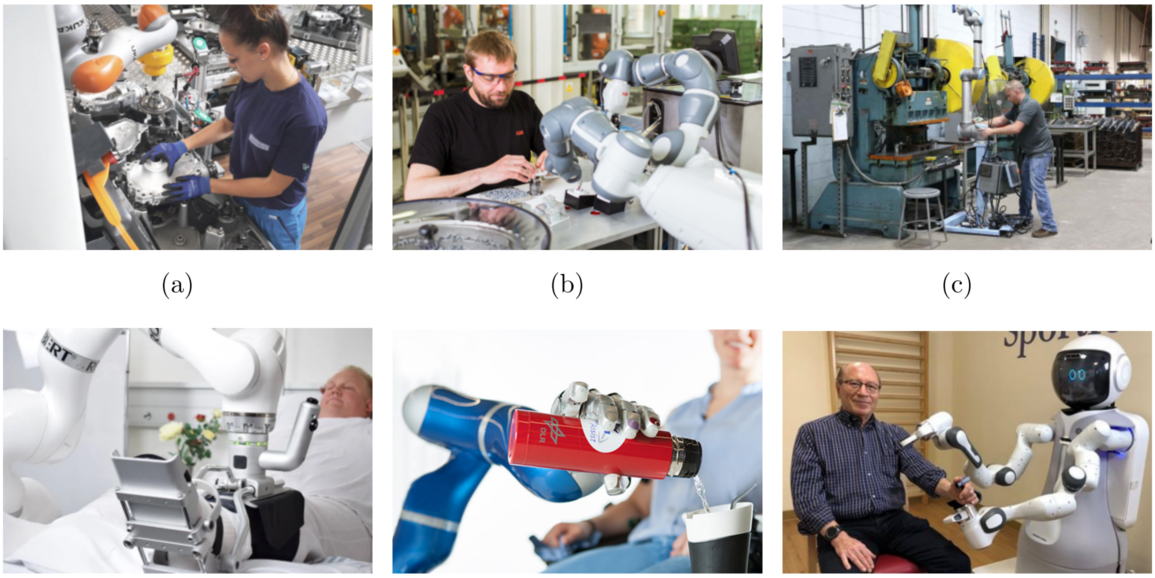
1 Introduction

1.1 Motivation



(a) (b) (c)

(d) (e) (f)

Figure 1.1: Application examples of cobots: (a) LBR iiwa, developed by KUKA, in BMW production line, (b) Yumi, developed by ABB, in Elektro-Praga assembly line, (c) UR10, developed by Universal Robots, in GM production line, (d) ROBERT, developed by KUKA, in rehabilitation of bedridden patients, (e) EDAN, developed by DLR, filling a drinking cup controlled from the wheelchair, (f) GARMI, developed by MSRM, assistant for the elderly.

In recent years, increasing applications of collaborative robots (in short "cobots") have been found not only in modern manufacturing systems (Fig. 1.1(a)-1.1(c)) but also in daily personal services such as nursing care, household, and physiotherapy (Fig. 1.1(d)-1.1(f)) [1]. According to the statistics from International Federation of Robotics, during

[1]Image source: KUKA, ABB, Universal Robot, DLR, MSRM,

the period from 2017 to 2019, the number of installed cobots in industry grew from $11,000$ to $18,000$ units[2]. The fast-growing demands for cobots have also led to increasing interest in the research community, which yields a new field: *human-robot collaboration* (HRC). As presented in [1], the number of publications per year on the topic of HRC grew from less than 20 to almost 800 from 1996 to 2015.

Despite the rapid growth of technologies and research in this area, today's HRC is still facing great challenges. In most industrial scenarios, although cobots work with humans in a shared workspace, their movements are sequential [2]. If the risk of collision arises, the robot completely stops until the human is out of the "danger zone". Very few applications can be found in which the robot adjusts its motion actively in real-time to the movement of the human partner. In the healthcare and service areas, most robots are still controlled by humans, either through teaching by hand or a teleoperation device. On the other hand, a recent survey[3] points out that from 2015-2018, the most developed research category in HRC is safety, which accounts for 64.2% of the identified papers. In summary, the technique and academic developments have achieved great success in solving the problem of "coexistence" between humans and robots in close proximity, but there is still a long way until "collaboration" can be realized.

What is a collaboration? Unfortunately, there is no unified definition of the term "collaboration". As reviewed in [4], different research communities such as robotics, human-machine interaction, cognitive science, multi-agent systems, etc., have their own domain-specific descriptions, and the boundaries between "collaboration", "cooperation", "coordination" and "joint action" are blurring. Nevertheless, it is commonly agreed that in a collaboration, each participant should meet the following fundamental criteria [5, 6, 7, 8]:

- representation of goals/tasks,
- monitoring and prediction of its own actions as well as the others',
- ability to interfere the individual and group behaviors towards goals.

To satisfy the "minimal" conditions listed above and achieve a true sense of human-robot collaboration, a "perception-analysis-interference" structure is suggested (Fig. 1.2) from the control engineering point of view, which has a similar formulation with classical feedback-control loop. Firstly, the perception module is responsible for measuring the states of humans which are not limited to the physical level (position, velocity, force) but also include cognitive features such as speech, emotion, gaze, etc. Wearable sensors have become extremely useful in providing accurate and reliable measurements of human activities [9]. Secondly, the analysis module interprets the measurements with appropriate models to recognize human intention, to predict human motion at a certain

[2]Souse: IFR World Robotics Report 2020

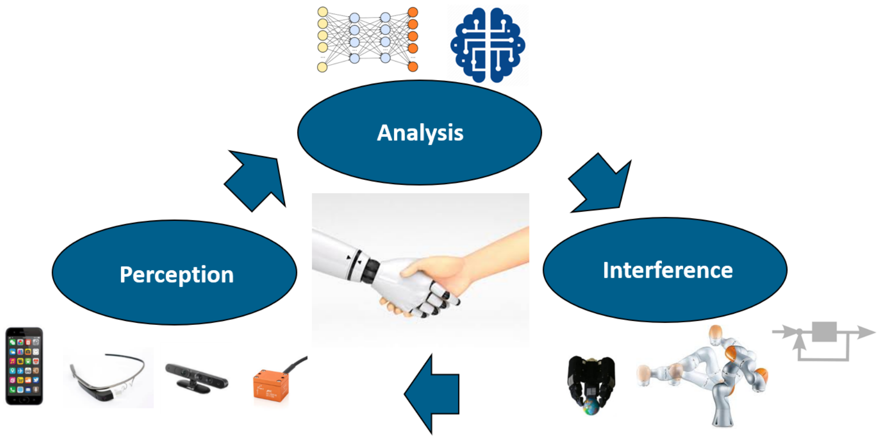


Figure 1.2: A perception-analysis-interference structure for human-robot collaboration

time in future, and to decide how the robot should react. Artificial intelligence and machine learning are the core technologies. Thirdly, the interference module follows the determined coordination strategies, generates local motion and control references, and executes in the physical environment. Control engineering plays an essential role in this process. The whole system should be able to run in real-time and adapt to the change of environments (including humans).

The structure has an interdisciplinary nature and includes many challenging problems. Although each component has been intensively studied by different research communities and yielded plenty of exciting results, there is still a fairly large gap between them. Very few examples can be found in which all the three fundamental elements are jointly considered. In the author's view, it is mainly due to the fact that systematic designs of HRC are still largely missing. Note that a systematic design does not simply mean the integration of various techniques into one system, which could be problematic Since they have been developed from different theoretical backgrounds and under different practical conditions. More importantly, the design should pay particular attention to interconnections between the three fundamental components from both theoretical and technical perspectives. For instance, when choosing a modeling approach for the representation and prediction of human activities, it should be considered whether it is appropriate and applicable for robot control design, especially for the stability and feasibility examination.

Based on the perception-analysis-interference structure, the main goal of this thesis is to develop a novel trajectory planning and control framework for a safe, natural and effective human-robot collaboration. More specifically, the thesis focuses on (1) monitoring and predicting human hand motion in a collaborative manipulation task, (2) adjusting robot trajectories and forces online based on human motion predictions.

1.2 Scenarios studied in this thesis

The proposed framework is validated through two typical benchmark applications for HRC: object handover and cooperative object handling.

Object handover is a must-have skill for robots in both industrial manipulations and daily personal services. For instance, a robot co-worker should pass a tool to a human operator [10]. A service robot needs to bring drinks or medicine to a human patient [11]. To perform a handover as efficiently and fluently as a human is still a challenging task for robots. As comprehensively reviewed in [12], a handover requires “perception, prediction, action, learning, and adjustment by both agents”.

This thesis concentrates on the ”pre-handover” phase, in which the human and the robot move towards each other to get close enough to transfer the object. Precise control of the grasping motion/force will not be discussed in this thesis. The goal is to perform an on-the-fly handover, i.e., the robot should move simultaneously with the human. To enhance the flexibility, the initial pose and the object exchange location are not fixed. The key aspect for achieving this goal is online trajectory planning based on human motion prediction. For this purpose, modeling of human hand movements is needed. The main challenges are: (1) The model should cover the most characteristic features of human motion. Due to the high complexity of the human body dynamics, proper approximation methods are required. (2) The model should be computationally efficient for real-time implementations. (3) Because of the randomness of human motion, the model should be capable of dealing with uncertainties.

The second application studied in this thesis is collaborative object handling, in which the human and the robot jointly transport a rigid object. It is one of the most common benchmarks to investigate physical human-robot collaboration (pHRC). The main challenge is that the human and the robot have to agree on their movement directions and speeds [1]. One possible solution is to control the robot to behave compliantly when interacting with human. Under this concept, the robot only works passively under human guidance and results in a human-centered collaboration manner. It causes extra human effort and reduces adaptability and flexibility of the collaboration [13]. To overcome these drawbacks, the robot should be able to make proactive contributions based on human intention recognition and motion prediction. Furthermore, contact force is an important interaction modality in pHRC. It should be particularly considered and carefully handled in robot control design.

1.3 State-of-the-art technologies

1.3.1 Human modeling

As reviewed in [14], there are various techniques for modeling human behaviors, depending on different timescales and levels. This thesis mainly focuses on the motion level, which aims to represent relationships among physical variables such as velocity, acceleration, force, torque, etc. Cognitive modeling of human learning and coordination mechanisms is beyond the scope of this thesis.

Physical-based approaches

Conventional physical-based approaches use differential/difference equations derived based on physical laws to describe human motion dynamics. Such physical-based modeling can be categorized into kinematic and dynamic models. Kinematic models usually do not consider the forces and torques that produce the motion. The simplest examples are constant velocity (CV) and constant acceleration (CA) models. Both assume piecewise constant states (velocity or acceleration) with additive white noise [15]. One common application of such simple kinematic models is pedestrian motion prediction [16, 17, 18]. If they are suitable for describing the reaching motion of the human hand remains unclear and needs to be verified. A more widely used approach considers multiple degrees of freedom (DOF) of the human arm, which result in a series kinematic chain consisting of several joints and links [19]. Applications of such models, also known as skeleton-based models, require motion capture sensing systems to measure human body segments [20]. Commonly applied techniques include wearable Inertial Measurement Units (IMU) [21], optical motion capture systems [22] and fusion-based multi-sensor systems [23].

Dynamic models aim to describe the relationship between force and motion. Such models are usually needed in studying contact-reach scenarios, e.g., physical therapy [24], physical human-robot collaboration [25], and designing of humanoid robots [26] as well as exoskeletons[27]. One approach regards the human arm as a rigid body and derives the dynamic equations based on Lagrange formulation. The other considers the human arm as a series of elastic actuators and builds a mechanical impedance model with several springs and dampers. Both approaches require force/torque measurements for the identification of model parameters. A typical setup is that human grabs a haptic device or robot end-effector with integrated force/torque sensors and moves along a pre-specified path [28]. It strongly limits the implementation of manipulation tasks. Alternatively, Electromyography (EMG) signal can be used to measure muscle activities and estimate the change of force [29]. However, the data acquisition requires skin preparation and a long setup time.

Besides, another approach assumes that the human central nervous system synthesizes motion by minimizing a cost function consisting of physical variables. Oft-cited forms include minimum jerk model [30], minimum torque change model [31], minimum energy [32] model, etc. These "minimum-X" models were first introduced in the 1980 - the 1990s to fit point-to-point motion trajectories in free space. Nevertheless, several recent works have shown that with some extensions, e.g. online correction terms or parameter adaption [33, 34], these models can still achieve satisfying performance in human prediction for collaboration.

Physical-based approaches are suitable for representing physically well-understood systems and usually generalize well. However, they are still facing some difficulties in modeling human behaviors. Due to the high complexity of the human body, unknown dynamics still exist, which are not completely describable by physical knowledge. Hence, it is necessary to make approximations. An over-simplified model usually leads to poor performances, while a comprehensive model is computationally expensive and requires a large number of sensors to measure the corresponding physical quantities. Sensor drifts and signal distortions may cause errors in parameter identification. Another drawback is that physical models cannot handle uncertainties and randomnesses in human motion.

Data-driven approaches

Another category of human modeling concepts is known as data-driven approaches, which aim to find a functional relationship between pre-defined input and output variables based on a human motion data set. Since this functional relationship is mainly represented by probabilistic distributions, data-driven approaches are also named probabilistic approaches [35] and strongly associated with Bayesian theory and Gaussian distribution.

Commonly used data-driven models include Gaussian Mixture Model (GMM) [36], Gaussian Process (GP) [37], Hidden Markov Model (HMM)[38], etc. In recent years, following the breakthroughs in machine learning techniques, Recurrent Neural Networks (RNN) [39], Adaptive Neural Networks (ANN) [40] and deep learning [41] have also been applied in human motion prediction, utilizing their strength in learning complex and high dimensional systems. Another approach is Inverse Optimal Control (IOC) [42, 43]. The basic assumption is similar to the "minimum-X" models introduced above. The main difference is that the cost function is unknown and needs to be learned through observed human behaviors. Hence, this thesis also categorizes IOC into data-driven approaches.

Data-driven approaches require little prior knowledge on the process to be modeled and are flexible in describing a wide range of systems, especially for those that are not physically well-understood or too complex for deriving a physical model. Moreover, probabilistic representations enable data-driven models to deal with uncertainties. However, there are several critical problems. Since the data set is usually collected under certain labor conditions, it can only represent part of the system behaviors under constraints. As a result, the model may work well on training and test sets but loses its validity with unseen data. Moreover, due to a lack of prior knowledge, it remains unclear if the chosen variables are representative for describing the actual system dynamics. To overcome these problems, more data and variables need to be included in the data set, which dramatically increases its dimensions and computational complexity. In addition, the errors in data acquisition, e.g., sensor drift, noises, aliasing, etc., can also reduce the model accuracy.

Hybrid approaches

A new category of modeling approaches has drawn growing attention in recent years. The model consist of a physical-based term to describe the physically well-understood part of the system and a data-driven term to learn the rest of unknown dynamics. This category is known as "theory-guided data science"[44] or "hybrid machine learning"[45].

Also, in HRC, several related works can be found where hybrid approaches have been applied for modeling human motion dynamics. Typical examples are latent force model[46], dynamic systems [47], and dynamic movement primitives [48]. The ideas are similar: using an overly simplified mechanical model (e.g. a mass-spring-damper system) to cover some "basic" behaviors (e.g. a reaching movement from point A to B), then "refining" the model through machine learning techniques with human motion data. Some details will be discussed later in Chapter 4. Moreover, the model parameters can be further adapted online using various of learning algorithms to approximate time-varying human motion profiles during collaborations [49, 50, 51].

Hybrid approaches seem promising since they attempt to combine the strength of both physical-based and data-driven approaches. On the one hand, since the human motion profiles have been roughly described by the physical-based term, the data-driven term is only responsible for learning the physically not interpretable behaviors or the approximation errors. It can therefore enhance the learning effectiveness and reduce the size of the training set. On the other hand, hybrid approaches can achieve better generalizability than a purely data-driven model since the cause-effect relations between variables have been partially represented based on physical principles.

So far, investigations on the hybrid approaches for human modeling in HRC are still rare. In particular, there is a lack of well and systematically designed experimental validations.

1.3.2 Robot control

The robot control problem can be categorized into motion control in free space and control of the interaction with the environment [52]. The former aims to track a pre-defined reference motion trajectory, while the latter concentrates on regulating the contact force. In the two scenarios studied in this thesis, both motion and interaction control need to be addressed. Hence, it is desired to design a unified framework that can deal with both problems.

One possible approach is the hybrid position/force control. The principle is to decouple the control of end-effector position and contact forces into two orthogonal frames so that they can be executed independently from each other [52]. However, in HRC applications, this approach suffers from several difficulties. Firstly, the decoupling of motion and force control may not always be possible. Considering the collaborative object handling task, the robot should follow a reference path and simultaneously handle the contact force along the movement direction. Secondly, the constraint frames may change over time due to the varying human-robot contact geometry and needs to be updated online [53]. Thirdly, how to define a reasonable force reference value in HRC is still an open question, especially with consideration of subjective factors such as human comfortableness.

Another approach, namely the impedance control [54], has been commonly used in pHRC. The control goal is to achieve a desired relationship between robot end-effector motion and contact force, which is categorized through a mass-spring-damper system, known as mechanical impedance. Note that without contact force, the impedance control can also be used as a motion controller for compensating the position errors.

Conventional impedance control with pre-specified constant impedance parameters is not sufficient in the context of HRC. For instance, when tracking a reference path, the robot should maintain high impedance to suppress disturbances that perturb its end-effector from the desired trajectory. On the other hand, when the human partner intends to correct the robot motion, it should decrease the impedance to generate less resistant forces. Hence, modulating the desired impedance parameters to adjust robot compliance depending on task and interaction specifications has become an urgent research topic [55, 56]. Some previous works attempted to adapt the impedance parameters based on sensor feedback, e.g., robot end-effector velocity, contact force, etc.[57, 58, 59] To further enhance the performance, optimization-based approaches have been investigated. The impedance parameters are optimized by minimizing a task-dependent cost function subject to the robot and environment dynamics [60, 61, 62]. A fundamental challenge is that including the human as a part of the environment model will introduce a certain level of uncertainties or even unknown dynamics, which dramatically influence the solution of the model-based optimization problem. In recent years, learning-based impedance control has gained growing interest from HRC research. This approach extends the classical impedance control framework with machine learning techniques. The purpose is to develop an adaptive controller that is able to learn the environment model (including human), the impedance parameters, and/or the desired trajectories [63]. A detailed review of related research will be presented in Chapter 7. Since learning-based impedance control has already shown its advantages in cluttered and complex manipulation tasks, this thesis attempts to combine it with human motion prediction and design an adaptive motion generation and control framework.

1.3.3 Design examples

This section briefly reviews several design examples, in which human motion prediction, robot learning and control have been jointly considered in one framework.

The author in [64] develops an integrated framework combining human motion prediction with robot planning in real-time. The framework contains a data-driven multiple-predictor system that automatically identifies informative prediction features and combines the strengths of complementary prediction methods. Taking the prediction results as input, a feedback path planning algorithm is designed to adapt robot movements.

In [65], the author develops a *learn-collaborate-discover* architecture for cobots. In the *learn* module, the author proposed a geometric knowledge base for the robot, in which a complex manipulation task is represented by a series of kinematic constraints. This design significantly reduces the complexity of the learning procedure. The *collaborate* module is built upon the *learn* module for a human-in-the-loop execution of manipulation tasks with a particular concentration on the share-autonomy. The *discover* module aims to answer the question of how robots can learn from both observational and self-exploration when collaboration with humans.

The author in [66] addresses the problem of designing the behavior of cobots in dynamic, uncertain environments. A unique parallel planning and control architecture is presented, which contains a cognitive module for human behavior estimation and motion prediction, a goal-oriented long-term motion planner, and a safety-oriented short-term planer. All the planning and control algorithms are developed based on non-convex optimizations. Furthermore, the classification and modeling of the interaction modes in HRC are discussed.

The dissertation [67] focuses on the model-based design of a control and learning framework in physical HRC. In the learning part, the author proposed two modeling approaches of human behavior: (1) time-based Hidden Markov Models, which regards human motion as time-series, (2) an impedance-based Gaussian process, which takes the human arm impedance as priors. Both models are developed for online human motion prediction. In the control part, the author designs a stochastic optimal control approach in which uncertainties are not only considered in system models but also in costs. Moreover, the author discusses the roles of interaction forces and load distributions for designing anticipatory control schemes in physical HRC.

1.4 Objectives and Outline

As motivated by the state-of-the-art discussion, the overall objective of this thesis is to develop a novel methodological approach for human motion prediction and control in HRC. In particular, the thesis focuses on two relevant challenges:

1. development of an analytical, predictive and adaptive human motion model that is capable of efficient online human motion prediction under uncertainties, with specific considerations of its usefulness for the control design,
2. development of an adaptive control structure that is capable of handling unforeseen and time-varying changes in the environment (including the human partner) and enables robots to make proactive contributions in the collaboration instead of working passively as a follower under human guidance.

A hybrid design concept is presented throughout this thesis. On the one hand, it combines physical-based and data-driven approaches for modeling and predicting human motion. On the other hand, the state-of-the-art impedance control structure for cobots has been combined with learning-based techniques.

A graphical illustration of the thesis' structure and relations among different chapters is shown in Fig. 1.3. At the beginning of each chapter, a brief introduction is provided, including open questions, related work, and main contributions of this thesis.

Chapter 2 begins with classical approaches for human motion trajectory prediction based on recursive Bayesian estimation in combination with simple linear kinematic models. Such methods have been widely used for human motion tracking, which usually provides good short-term predictions. This chapter demonstrates two of the most commonly used kinematic models, constant acceleration model and minimum jerk model, with an extensive evaluation on the basis of two human motion datasets. The main focuses are

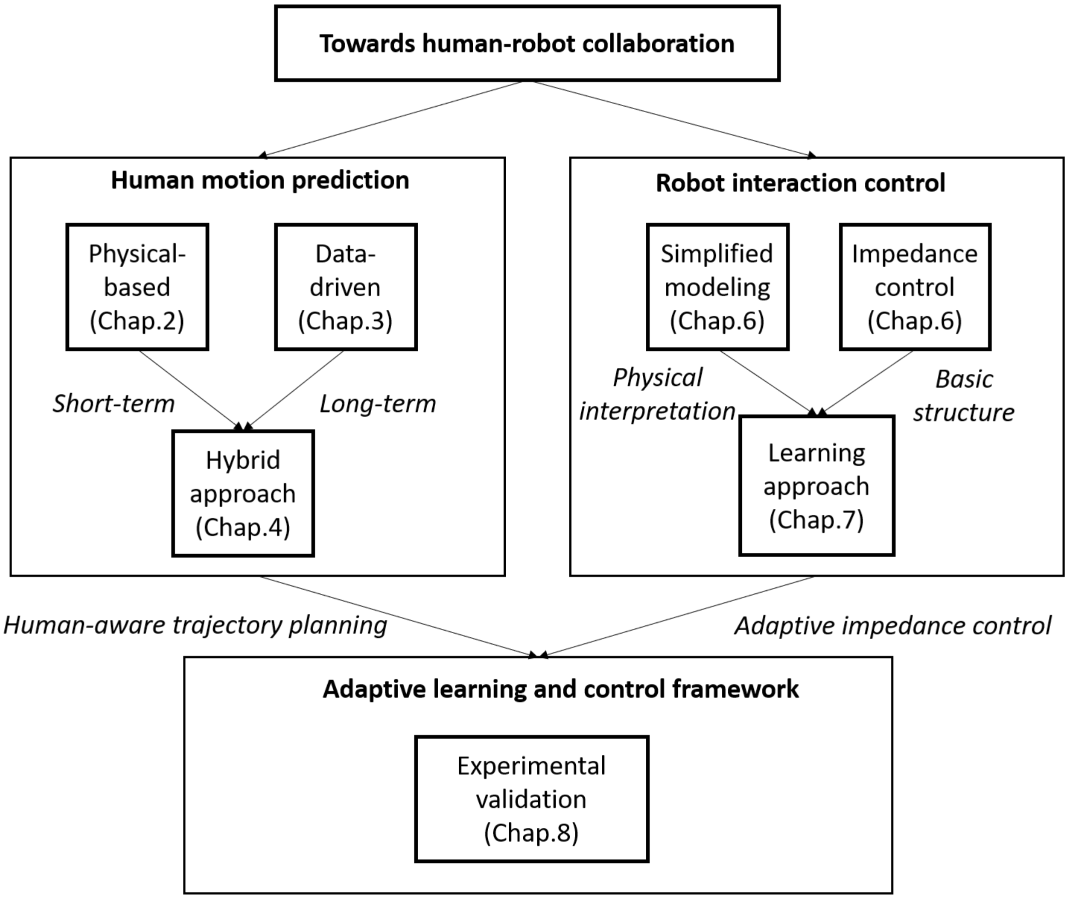


Figure 1.3: A structural overview of thesis and relations between each chapter.

analyses of the error rates with respect to prediction horizons and possible error sources.

Chapter 3 investigates data-driven approaches for human motion prediction. The purpose is to utilize their strength in representing complex systems to achieve long-term predictions. Motivated by the findings in the neuroscience literature, i.e., the human central nervous system works as an optimal feedback control system, the first part of this chapter aims to identify the objective function that the human tries to optimize, yielding an inverse optimal control problem. The second part focuses on modeling human motion through Gaussian process (GP), which belongs to non-parametric approaches. This work employs an online sparse GP regression method to overcome a well-known drawback of GP, namely the high computational complexity. Furthermore, the proposed method enables an adaptation of the GP model with new coming data. The evaluation of both methods includes not only the prediction error, but also their implementation complexity and generalizability.

Based on the findings in previous chapters, Chapter 4 introduces the concept of developing a hybrid physical-based and data-driven approach, i.e., using an overly simplified mechanical model to roughly describe the transitions of the observable physical states, then refining the model through machine learning techniques to achieve a more precise approximation of the system's dynamic. Within this concept, the chapter studies Dynamic Movement Primitives (DMP) and proposes special designs to overcome several limitations in the conventional DMP formulation. Results show that the proposed method outperforms all the other techniques that have been implemented so far in this work. Moreover, an extended DMP formulation to describe the interactive dynamics between humans and robots is presented at the end of this chapter.

Chapter 5 summarizes all the methods that have been studied in this work for human motion prediction and comprehensively discusses their scope of application, accuracy in different time scales, and implementation complexity. Afterward, an outlook on possible future research trends in human motion prediction based on hybrid approaches is stated.

Chapter 6 addresses robot interaction control in physical human-robot collaboration (PHRC). This work studies one typical benchmark application in which humans and robots jointly move a rigid object. Instead of a comprehensive kinematic and dynamic modeling of each agent with consideration of all degrees of freedoms, a more efficient approach is introduced, in which the compliance control behavior of both robots and humans is incorporated into the object dynamic. Accordingly, the basics of impedance control and its common forms are introduced. Lastly, the problem formulation of PHRC based on differential game theory is discussed.

Due to unknown parameters and high uncertainties in the human compliance control model, it is challenging to design robot control algorithms using model-based approaches. Reinforcement learning (RL) offers the possibility to learn an optimal control policy online through interaction with humans. Chapter 7 proposes a novel RL-based adaptive impedance control framework. Numerical simulations show that RL can achieve near-optimal performance without fully knowledge of the system dynamic. Moreover, possible extensions of the proposed method with consideration of constraints handling are discussed.

Chapter 8 presents the validation of the proposed learning and control methods by several human-robot collaboration experiments. Two typical benchmark applications, object-handover and object-handling are chosen so that both contact-free and physical interactions are included. To deal with various practical issues, several additional designs have been made to enhance the safety and adaptbility of the proposed framework. Comprehensive analyses and discussions on the experimental results are presented.

Chapter 9 provides conclusions of the main findings in this thesis and suggestions for future work.

1.5 Publications

Several articles on the motion prediction and control in HRC have been published during the doctoral studies. A chronological list of these articles together with their topic and their relation to this thesis is given below.

1. Min Wu, Bertram Taetz, Yanhao He, Gabriele Bleser, and Steven Liu: An Adaptive Learning and Control Framework based on Dynamic Movement Primitives with Application to Human-robot Handovers, *Robotics and Autonomous Systems* 148, 103935, 2022. (Chapter 4 and Chapter 8)

2. Min Wu, Yanhao He, and Steven Liu: Adaptive Impedance Control Based on Reinforcement Learning in a Human-Robot Collaboration Task With Human Reference Estimation, *International Journal of Mechanics and Control* , 21(01):21-32, 2020. (Chapter 7 and Chapter 8)

3. Min Wu, Bertram Taetz, Ernesto Dickel Saraiva, Gabriele Bleser, and Steven Liu: On-line motion prediction and adaptive control in human-robot handover tasks, *2019 IEEE International Conference on Advanced Robotics and its Social Impacts (ARSO)*, 1-6, 2019. (Chapter 3 and Chapter 8)

4. Min Wu, Yanhao He, and Steven Liu: Shared Impedance Control Based on Reinforcement Learning in a Human-Robot Collaboration Task, *International Conference on Robotics in Alpe-Adria Danube Region*, 95-103, 2019. (Chapter 7 and Chapter 8)

5. Min Wu, Yanhao He, and Steven Liu: Collaboration of multiple mobile manipulators with compliance based leader/follower approach, *2016 IEEE International Conference on Industrial Technology (ICIT)*, 48-53, 2016.

6. Yanhao He, Min Wu, and Steven Liu: A cooperative optimization strategy for distributed multi-robot manipulation with obstacle avoidance and internal performance maximization, *Mechatronics*, 76:12560, 2021.

7. Yanhao He, Min Wu, and Steven Liu: An optimisation-based distributed cooperative control for multi-robot manipulation with obstacle avoidance, *IFAC-PapersOnLine*, 53(2):9859-9864, 2020.

8. Yanhao He, Min Wu, and Steven Liu: Decentralised cooperative mobile manipulation with adaptive control parameters, *2018 IEEE Conference on Control Technology and Applications (CCTA)*, 82-87, 2018.

9. Henghua Shen, Ya-Jun Pan, Usman Ahmad, Steven Liu, Min Wu, and Yanhao He: Tracking Performance Evaluations on the Robust Teleoperative Control of Multiple Manipulators, *2019 IEEE 28th International Symposium on Industrial Electronics (ISIE)*, 1268-1273, 2019.

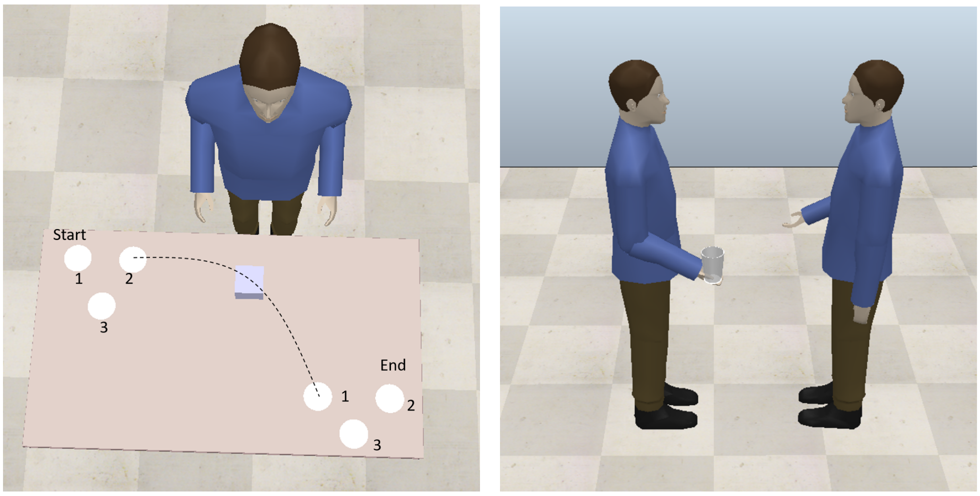
2 Human Motion Prediction based on Simple Kinematic Models

2.1 Introduction

This thesis investigates human motion prediction based on kinematic models. In particular, the human reaching motion has been studied, which is mainly generated by arm movements. Comprehensive modelling of the human arm with consideration of multiple degree-of-freedoms in shoulder, elbow and wrist is extremely complex [68] and is not suitable for control design. For simplification, this thesis focuses on describing human hand translational motion trajectories in Cartesian space without considering its dependency on the joint movements. This idea belongs to classical approaches in the area of human motion tracking. Commonly used models include constant velocity and constant acceleration models. Such models are usually combined with Bayesian filters (e.g. Kalman Filter) to deal with uncertainties [69]. Another approach assumes that the human central nervous system generates motion by minimizing an objective function over a time interval. Constraints such as initial and final conditions or via-points can be added to the optimization problem. The analog solutions usually result in a polynomial function of time.

These simple kinematic models are physics-based, easy to implement and do not occupy much computational resource when performed online. Hence, they have been still widely used and studied in various of human-robot-interaction scenarios. A recent study shows that in some cases such simple kinematic models can outperform even state-of-the-art neural network models [18]. This chapter presents a simulation study of two most commonly used kinematic models in literature, namely constant acceleration and minimum jerk model. Evaluation of both models is performed based on a human data set recorded by an optical motion capture system. Performances of both short-term and long-term predictions are analyzed and the possible source of error is discussed.

The remainder of the chapter is organized as follows. The scenarios studied in this thesis and the preparation of a human motion data set are briefly introduced in Section 2.2.



(a) (b)

Figure 2.1: Graphical illustration of the scenarios for data collection: (a) pick and place with different initial- and goal positions, (b)human-human object handovers

Section 2.3 describes the mathematical formulation of the two kinematic models and their combinations with Bayesian filtering techniques. Section 2.4 presents the evaluation of both models with measurement data and discusses the results. Section 2.5 summarizes the pros and cons of the two models and gives references to further applications.

2.2 Data set preparation

For analysis and learning of human movements it is beneficial to build a human motion data set, including trajectories performed by different participants under various experimental conditions. With the support of AG wearHEALTH at TU- Kaiserslautern [1], a data set of human motion was built. The measurements were provided by OptiTrack [2], a marker-based optical motion capture system contains 12 3D-range cameras with maximal frame rate of 240 fps. The accuracy of motion tracking reaches 0.5 mm.

This thesis focuses on human reaching movements. Fig. 2.1 shows the two application scenarios considered in the data collection. The left one is a typical "pick and place" task with different initial and target positions. This scenario is usually seen in tabletop manipulation tasks. For instance, in laboratories, the employees need to take and transfer test tubes. Or in an assembling task, the workers collect and bring parts to different

[1] https://agw.cs.uni-kl.de/ Last visited: 01.02.2022
[2] https://optitrack.com/Last visited:01.02.2022