to desired results in a wide variety of situations, especially when the system topology is time-varying (interactions are happening among different agents at different times).

Chapter 7 discusses two ways to encourage cooperation. The first method introduces compensations of other agents' wrong estimations in the ego agent's learning strategy. In this way, even without explicit communication, the multi-agent system can still achieve the mutual goal. The second method allows agents to communicate with each other to resolve the conflicts. A conflict resolution mechanism is developed to form a consensus.

1.5 SYSTEM EVALUATION

The designed robot behaviors need to be evaluated in human-robot systems. The evaluation can be performed theoretically as well as experimentally.

1.5.1 THEORETICAL EVALUATION

During theoretical analysis, the questions to answer are:

1. Is the logic optimal and safe?
2. Will the learning process generate converging sequences to the ground truth?
3. Will the designed behaviors lead to desired outcomes of the multi-agent system?

The first two questions are modular-wise. The third question is system-wise which concerns with the stability, robustness stability and optimality of the closed loop system, e.g., whether the closed loop multi-agent system is self-organized [140]. System level analysis is challenging due to (1) the complication of interactions among different agents, (2) the difficulty in justifying the assumptions on human behavior; (3) the insufficiency of existing tools in game theory to analyze suboptimal agents.¹⁰

1.5.2 EXPERIMENTAL EVALUATION

In addition to theoretical analysis, experiments should be conducted to evaluate the performance of the designed robot behaviors. However, to protect human subjects, it is desirable if we can separate human subjects and the robot physically during the early phase of deployment. Figure 1.4 shows five different platforms that have been developed for experimental evaluations.

The first platform is the virtual reality-based human-in-the-loop platform. The robot's motion is simulated in a robot simulator. A human subject observes the robot movement through the virtual reality display (e.g., virtual reality glasses, augmented reality glasses or monitors). The reaction of the human subject is captured by sensors (e.g., Kinect or touchpad). The sensor data is then sent to the robot behavior system to compute the desired control input. The advantage of this platform is that it is safe to human subjects and convenient for idea testing. The disadvantage is that the robot simulator may neglect dynamic details of the physical robot, hence reducing the reliability of the results.

The second platform is the virtual reality-based hardware-in-the-loop platform. Its difference from the first platform is that the robot motion is no longer simulated, but directly measured from the robot hardware. This solves the problem of dynamic mis-match that the robot simulator may have. However, as the interaction happens virtually, the human subjects may not react in the same way that they do with real robots.

The third platform is the dummy-robot interaction platform. The interaction happens physically between the dummy and the robot. The human directly observes the robot motion and controls the dummy to interact with the robot. As there are physical interactions, an emergency check module should be added to ensure safety. The advantage of this platform is that it is safe to human subjects, while it is able to test interactions physically. However, the disadvantage is that the dummy usually has fewer degrees of freedom than a human subject.

The fourth platform is the robot-robot interaction platform. Each robot regards the other as a "human". In general, such a platform allows us to inquire whether the designed behavior system can cope with intelligent entities other than humans. Moreover, it can examine whether the multi-agent system consisting of those intelligent robots are stable or not.

¹⁰The basic assumption in game theory is that all agents are rational, e.g., always behaving optimally. However, the logic that we designed for the robot may not be optimal.

(a) Virtual reality-based human-in-the-loop platform.

(b) Virtual reality-based hardware-in-the-loop platform.

(c) Dummy-robot interaction platform.

(d) Robot-robot interaction platform.

(e) Human-robot interaction platform.

Figure 1.4: The evaluation platforms.

The fifth platform is the human-robot interaction platform where human subjects directly interact with robots. Such platform should be designed to illustrate the performance of the robot in real tasks.

In Part III of the book, evaluation results on those platforms will be discussed.

1.6 OUTLINE OF THE BOOK

This book aims to establish a set of methodologies for robot behavior design in order to maximize their performance in human-involved dynamic uncertain environments. The emphases of design objectives are safety, efficiency, imitation, dexterity, and cooperation.

As illustrated in Fig. 1.5, the remainder of the book is organized as follows.

Figure 1.5: Overview of the book content.

Part I is for introduction. Chapter 2 overviews the mathematical methods for robot behavior design in a multi-agent framework.

Part II discusses theory. Chapter 3 is for safety. Chapter 4 is for efficiency. Chapter 5 is for imitation. Chapter 6 is for dexterity. Chapter 7 is for cooperation.

Part III discusses applications. Chapter 8 discusses space-sharing human-robot interactions, such as the interaction between industrial co-robots and human workers,

and the interaction between autonomous vehicles and other road participants. Chapter 9 discusses hierarchical human-robot interactions where a robot learns skills from human teachers. Chapter 10 discusses time-sharing human-robot interactions where a robot and a human collaborate to finish a joint task.

Part IV discusses future vision and concludes the book.

Each chapter is intended to be self-contained. Some of the work has been published in [117, 118, 119, 120, 124, 127, 128, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 206, 207, 208, 209].

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