Modular Approach of Learning Robot Grasp and Manipulation

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Summary

In this thesis numerous seminal results are proved which will decisively shape the future development of the subject.

Contents

Chapter 1

Introduction

Grasping and manipulation are essential skills for service robots. Equipped with these skills, robots would be able to provide great assistance to humans in many aspects of daily life from hospital to household environments. Grasping and manipulation has been extensively studied for more than two decades. In industry, robot grippers have been widely used for fast and accurate operations. Outside industry, however, there is still no universal robust solution for grasping or manipulation in a human dominated environment.

The main challenge of robot grasping and manipulation comes from the large variety of tasks and the complicated dynamics of the robot-environment interaction. A versatile service robot is expected to be able to handle many tasks in human daily life, from simple pick-and-place tasks to multifinger dexterous manipulation tasks like writing and using tools. Different tasks have different instructions and constraints. Programming each of them by hand coding is painstaking. Further, grasping and manipulation are contact tasks, for which handling contacts between the robot end-effector and the environment is essential. The dynamics of the contacts are usually complicated and involve the study of friction and materials. An analysis of the dynamics of contact tasks requires both a deep understanding of the task, the mechanics of the robot and control theory. It is infeasible for the end user to program such tasks.

To tackle this problem, robot learning has been proposed as an alternative to an analytical solution. Learning by demonstration (also called imitation learning and programming by demonstration) has been extensively studied as a promising and user-friendly approach to build robot intelligence (Schaal et al., 2003; Dillmann, 2004; Billard et al., 2006; Calinon and Billard, 2007). This approach is data-driven. It aims to program the robot to extract the success pattern of a particular task from the demonstration data (either from teaching or self-exploration) and to encode this pattern. This approach allows us to model strategies for tasks without deriving the complex dynamics of the environment. The strategies are usually encoded by statistical models allowing certain level of noise. It is particularly useful for tasks where analytical expression of the system is hard to derive, such as contact tasks.

Although the learning by demonstration approach provides a user-friendly method for the end-user to program robot, learning grasping and manipulation tasks is still challenging. Even for the same task, the planning or control strategy can be different according to the task context. A single model is not adequate for these tasks.

In this thesis, we propose an approach to further reduce the task complexity: the modular approach. This approach focuses on the problem of decomposing a complex task into small subsections and developing solutions for each subsection separately. These solutions are then recombined to provide an integrated solution of the task. The benefit of this approach is that it translates a complex problem into many smaller problems, the solutions of which are easier to find.

The modular approach is particularly suitable for tasks involving different contexts or requiring multiple strategies. While switching between multiple modules allows the robot to quickly adapt to a changing environment, combining the modules allows the robot to generate new skills to adapt to new contexts. We apply this approach to the problem of grasping and manipulation tasks, to simplify the learning problem of contact tasks and to build an easy-to-use interface for teaching a robot. This dissertation introduces different ways to modularize tasks and then to combine the modules to accomplish the tasks. It provides a framework to model the modules as statistical models via a learning approach. The work shows that the modular approach in robot grasping and manipulation is not only theoretically attractive but also a practical method.

In the next section, we provide a brief overview in Section 1.1 of the use of the modular approach in robotics. We first show the study of modularity in artificial intelligence (AI) and control theory and then show the application of modularity in robotics as the intersection of those two realms. In Section 1.2 and 1.3, we outline the contributions of this dissertation and present its organization.

1.1 Existing modular approaches

Robotics is an interdisciplinary area. It is an intersection of many fields in engineering and cognitive science. Two of the most important fields in robotics are AI and control theory. While AI concentrates on the high level perception and action planning, control theory focus on robustly and stably delivering the robot to the desired state. Modular approaches have been independently studied in these two areas and shown to be effective for developing autonomous and intelligent systems.

Modularity in AI AI is a field of studying how to enable machines to have animal level intelligence (Brooks, 1991). Modular approaches in AI are inspired by two factors: the evidence of modularity in cognitive science and the efficiency of the modular approach in software engineering. As a research area that aims to produce animal level intelligence in machines, a branch of AI studies the source of the intelligence, e.g. neuroscience and psychology, and tries to mimic the mechanisms. In both neuroscience and psychology, evidence shows that brain and mind have some modularized structures (Fodor, 1983; Peretz and Coltheart, 2003; Barrett and Kurzban, 2006; Sztarker and Tomsic, 2011). It is suggested that the modularity in brain and mind helps animals to organize the functionalities and handle complex situations. This evidence motivates researchers in AI to develop modular architectures for machine intelligence. On the other hand, from the software engineering point of view, a modular approach is an effective way of building large complex systems. It is widely used for separating the functionality of a program into independent modules, such that each contains everything necessary to execute only one aspect of the desired functionality. Therefore building a complicated intelligence system inevitably prefers a modular approach. Many forms of modularity have been proposed to study different aspects of AI (Bryson, 2005).

Modularity in control Modular approaches are used in adaptive control and their benefit has been long discussed (Jacobs et al., 1991; Narendra and Balakrishnan, 1997). They are used to solve the control problem in a dynamic environment, where changes can happen rapidly or discontinuously. Classic adaptive control approaches such as model identification (Khalil and Dombre, 2004) are inadequate for these environments, as instability or error may occur during the optimization of the model variables. To quickly adapt, the multiple model approach referred as modular approach here has been proposed by Narendra et al. (1995). In this approach multiple controllers are designed, each of which is in charge of a certain task context. During control, the task context is estimated online and the corresponding controllers are activated. When the task context changes, the system automatically switches to another strategy that is suitable for handling the current context. This ensures that the system reacts quickly enough to adapt to the environment.

Application of modular approaches in robotics Briefly speaking, modular approaches in AI mainly target decomposing tasks to simplify the design of agents, while control theory mainly aims to build a fast adaptive control policy. In robotics, modular approaches are used for both of these two purposes. Roboticists usually focus on more specific tasks, such as grasping and walking, and try to develop robust and stable plans to accomplish those tasks. In fact, the divergence of the research interests, e.g. grasping and walking, is itself a modular approach: the high level modularity divides the research community into different interest groups that each try to provide a generic solution for a specific task.

Further, even for the same research interest group, modular approaches are used to reduce the complexity of design and increase the flexibility of the planning. Some of the most well known modular approaches in robotics use motion primitives for motion planning (Ijspeert et al., 2002; Inamura et al., 2004; Kulić et al., 2008; Peters and Schaal, 2008), hand synergies (Santello and Soechting, 2000; Gabiccini et al., 2011; Gioioso et al., 2013), eigengrasp (Ciocarlie and Allen, 2009) and grasp by shape primitives (Miller et al., 2003; Huebner et al., 2008) for grasp planning and etc.

In conclusion, modular approaches are widely used in robotics. They are mainly used to tame the complexity of high level task planning and low level strategy selection. However, how to modularize a task in order to facilitate robot learning is rarely discussed in literature and remains an open problem.

1.2 Our modular approach in robot grasping and manipulation

The definition of a module varies by discipline. Here we define a module as a functional unit that takes certain inputs and provides certain outputs. The computation from the inputs to the outputs is independent to other units. Although the concept of modularity in cognitive science is still in debate, its efficiency in software design is well recognized. In this thesis, we do not try to argue the role of modularity in animal brains. We simply take the concept and exploit its effectiveness in programming robots to carry out tasks. The tasks we discuss here are primitive tasks that can be described by a simple language such as "grasp" and "open" and no further subtask needs to be decomposed. Therefore the modularity we study is task-specific: multiple modules serve one task and each module serves one task context. We hence call our modularity "task level modularity". Not all primitive tasks are in need of a modular approach. Some simple tasks such as "close your eyes" have a generic solution. However, in grasping and manipulation, this is usually not the case. As discussed before, the contacts between the robot end-effector and the environment makes the system hard to analyze and the large variety of tasks makes it hard to find a universal solution. In our studies, we explore a few possible ways to use a modular approach to tame these problems.

We apply the modular approach in the three main domains of grasping and manipulation: grasp planning, manipulation force control and reaching. These three tasks have different challenges and require different modularization methods. For grasp planning, we modularize the strategy by the object shape and propose a method to quickly plan grasps for novel objects. For manipulation, we modularize the control policy by task context and equip the robot with human level adaptive skills. For reaching, we modularize the movement by human command, which builds an understanding base between robots and humans by language and allows the human user to easily teach robot new motion primitives.

These three approaches enable the robots to accomplish tasks that are complex but can be pre-planned, need to adapt in real time, or need to follow human instructions.

Grasp planning: modularize by perception (Chapter ??) The first contribution is modularity in multifinger grasp planning. Previous research in robot grasping focus on synthesizing grasps analytically, using precise and accurate models for the objects (Sahbani et al., 2011). Those approaches are usually computationally expensive for the high degree of freedom of the multifinger robot hand and the universal representation of the object, which usually have many variables. To tackle this problem, we modularize grasping by the shape of the objects. In our work, we first focus on fast generation of grasps for familiar objects and then extend the approach to generate grasps for novel objects. Initially, we learn the statistical model for the feasible grasps of a familiar object. This distribution is then used to quickly generate grasps. A novel object can then be represented as a compound of shape primitives, e.g. sphere, cylinder and box. The grasp distribution of these shape primitives are pre-trained and each acts as a module. We combine the grasp distributions of the shape primitives to form a new grasp distribution for the novel objects. When combining, the overlapping and conflicting regions between shape primitives are excluded. This approach does not require a general and accurate representation of the object. As grasps can be planned quickly, fast correction can be done for small modelling error. The first part of the work is published in ICRA 2013 (Huang et al., 2013b).

Dexterous manipulation: modularize by action (Chapter ??) The second contribution concerns manipulation. Object manipulation is a challenging task for a robot as the complicated physics involved in object interaction is hard to express analytically. In this work we introduce a modular approach to learn the human manipulation strategy. After a human demonstrates a task in different contexts, we modularize the control strategies according to the contexts. Strategy in each module is encoded by a pair of forward and inverse models. All modules contribute to the final control policy, according to their estimation errors of the current task context. We validate our approach on a robot platform with a task to open a bottle cap. We show that our approach can modularize the adaptive control strategy to generate appropriate motor commands for the robot to accomplish the task. Fast estimation of the current task context and choice of the correct module enables the robot to react to changes of environment. This work is submitted to the journal Autonomous Robots.

Motion primitive: modularize by language (Chapter ??) The third contribution concerns learning reaching motion primitives for manipulation tasks. In this work, we develop an easy-to-use human interface for teaching and commanding a robot to carry out manipulation tasks. The human-demonstrated manipulation motion primitives are initially encoded by statistical models. The models are then projected to a topological space where they are labeled by a language description of their properties. We explore the unknown area in this space by interpolation between the models. New motion primitives are thus generated from the unknown area to meet new manipulation scenarios. Human commands are understood by matching with the labels of the motion primitives. Humans can give new commands during execution to correct improper robot behaviour. Here we make use of the modular nature of human language to modularise robot motion. This work is published in ROBIO 2013 (Huang et al., 2013a).

1.3 Organization of the thesis

This dissertation has 6 chapters. Chapter 2 gives an overview of existing modular approaches in robotics, discusses its benefits and challenges and describes the framework of our approach. Chapter **??** to **??** details our work in learning grasp planning, manipulation and reaching motions. We discuss the advantages of our modular approach in grasping and manipulation tasks and the potential to extend it to other areas. Chapter six discusses the achievement of our work and summarizes the contribution.

Chapter 2

Related work

This chapter gives an overview of the related research areas: robot grasping and manipulation, imitation learning and modular approaches. In Section 2.1 we summaries the studies in robot grasping and manipulation, outlining the current challenges in this area. In Section 2.2, we introduce the technique of robot imitation learning (program by demonstration) and particularly look at its applications in robot grasping and manipulation. In Section 2.3 we first discuss the motivation for modular approaches and its biological inspiration. We then give a brief review on modular approaches in control theory (multiple module adaptive control). The final part of this section focuses on the applications of modular approaches in robotics, especially in grasping and manipulation. Figure 2-1 depicts the structure of this section.

2.1 A review of robot grasping and manipulation

Robot grasping and manipulation research aims to enable robots with a human level ability of handling objects. Grasping and manipulation are usually included in the same research category and are studied by the same robotics community, as they both try to tackle the "contact tasks", which use robot hands (end-effectors) to get physical contacts and interact with target objects. Robot grasping focuses on how to stabilize the target objects with the support from the robot hand. This involves the problem of where and how to place the contact points between the robot hands and the objects. Robot manipulation focuses on delivering the target objects from the current state to a desired state, which involves the problem of how to apply forces and torques on the object to achieve the desired state. Besides these two problems, one problem is often discussed by the same community – the reaching problem. How to move the robot hand to reach the object so that the planned grasps or manipulation strategy can be achieved, for example making contacts in the right places to pick up a box, is the problem studied in reaching. In the later three sections, we will present an overview of these three topics.

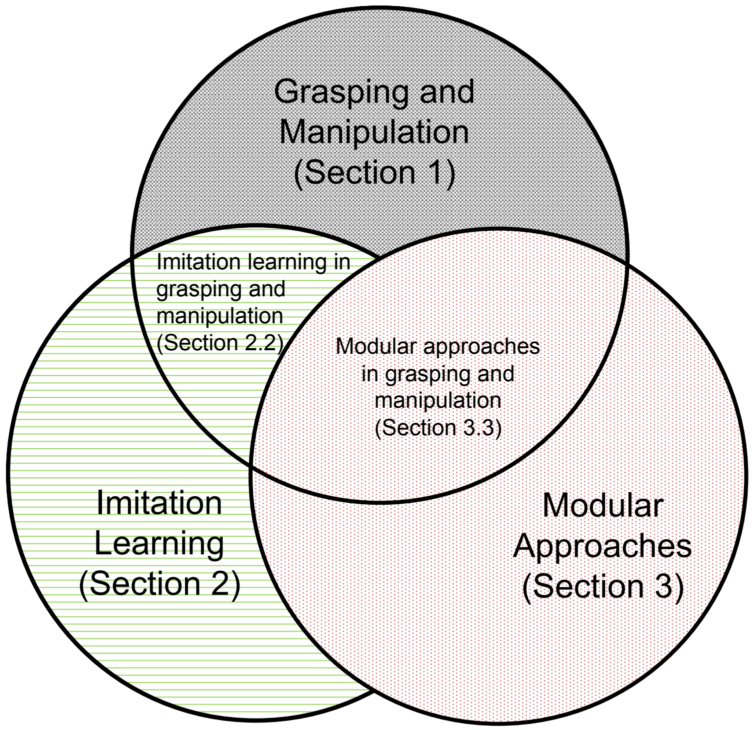

Figure 2-1: Structure of this literature review. This chapter reviews studies in three areas: robot grasping and manipulation (Section 2.1), imitation learning (Section 2.2) and modular approaches (Section 2.3). Approaches involving imitation learning in grasping and manipulation are reviewed in Section 2.2.2. Applications of modular approaches in grasping and manipulation are reviewed in Section 2.3.4.

2.1.1 Robot grasp planning

Given a robot hand and an object, there are an infinite number of ways to grasp the object. These grasps have different performances and functionalities. Grasp planning is usually formulated as an optimization problem of grasp performance, by finding the contact point locations or robot hand configuration. This technique is call optimal grasp synthesis. The most important criteria in the optimization is the stability of the grasp. In the robot grasping literature, two of the most extensively used mechanisms for guaranteeing grasp stability are the force-closure and form-closure criterion (Nguyen, 1987). A grasp is said to achieve force-closure when the fingers can apply appropriate forces on an object to produce wrenches in any direction (Salisbury Jr, 1985). Form-closure is a stronger condition than force closure, which can only be achieved if a grasp is force closure with frictionless contact points (Dizioğlu and Lakshiminarayana, 1984).

To measure grasp stability qualitatively, the concept of grasp quality is introduced. Various grasp quality metrics are proposed for different purposes. Starting from the idea of minimizing the sum of the contact forces, (Li and Sastry, 1988; Kirkpatrick et al., 1992; Ferrari and Canny, 1992) propose different measurements of the grasp quality based on the hand wrench space. These metrics are "object-centric", i.e. they only consider the contact point locations and the object geometry, while the robot hand configuration is not taken into account. Miller and Allen (1999) take one step further: they use a simulation method to compute the grasp quality of a given object and robot hand configuration. They later develop the physical simulator GraspIt! for grasp quality analysis (Miller and Allen, 2004). Our work in grasp planing described in Section **??** is based on this simulator.

Optimal force-closure grasp synthesis concerns determining the contact point locations so that the grasp achieves the most desirable performance in resisting external wrench loads. Based on the grasp quality concept, some approaches optimize an objective function according to a pre-defined quality criterion (Zhu and Wang, 2003; Zhu and Ding, 2004) in the grasp configuration space. These approaches do not take into account the kinematics of the hand, which is difficult to achieve. To bridge this gap, Khoury et al. (2012) propose a one shot grasp synthesis approach that formulates and solves the problem as a constraint-based optimization.

Multi-finger grasps usually involve a large number of degrees of freedom. Searching the grasp space for an optimal grasp requires massive computing time considering the huge number of possible hand configurations. To solve this problem, imitation learning and modular approaches are introduced to constrain the searching space. The relative literatures are reviewed in Section 2.2.2 and Section 2.3.4

The above methods are for static grasp planning that rely on precise and accurate object models. These methods are well suited in controlled industrial environments, for example picking up aligned boxes from the assembly line. However, they are not very applicable for service robots working in human dominated environments. For this reason, in recent years the research has shifted to tackle the problem of maintaining the grasp stability in dynamic and cluttered scenes. These studies include handling uncertainty and noise in the perceptual data and handling unseen (novel) objects and unforseen situations. To tackle the former problem, one approach is to take the uncertainty and noise into account in the planning and generate robust grasps (Brost, 1988; Zheng and Qian, 2005; Hsiao et al., 2011a).   try to handle the uncertainties in object shape estimation by finding a common grasp of the few most possible object shapes. Besides synthesis, grasping motion is also studied (Kehoe et al., 2012), where the uncertainty is handled by the compliant finger motions. For grasping novel objects, different general object shape representations are proposed. The most studied representations are 2D or 3D local features such as edge, contour and color (Saxena et al., 2008; Detry et al., 2009; Kroemer et al., 2010), combination of shape primitives (Miller et al., 2003; Huebner et al., 2008; El-Khoury and Sahbani, 2010) and exclusive mathematical representation of the global object surface geometry and topology (El-Khoury et al., 2013; Pokorny et al., 2013). Local features allow quick computation of grasps on a sub-part of an object, while the global representations allow a global search of good grasps with large computation expenses. Planning grasps for novel objects effectively and robustly remains a challenge.

2.1.2 Robot manipulation

Different from grasping which aim to stabilize a object, manipulation aim to change the object status, usually its position and orientation, from the current one to the desire one. This means the problem of manipulation is two-fold: controlling the hand movement to control the object movement. Studies in manipulation can briefly split into two topics: manipulation planning and task execution. The former focus on reasoning how to accomplish a complex task by a sequence of motions, while the later focus on answering the question of how to apply force and torque to deliver a target object to the next desire status. The former problem is mostly addressed by learning from human and extracting motion primitives from human demonstration, which can be used to build complex behavior for accomplishing a task. We will review those works in Section 2.2 and 2.3. In this section we will concentrate on the later problem.

A classic approach of manipulation is impedance control (Howard et al., 2010; Wimböck et al., 2012). Given the desired impedance of a task, we can compute proper motor commands for the robot to accomplish it. Fixed impedance control is limited to simple tasks. In many manipulation tasks such as opening a bottle cap, variable impedance is required: at the beginning we need a large impedance to break the contact between the bottle and the cap, and later we need a small impedance to drive the cap smoothly. For such tasks fixed impedance control will either lead to task failure or cause hardware damage. However, computing the impedance for a given task involving variable impedance is difficult. In many cases the impedance is roughly approximated by a linear model, but this is inadequate for non-linear tasks.

Variable impedance can be learnt by humans physically correcting the robot impedance, i.e. wiggling the robot arm, in different stages of the task (Kronander and Billard, 2012). For learning manipulation, however, wiggling the robot fingers will interrupt the task and may cause task failure. Variable impedance can also be learnt by the Policy Improvement with Path Integrals (PI^2) reinforcement learning algorithm, with a task specific cost function (Buchli et al., 2011). Designing this cost function requires insight into the task and is usually difficult.

2.1.3 Reaching motion planning

Reaching motion is another key component in the robot grasping and manipulation problem. Given a computed stable grasp, the question to answer in this study is how to deliver the robot hand to the desired position and form the desired hand posture. This is not a simple path planning problem for the robot arm, but a high dimensional planning problem taking the multiple finger movement into account. On one hand, most studies try to plan a motion to avoid premature collisions between the hand and the object. To this end, the finger movement and the arm movement always need to couple in order to ensure the fingers clutch at the right moment (Shukla and Billard, 2011), and curve around the object to form the desired grasps (Kroemer et al., 2011). To increase the robustness of a grasp, the uncertainty in perception is also taken into account (Stulp et al., 2011). On the other hand, however, some researches study how to deliberately produce "premature" contact with the object.

Chang et al. (2010) study the human "pre-grasp" movements such as sliding a coin to the table edge in order to pick it up, and rotating the handle of a pan to a proper position to grasp it. These methods largely increase the chance of successfully executing a grasp by changing the object status.

2.2 A review of imitation learning

This section provides a brief introduction to robot imitation learning and then reviews its applications in robot grasping and manipulation.

2.2.1 Robot imitation learning

Since the first study on robot imitation learning (Friedrich et al., 1996), this approach has become one of most popular research areas in robotics. It is considered to be a designer-friendly approach to teach robots new tasks. The aim of imitation learning, also referred to as "Learn by Demonstration" (LbD) or "Program by Demonstration" (PbD) in some literature, is to enable a robot to learn new skills by observing human demonstrations and then to reuse these skills in similar tasks. In recent years, this approach has been extensively studied (Calinon et al., 2007; Calinon, 2008; Dillmann, 2004; Kulić et al., 2012) as a promising approach to build robot intelligence.

2.2.2 Robot learning grasping and manipulation

As discussed in Section 2.1, conventional grasp and manipulation planning methods suffer from the curse of dimensionality. Learning techniques have been introduced to avoid the complexity of computing kinematical constraints guaranteeing stable grasps. Briefly speaking, robot grasping has two learning sources: imitation learning from human demonstration and learning from data collected from the simulation. In imitation learning, some researchers use datagloves for human demonstration. The human hand configuration is then mapped to an artificial hand workspace and the joint angles (Fischer et al., 1998; Ekvall and Kragic, 2007), or hand preshapes (Kyota et al., 2005; Pelossof et al., 2004; Ying et al., 2007) are learnt. Some other researchers use stereoscopy to track the hand when a demonstrator is performing a grasp (Hueser et al., 2006) or to match the hand shape to a database of grasp images (Romero et al., 2008). For long term automatic learning, markerless methods to track human hand and arm movements in the approach and grasp execution are studied (Ekvall and Kragic, 2007; Do et al., 2009). These learning based approaches succeed in taking into account the hand kinematics and generate hand preshapes that are compatible with the object features. Human grasp postures are usually mapped to robot hand postures in fixed schemes, according to the shape of the object and the type of grasp chosen by human. The learn from simulation method gets around this mapping step: it directly generates grasps with the robot hand's mechanical constraints. For a given object shape and a robot hand, thousands of grasps are generated in the simulator and later used as training data. Pelossof et al. (2004) use a discriminative Support Vector Machine model to learn the correlation between the grasp configuration and grasp quality, while Huang et al. (2013b) use a generative Gaussian Mixture Model to learn the distribution of force closure grasps. Both models are used to generate new grasps. Grasp training data can also be generated in a real robot platform rather than a simulator (Herzog et al., 2014). However, this method is much more time consuming and hence it focuses on finding a way to maximize the use of the grasping experience, i.e. generalizing grasping strategies for novel objects.

To further reduce the complexity of the grasping problem, modular approaches are used. This will be discussed in the Section 2.3.

Besides reducing the complexity of the grasping problem, learning approaches are also used to tackle those common problems that appear in the human environment: uncertainty and noise in perception data, novel objects and unforeseeable situations. Most of these learning approaches study how human handle those situations and imitate the strategies. Ekvall and

Kragic (2007); Stulp et al. (2011) study human grasp motion and try to learn how humans choose the approach vector that is robust to noise in pose estimation. Driven by the same idea, the human grasp postures are also studied and mapped to robot hands (Tegin et al., 2009). Inaccurate execution of a grasp can also cause problems. Human handle this issue by using tactile feedback. With the recent advances in tactile sensing technology, many attempt to include the tactile sensory data in assessing the grasp stability. After grasp execution, feedback from tactile sensors provide a more accurate estimation of grasp stability then which provided by vision. This allows grasp correction and can avoid failed lifting of the object caused by instable grasp (Li et al., 2014). Bekiroglu et al. (2011) integrate the information of the object shape primitive, approach vector, tactile data and hand joint configuration to estimate a grasp quality. In the later work, contact point locations are also taken into account (Dang and Allen, 2012, 2014). The support vector machine (SVM) is the most used model in discriminating stable and instable grasps. These tactile based methods are also used to evaluate grasps of novel objects.

Human's ability in generated grasps for novel objects is also studied and imitated. Detry et al. (2009) study the human Early-Cognitive-Vision (ECV), which includes colour and edge information that can be used to describe any objects. These features are associated with appropriate grasps and hence grasps of novel objects with matched features can be generated. El-Khoury et al. (2007) try to imitate the human mechanism of representing objects by segmenting objects into a set of superquadric shape primitives. The mechanism of a human choosing the grasp component is then learnt by a Neural Network (El-Khoury and Sahbani, 2010).

The human environment is dynamic and full of perturbations. These perturbations cannot be foreseen and can only be handled when they happen. A learning approach is also used here to provide methods for quick adaptation. Methods are proposed to simplify the generation of grasps such that a moving object can be caught (Harada et al., 2008; Kim and Billard, 2012; Huang et al., 2013b) Besides using visual features, tactile sensors can provide additional useful information not accessible by vision. Many methods for quick adaptation to the actual contact conditions are proposed (Hsiao et al., 2010, 2011b; Kazemi et al., 2012; Sauser et al., 2011; Li et al., 2014).

2.3 A review of modular approaches

This section first briefly reviews the modular approaches studied in cognitive science and control theory, and then concentrates on modular approaches in robotics.

2.3.1 Modular approaches in cognitive science

One typical hypothesis of a modular model in motor control is MOSAIC: the Modular Selection and Identification of Control. It is a paradigm of multiple module control, where each module is composed of a forward model and an inverse model. The forward models are responsible for estimating the task context in real time, and the inverse models are used to generate appropriate motor commands for the context. The inverse models are weighted by the accuracy of the estimations of their corresponding forward models. The final motor command is the linear combination of the commands factored by their weights.

TO BE EXTENDED

2.3.2 Modular approaches in control

In control theory, modular approaches are mostly used to handle the adaptive control problem, which is usually referred to as multiple model adaptive control (MMAC). Adaptive control is a control method where the controller changes itself to adapt to the changes in the control condition. A commonly used example is where the controller of an aeroplane adapts to a reduction in the weight of the jet fuel. The concept of MMAC is as follow. There is a set of plants and multiple controllers. Any plant in this set can be satisfactorily controlled by at least on of the controllers. When the plant switch from one to another, i.e. the environmental condition changes, the control system also switch from one set of controllers to another. Compare to other control methods, MMAC has the advantage of fast adaption. Conventional adaptive control methods rely on state estimation. The controller tries to estimate the changes of the system dynamics and then modulates its control parameters to adapt to the changes. For frequently changing environments, however, the period of modulation of the control parameters may cause a transient error, where strong fluctuations can downgrade the performance and damage the hardware. MMAC is used to reduce the transient error by conducting a fast adaption.

A MMAC system is composed of several different controllers, each particularly designed for one control condition. During the control process, the environment is monitored in real time and one or more controllers suitable for this environment are activated to generate the control command. When the system encounters a sudden change, it will adapt to it by activating another set of controllers. It does not need to re-optimise the control parameters and hence the transient error is reduced.

MMAC dates back to the 1970s. Athans et al. (1977) use multiple Kalman filters in controlling equilibrium flight, to handle sensor errors and to reconstruct the state variables in different flight conditions. The final adaptive control signal is computed by the linear combination of the control signal generated by each model, weighted by the associated probability. Later, a switching MMAC is proposed and its stability is studied (Fu and Barmish, 1986). Narendra and Balakrishnan (1994) use MMAC to improve the performance of the controller in multiple environments, particularly to reduce the transient error that is caused during the transition of the control parameters from one set of optimal values to another. They later use neural networks to build models for the non linear system (Narendra et al., 1995; Narendra and Balakrishnan, 1997). This controller is implemented in a robot manipulator to follow a predefined trajectory and shows improved performance compared to single model control.

To apply MMAC to a practical control problem, the first step is to design how many modules to use and how to decompose the problem space. The previous mentioned methods do this manually. To automate this step, Anderson et al. (2000) propose a method for linear plants. They use the Vinnicombe distance (Vinnicombe, 1993) to span and decompose the space, where the plants lie on. Firstly, an initial random starting point is chosen, where a controller is determined. The controller finds its boundary in the neighborhood where it can control satisfactorily. At the boundary, a new starting point is chosen and a new controller is determined. This process continues until the whole space is covered. Based on this method, Lourenco and Lemos (2006) propose an approach to recognize the new condition and learn new controls online to adapt. These methods, however, are applicable for linear plants. How to apply MMAC in nonlinear systems remains a open question.

In robot control, MMAC has many applications for conducting a task in frequently varying environments. These changing environments can be caused by many factors, such as object interactions. Works on this topic include Petkos et al. (2006) learning multiple inverse models for controlling robots to follow a trajectory with different workloads on the arm; Nakanishi et al. (2013) proposing a time-based switching method for robot systems with variable stiffness actuation to handle the different phases of interaction with the environment; the "eMOSAIC" (Sugimoto et al., 2012) to bring the MOSAIC from simulation to real robot control. In the last work, the performance of MOSAIC under large observation noise is improved by using an optimal control technique. The method is implemented on the 51 DOF humanoid robot CB-i for a squatting task and a carrying load task. As far as we know, this is the first MMAC implementation for a real robot.

Despite the remarkable theoretical accomplishments and many successful applications of MMAC, its application in controlling service robots is not flourishing. At one hand, this is because robotics always involves non linear control problems, for which the modularization remains a open question. Also, a MMAC controller itself is difficult to design. Control problems in robotics are highly task specific and the service robots are expected to handle a huge number of tasks. Hand designing a MMAC for these tasks is not cost effective.

2.3.3 Modular approaches in robotics

In the previous two sections we list a few applications of the modular approach in robotics from the AI and control prospectives. Modular approaches in robotics go further. In recent years, there have been many studies in the modular approach, especially in robot motion planning, grasp planning and manipulation planning. This is mainly due to the trend to try to move robots from the industrial controlled environment to the human dominated environment, where the robots have to handle dynamic and complex situations. In this section, we will give an overview of modular approaches to motion planning. Applications in grasp planning and manipulation will be reviewed in detail in the next section.

Modularities in robotics always refer to "primitives", such as "object shape primitives", "motion primitives", "grasp primitives" and "manipulation primitives". Among these, the most extensively studied area is motion primitives. To build a versatile service robot that can work in a human dominated environment and assist a human, high level behaviour planning is required. This means robots need to be equipped with the ability to plan a sequence of movements that fulfil a commanded task, such as "clean the table" and "put the food into the fridge". The conventional method of motion planning is to search in a high dimensional space formed by the numerous degree of freedoms of the robot. The number of possible solutions to accomplish a task is therefore nearly infinite.

This redundancy is useful. In reality, additional constraints such as avoiding obstacles and robot joint limit may be added to a task. Due to the redundancy, we are able to find feasible solutions under multiple task constraints. However, this redundancy also makes planning difficult as it makes the search space extremely large. One common solution of planning is to carry out optimization for the robot motion with constraints that are mathematically equivalent to the task constraints. The drawback of this optimization approach is that defining a proper cost function and proper constraints for the task is not easy. This requires a certain amount of knowledge in mathematics and mechanism, as well as a deep understanding of the task.

As an alternative, modular approaches can be used to reduce the search space, without discarding good solutions. To this end, the concept of the motion primitive is introduced into robotics. This is a concept from neuroscience research. Neuroscientists have found evidence to suggest that the vertebrate motor system generates motions by combining a small number of motor primitives (Mussa-Ivaldi et al., 1994; Mussa-Ivaldi, 1999; Bizzi et al., 2008; Grillner, 2011). These show the modularized mechanism running in brains: each motor primitive is one module, the combination of many modules generates the complex behaviour.

This idea inspired roboticists to develop simple motion primitives and use them as substrates to develop complex behaviours. In robot motion planning, motion primitives are defined as the most elementary motions, each of which serves one particular purpose. A common way to generate motion primitives is to extract them from human demonstrations: motion sequences demonstrated by humans are discretized to a sequence of motion primitives. Modularized by the motion primitives, the task planning problem is brought from a huge high dimensional search space to a finite discrete space.

Motion primitive studies mainly focus on three problems, which are also the typical problems in a modular approach: how to model the motion primitives, how to extract motion primitives from a complex motion sequence and how to combine them to form a complex behaviour.

In studies of the first problem, many roboticists encode the motion primitives with statistical or analytical models, which can be modulated to some extent by varying the parameters according to the requirements of a certain task. The most used modeling methods for motion primitives are The Hidden Markov Model (HMM), mixture models such as the Gaussian Mixture Model (GMM) and the dynamical systems model represented by a set of non linear differential equations. HMM is used to encode temporal motions (Inamura et al., 2004; Kulić et al., 2008; Takano and Nakamura, 2008; Lee and Ott, 2010; Huang et al., 2013a). For time independent motions, Gribovskaya et al. (2010); Khansari-Zadeh and Billard (2010) use GMM to model multiple human demonstrations in the state space, while Ijspeert et al. (2002, 2003); Schaal et al. (2005); Peters and Schaal (2008) use nonlinear differential equations to capture an observed behaviour in an attractor landscape. The later is referred as the Dynamical Movement Primitives (DMP), of which the design principle and roadmap is reviewed in (Ijspeert et al., 2013).

Many of the algorithms mentioned above obtain the motion primitives from manual segmentation of motions. However, it is still not clear to us how many motion primitives we need to compose all the human daily behaviours and what these primitives should be. To obtain these primitives, demonstrating all primitives or manually extracting motion primitives from demonstrations is not practical. Even if a library of motion primitives existed, to learn a complex behaviour from human demonstration, a robot still needs to recover the motion primitives from demonstrated motion sequences. Hence, a general automatic mechanism to extract motion primitives is required.

To this end, segmentation of a motion sequence (Takano and Nakamura, 2006; Pais et al., 2013) and clustering of data (Kulic et al., 2009; Kulić et al., 2012) are the most used techniques. These approaches usually rely on a carefully chosen threshold to decide when to segment and stop clustering. A method is to set boundaries on the kinematic variables such as the velocity: Fod et al. (2002) segment a sequence when a Zero Velocity Crossing (ZVC) is observed. Takano and Nakamura (2006) perform the segmentation according to the correlation among short motions. They first divide the sequence to a set of short notes. When a new motion is demonstrated, they segment it at the moment that the difference between the predicted next note and actual observed one is larger than a threshold. Kulić et al. (2008) use a hierarchical clustering method to extract primitives from human motion sequences. Different cut off parameters are tested to evaluate the trade off effect between facilitating quick group formation and introducing misclassification. Pais et al. (2013) extract the primitives according to the variances of the motions in a few demonstrations for a same task. Many other approaches have been proposed to extract motion primitives according to their task requirements. All of these approaches aim to extract a set of motion primitives that are independent functional units and generalized enough to be reused in many tasks. With these pre-defined motion primitives, online recovery of a sequence of motion primitives is feasible. With the presumption of an existence of a motion primitives library we can reduce the segmentation problem to an online motion recognition problem Meier et al. (2011).

The intention of modelling motion primitives is to use them to help with the motion planning problem. According to the task, the use of the motion primitives can be in the form of selecting, mixing or sequencing. The selecting and mixing are for adaptive behaviour: the robot needs to select one or mix a few motion primitives according to the current task context such that it can finish the task. Selection can be decided by a pre-learned correlation between the primitives and the task contexts: the highest correlated primitive with the current task context is the one to choose (Takano et al., 2006). On the top of this, Daniel et al. (2013) use Relative Entropy Policy Search (REPS) to optimize the joint state-action distribution and hence choose the optimal set of parameters for the primitive. Some others choose the primitive that can result in a system state closest to the desired next system state (Hauser et al., 2008). A similar idea is used in the mixing method, where more than one motion primitive can be activated at the same time. The weight of each motion primitive is computed to make sure the resulting motion can bring the system to the desired state (Huang et al., 2013a; Sugimoto et al., 2012). From the human robot interaction perspective, the robot should be able to understand human verbal commands and plan the action. Takano and Nakamura (2008) propose a method to associate morpheme words with motion primitives. This potentially enables the robots to understand human commands and plan motion by parsing the sentence.

2.3.4 Grasping and manipulation by modular approaches

Modular approaches in robot grasping and manipulation to reduce the problem complexity. Modularization in grasping and manipulation are mainly done in two approaches: modularize by perception and modularize by action. Perceptual modules are mainly used in planning, while action modules are mainly used in execution.

Modularize by perception

The first step of making a plan of grasping and manipulation is observing the object. Most of grasp stability analysis are done based on the shape of an object. In human dominated environment, the possible shapes of objects to grasp and manipulate is infinite. Conventional methods to model these object are only effective in convex models. For highly non-convex shapes, local vision features such as edges and colors are used to generate grasping plans at the local areas. To generate grasp for the whole object, Miller et al. (2003) propose a modular approach, i.e. planning grasps by shape primitives. The key idea is to approximate a complex object, e.g. non-convex shape, to a set of shape primitives such as boxes, cylinders and spheres. Planning on these shape primitives is relatively easier or pre-trained. Therefore the complex planning problem is tamed to a set of simple problems. According to different purposes, different shape primitives are proposed. Miller et al. (2003) use four primitives including box, cone, cylinder and sphere; Huebner et al. (2008) use minimum bounding box to decompose an object and El-Khoury and Sahbani (2010) use superquadric as the shape primitive. These methods are based on the complete object point clouds, which may not be fully accessible in the real scenario. Methods to split objects to shape primitives and detect primitives parts are proposed, which mainly exploit the techniques in graphics such as the RANdom SAmple Consensus (RANSAC) (Garcia, 2009; Gallardo and Kyrki, 2011). Faria et al. (2012) use multiple sensors to track human hand trajectory and tactile data, and hence extract motion primitives and contact primitives from the demonstration. These information is then merged to form a object probabilistic volumetric model, which is decomposed to multiple superquadrics.

Modularize by action

The motion primitive concept is also introduced to grasping and manipulation. These differ from the reaching movement primitives discussed in the previous Section **??**, where the goal is to reach the targeted points. The grasping and manipulation motion primitives are more task-oriented, i.e. each primitive is associated with a specific impact on the environment, such as getting contact with the object and pushing the object. Therefore in the literature these primitives are sometimes referred to as "task primitives". Because of the variety of tasks and their complexity, these task primitives are usually manually defined. Transitions between them are usually decided by contact events that indicate the impacts on the environment (Morrow and Khosla, 1997). Michelman and Allen (1994) propose the representation of the relationship between task primitives by a finite state machine. Kazemi et al. (2012) define three task primitives for force compliant grasping of small objects from a table top. The Dynamical Movement Primitives (DMP) mentioned previously, which model desired motion by an attractor landscape, is extended to deal with various problems when executing a grasp. The combination of the DMP and the Early Cognitive Vision Descriptor (ECVD) for grasp planning enable a robot to plan the path of approach of the hand and the finger to avoid premature contact between finger and object (Kroemer et al., 2011). Taking the object poses distribution into account, a new optimization method of the DMP is proposed to find an approach trajectory that produces robust grasps with object pose uncertainty (Stulp et al., 2011). In a later work, the uncertainty of object shape is also taken into account. The DMP can change the end point of the movement according to the shape of the object (Stulp et al., 2012).

A number of frameworks are proposed to model and organize the task primitives. Laaksonen et al. (2010); Felip et al. (2013) propose a hierarchical framework to solve the embodiment problem of sharing experience among different robot platforms. The task primitives is defined in an abstract layer and an embodiment layer. The former can be translated to the latter. This enables the robot to plan tasks with the higher level abstract primitives, and execute them with the embodiment specific task primitives. To facilitate manipulation motion planning, Barry et al. (2013) use a Rapidly exploring Random Tree (RRT) to sequence motion primitives. Detry et al. (2013) modularize a grasp planning task by two constraints: gripper constraints and task constraints. While the former modules handle grasp stability, the latter modules select grasps from the task requirements.

Besides task-specific motion primitives, modular approaches are also used to tame the complex grasp planning problem. The concept of “hand synergies” for example, is a modular approach originating in neurophysiological studies (Santello et al., 1998; Santello and Soechting, 2000). In this field of study, roboticists try to understand how the human central neural system (CNS) simplifies the grasping strategy and how to mimic this mechanism in robot systems. This concept is used in grip force control (Gabiccini et al., 2011) as well as grasp planning (Gioioso et al., 2013). Similar to this idea, robot “Eigen grasps” have been proposed to study the modularity in robot embodiment. Instead of directly searching for good grasps in the high dimensional configuration space of robotic hands, this space can be reduced by generating a set of grasp starting positions, hand preshapes Miller et al. (2003) or eigengrasps Ciocarlie and Allen (2009) that can then be tested on the object model. Such approaches reduce the dimensionality of the hand configuration space, but doing so implies a corresponding reduction in the accessible hand postures.

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