Dexterous Robotic Manipulation of Deformable Objects with Multi-Sensory Feedback - a Review

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1. Introduction

Designing autonomous robotic systems able to manipulate deformable objects without human intervention constitutes a challenging area of research. The complexity of interactions between a robot manipulator and a deformable object originates from a wide range of deformation characteristics that have an impact on varying degrees of freedom. Such sophisticated interaction can only take place with the assistance of intelligent multi-sensory systems that combine vision data with force and tactile measurements. Hence, several issues must be considered at the robotic and sensory levels to develop genuine dexterous robotic manipulators for deformable objects. This chapter presents a thorough examination of the modern concepts developed by the robotic community related to deformable objects grasping and manipulation. Since the convention widely adopted in the literature is often to extend algorithms originally proposed for rigid objects, a comprehensive coverage on the new trends on rigid objects manipulation is initially proposed. State-of-the-art techniques on robotic interaction with deformable objects are then examined and discussed. The chapter proposes a critical evaluation of the manipulation algorithms, the instrumentation systems adopted and the examination of end-effector technologies, including dexterous robotic hands. The motivation for this review is to provide an extensive appreciation of state-of-the-art solutions to help researchers and developers determine the best possible options when designing autonomous robotic systems to interact with deformable objects.
Typically in a robotic setup, when robot manipulators are programmed to perform their tasks, they must have a complete knowledge about the exact structure of the manipulated object (shape, surface texture, rigidity) and about its location in the environment (pose). For some of these tasks, the manipulator becomes in contact with the object. Hence, interaction forces and moments are developed and consequently these interaction forces and moments, as well as the position of the end-effector, must be controlled, which leads to the concept of "force controlled manipulation" (Natale, 2003). There are different control strategies used in

general to solve the force controlled manipulation problem and to develop the required contact task control with the environment. These are respectively the hybrid position/force control scheme (Raibert & Craig, 1981) and the impedance control scheme (Hogan, 1987), the hybrid impedance control (Anderson & Spong, 1988), and the parallel force/position control (Siciliano &Villani, 1999).

Alternatively, to enhance interaction with the object, the process of measuring the variables resulting from the application of the forces on the object must be considered. Another important aspect of interaction with the object is the derivation of a contact model and the selection of proper grasp points (Mason & Salisbury,1986; Salisbury & Roth, 1983; Cutkosky, 1989; Bicchi & Kumar, 2000; Mason, 2001). These have a crucial role in performing the grasping process where the objective is usually to mimic the human hand (Kaneko *et al.*, 2007). To achieve the resemblance with human arm/hand in robotics, force/tactile sensors (Javad & Najarian,2005; Tegin & Wikander, 2005) can be mounted on robotic hands. These are usually comprised of two or more fingers. These types of sensors give crucial information such as the occurrence of a contact with the object, its size and shape, the exchanged forces between the object and the robot hand, the mechanical properties of the object in contact, and the detection of slippage of the body in contact. A smart combination of all this information opens the door to more sophisticated manipulation known as dexterous manipulation (Bicchi, 2000; Okamura *et al.*, 2000). Hand dexterity refers to the capability of changing the position and orientation of the manipulated object from a given reference configuration to a different one arbitrarily chosen within the hand workspace. It is a rather broad concept that involves aspects of, and usually a compromise between, ability and stability in performing motions of the manipulated object by hand palm and fingers.

2. Robotic Interaction

Handling rigid objects has been a dominant subject of study, and the literature reports numerous works on this aspect. Modeling and control of robots whose tasks include interaction with their environment is still a very active area in the robotic community. When robot manipulators are performing such tasks, motion planning is carried out during the unconstrained phase of the task where the robot moves toward the object. During this phase, sub-goals over the motion trajectory are calculated to control the robot until completion of the task. In this case position controllers are adequate as the robot is required to follow a desired motion trajectory. During the contact phase which follows, the interaction forces and moments between the robot manipulator and the environment, as well as the position of the end-effector, must be controlled. Modeling and control of robots based on contact dynamics is a challenging research field which attracts the interest of many researchers in the robotics community. A good coverage on the robotic manipulators foundations and different aspects of kinematics and dynamics modeling are presented in (Siciliano & Khatib, 2008; Pires, 2006), as well as on the related force and motion control strategies. The book (Vukobratovic *et al.*, 2003) reviews the different effects of robot dynamics while the manipulator is in contact with the environment. It provides an interesting overview of the research efforts carried out by the robotics community to tackle the problem of contact dynamics with the environment.

After the contact is established the required manipulation process can be performed. Manipulation processes are carried out by controlling both the interaction forces and the corresponding position at the contact points with the object. The different control schemes that were introduced for the purpose of interaction control when dealing with rigid objects are reviewed in the following sections.

2.1 Robotic Interaction Modeling and Control

The robot manipulator system, that is the arm and gripper, or the finger manipulator in case of a multi-fingered dexterous hand, is a complex nonlinear dynamical system. Moreover, its subsystems, the links and joints, can be coupled. This eventually leads to sophisticated modeling and control approaches. However, when a robot manipulator becomes in contact with its environment (Vukobratovic *et al*., 2003) its motion becomes constrained, and a deformation process occurs. The amount of deformation is depending on the stiffness characteristic of the environment or object, whether it is deformable or rigid, as well as depending on the end-effector type and shape. Consequently, due to this interaction, some reaction forces at the end-effector will be generated and felt at each joint.

The research efforts reported in the literature to solve the interaction problem, which involve force control and contact dynamics with the object, are designed with the aim of creating efficient control schemes for contact task control. For this reason different control schemes were developed to achieve effective force control during the interaction with the object. According to (Siciliano & Villani, 1999), these schemes belong to two main categories. The first category is the "direct force control" which achieves force control by means of explicit closure of the force feedback loop. The second category is the "indirect force control" which achieves force control through motion control. However, two classical control strategies are used in general to solve the force controlled manipulation problem and the required contact task control with the environment. They are namely: the hybrid position/force control scheme, which belongs to the first category; and the impedance control scheme, which belongs to the second category.

The hybrid position/force control scheme which was originally proposed in (Raibert & Craig, 1981) tries to decouple the directions in which the force is controlled, e.g. the force normal to the surface, from those in which the position is to be tracked, e.g. forces along the surface. This scheme is developed originally in response to the simultaneous presence of constrained and unconstrained directions for a robot manipulator in contact with the environment. The unconstrained direction is treated as a position control problem, while the constrained direction is explicitly force controlled. Therefore, the scheme structure consists of two parallel feedback loops, one for the position and another for the force. Each of these loops uses separate sensors and separate control laws. In fact, this separation results in two perpendicular subspaces: one for position and another for force. Due to this orthogonal structure, switching from force control to position control and vice versa might not be smooth and fast enough to cope with an interaction carried out in unstructured environment under real-time constraints. The hybrid position/force control scheme neglects the dynamic coupling effects that exist among each of the robot joints. This problem was subsequently investigated in (Khatib & Burdick, 1986). Exact decoupling of motion and force equations and linearization of the resulting system via nonlinear feedback has been accomplished in the joint space in (Yoshikawa, 1986) and in the task space in (McClamroch, 1986) .

In contrast to hybrid position/force control, the impedance control scheme (Hogan, 1987) combines the position and force control rather than separating them. This approach aims at softening the rigidity of robotic manipulators by assigning desired impedance to the end-effector and therefore represents a strategy suitable for constrained motion. The objective of this control approach is to achieve target impedance by having the end-effector perform a certain mechanical behavior. In other words, this method aims at controlling the position and force at the same time by translating a task into some desired impedance. The actual achieved position and corresponding forces will then be a function of the robot impedance, the environment admittance, and the desired position and force. The design concept adopted here is that the controller should be used to regulate the dynamic behavior between the robot manipulator motion and the force exerted on the environment. Therefore, impedance control has been considered as one of the most suitable control schemes to solve the interaction problem in unstructured environments. However, errors in the manipulator kinematics or due to unmodeled dynamics could cause excessive control action. Using hybrid position/force control for controlling dexterous hands was investigated in (Yin *et al.*, 2003) and impedance control in (Biagiotti *et al.*, 2003).

The method developed in (Anderson & Spong, 1988) benefited from the concepts of these two approaches and developed an alternative unified strategy under the name of hybrid impedance control which combines the two classical control techniques described above. The structure of the hybrid impedance control consists of inner and outer control loops. The inner loop provides the inverse dynamics control while the role of the outer loop is to achieve the desired characteristics like set-point tracking, disturbance rejection, and to cope with the robustness issue. Hybrid impedance control in general has been applied over the past two decades to enable robot end-effector to smoothly move between contact and non-contact phases of motion. The idea of this type of control has in fact emerged from the examination of how humans interact with their environment. Impedance control defines the relationship between the manipulator end-effector and the external forces generated when the end-effector is in contact with the environment. Depending on what is required to be controlled, that is force or position, the hybrid impedance control can use either position-based impedance (sometimes termed as admittance control) or a force-based impedance. Consequently this requires different control structures to be applied orthogonally to satisfy the nature of the hybrid position/force control. Position-based impedance control can be applied in the direction of the manipulated object to ensure that the contact point does not shift during the manipulation process; while the force-based impedance control can be applied in the direction perpendicular to the surface of the object. Applying these two structures in two directions can compensate for the change in object location because of its motion due to the manipulation process.

At the controller level, many control algorithms from both classical and modern control theory are found in the robotic literature for the purpose of controlling the manipulator motion. These controllers range from the traditional three term PID controller to more sophisticated nonlinear ones, like variable structure, adaptive and robust controllers. The book (Lewis *et al.*, 2004) reviews the application of these controllers and provides a critical evaluation of each stating the purpose of use, as well as their respective advantages and disadvantages. However, recently the attention of the robotic community has drifted more toward artificial intelligence (AI) concepts like experts systems, fuzzy logic or neural networks where more research efforts are reported since the mid 1990s (Katic & Vukobratovic, 2003). Still the industry remains favorable to the analytical solutions and hence simple analytical learning algorithms are always potential candidates for industrial applications, especially at the task level.

2.2 Robotic Interaction Feedback Instrumentation

Alternatively, interaction control has also been considered as a sensor-based problem, in which two categories of research efforts can be distinguished. Force sensing is considered in the first category such that the manipulator can sense the interaction with the object during the interaction execution phase. In this case force sensors can be used effectively to implement hybrid position/force control or impedance control strategies. However, force sensing can usually provide 3D information only about the local contact points with the grasped object. On the other hand, vision systems, which are considered in the second category, can produce global information about the 3D environment. In the latter case the interaction control comes in form of visual feedback, to enable the robot to see the object and refine accordingly the interaction process. Unfortunately, vision approaches are generally not suitable to establish and maintain contact with the object surface if precise position and orientation are unknown.

Another trend emerged following some attempts to combine the two complementary sensory systems, that is vision and force. Different sensor fusion strategies have been proposed to merge force/torque-based and vision-based measurements where combined vision/force control scheme are developed.

2.2.1 Visual Servoing

One of the early control methods used with robot manipulators is visual feedback, which is often referred to as visual servoing. Visual servoing has proven to be a way of performing accurate movement in free space of the robot work cell without the need for accurate a priori models. The early work in visual servoing was initiated in the late 1970's with the pioneering work presented in (Hill & Park, 1979; Weiss *et al.*, 1987). More recently, various visual servoing systems have been reported in the literature where different approaches have been developed for robot task planning and to identify the geometry of unknown objects. In visual servoing two camera configurations are typically used: fixed and eye-in-hand, where a camera is mounted on the end-effector. Lately, these configurations became common in industrial settings to guide robots to perform manufacturing tasks on unknown objects. An extensive tutorial and survey on visual servoing can be found in (Hutchinson *et al.*, 1996; Hager *et al.*, 1996; Kragic & Christensen, 2002; Hashimoto, 2003).

For the visual servoing approaches used in practice, the depth information of an object cannot be measured directly. Therefore, different methods have been developed to obtain 3D coordinates of the manipulated object. One method is to use the images from multiple perspectives, either through stereovision or by moving the camera to multiple locations. In general, the approaches for visual servoing can be classified into two categories: position-based and image-based (Hutchinson *et al.*, 1996). In the position-based approach, a set of images are utilized together with a known camera model to extract the 3D pose of an object. The measured variables to be controlled are the Cartesian position and orientation of the object. In the fixed camera case, where the pose of the end-effector is to be controlled, pose has to be reconstructed from the available image data. Consequently, object tracking can also be performed by computing the error in the 3D space, and the position of the object is

extracted using the image information and a calibrated camera model. Therefore, a series of calibrations are necessary, such as between the robot base and the camera, between the tool and the camera, and for the camera itself.
Alternatively, in the image-based approach, the variables to be controlled are defined directly as features in the image space and hence it is not necessary to perform a complete 3D reconstruction of the scene. Tracking objects with the image-based approach is performed by computing the error on the image plane and asymptotically reducing this error to zero such that the robot is controlled to track a target, based on the errors in the image frames. For the fixed camera configuration, the image Jacobian can be calculated using the camera model. Because there are distortions of the targets in the image frame for the fixed camera configuration, the identification of features is not accurate. On the other hand, for the eye-in-hand configuration, the image Jacobian is more difficult to compute (Hutchinson *et al.*, 1996). However, the feature identification errors can be greatly reduced if the end-effector is perpendicular to the features on a surface.
However, due to the lack of precise position and orientation, none of the above two approaches is suitable to establish and maintain contact with the object surface. Many of the early research in visual servoing also ignored the dynamics of the robot and focused on estimating motion or recovering the image Jacobian. The paper (Papanikolopoulos *et al.* 1993) proposed an adaptive control scheme for an eye-in-hand system in which the depth of each individual feature is estimated at each sampling time during execution. Another method introduced in (Castano & Hutchinson, 1994) called visual compliance, which is a vision-based control scheme, was achieved through a hybrid vision/position control structure. In (Smits *et al.*, 2008) the possible visual feedback control transformations are studied among different spaces, including image space, Cartesian space, joint space or any other task space defined in a general task specification framework. In (Moreno *et al.*, 2001) a 3D visual servoing system is proposed based on stability analysis. They used Lyapunov's theorem to ensure that the transformation from the image frame to the world frame for 3D visual servoing system is carried out with less uncertainty. Several design issues for 3D servoing controllers in eye-in-hand setups were discussed by (Bachiller *et al.*, 2007). Especially they proposed a benchmark for evaluating the performance of such systems.

2.2.2 Feedback Control Based on Vision and Force Sensing

More recently modern robotic systems have been developed to enhance robot autonomy such that robots behave as artificially intelligent devices and act according to what they can perceive from their environment, either by seeing or touching the objects they manipulate. Thus, an important trend emerged to combine different sensory information, mainly vision and force feedback. In these dual sensory schemes, force sensing may result in full 3D information about the local contact with the grasped object, and hence enables the control of all possible six degrees of freedom in the task space. On the other hand, the vision system produces the global information about the 3D environment from 2D or 3D images to enable task planning and obstacle avoidance. Even if the exact shape and texture of the object remain unknown, the vision system can adequately measure feature characteristics related to the object position and orientation. Therefore, the levels of such vision/force integrated controller are classified into different categories (Lippiello *et al.*, 2007b): shared and traded, hybrid visual/force and visual impedance control. In shared control scheme, both sensors control the same direction simultaneously while in traded control, a given direction is alternately controlled by vision or by force. The Hybrid control scheme involves the simultaneous control of separate directions by vision and force, while the impedance scheme rather combines the two control variables.

In an integrated vision/force control scheme, however, defining how to divide the joint subspace in vision or force controlled directions, or assigning which direction to share and how to share among others, is not always a clear problem. A review and comparison of the different algorithms that combine both visual perception and force sensing is presented in (Deng *et al.*, 2005). A critical evaluation of the two main schemes for visual/force control, namely the hybrid and impedance control is also presented in (Mezouar *et al.*, 2007).

Combining force with vision, which are in fact highly complementary to each other, was reported earlier in (Nelson & Khosla, 1996). Their implementation proposed to switch between vision-based and force-based control during different stages of execution. The paper (Hosoda *et al.*, 1998) introduced an integrated hybrid visual/force control scheme. Another hybrid visual/force control algorithm was proposed for uncalibrated manipulation in (Pichler & Jagersand, 2000). In these hybrid control methods the transform between the two sensory systems, force and vision, can be learned and refined during contact manipulations. Alternative visual impedance control schemes are introduced in (Morel *et al.*, 1998; Olsson *et al.*, 2004). Damping and stability issues of the interaction control at contact point in combined vision/force control schemes were investigated also in (Olsson *et al.*, 2004). Interaction control under visual impedance control using the two sensors was studied in (Lippiello *et al.*, 2007a), proposing a framework that allows to update in real time the constraint equations of the end-effector. In a hybrid force/position control scheme, the same authors also proposed in (Lippiello *et al.*, 2007b) a time varying pose estimation algorithm based on visual, force and joint positions data. A stereoscopic vision is used in (Garg & Kumar, 2003) to build a 3D model for the manipulated object and with a learning algorithm they map the object pose from camera frame to world frame. In (Kawai *et al.*, 2008) the hybrid visual/force control is extended to accommodate 3D vision information analysis taken from fixed camera based on a passivity dynamic approach.

Based on such integrated sensory systems, research efforts were reported on using fixed camera configuration and hybrid position/force control (Xiao *et al.*, 2000). In contrast to these efforts, others privileged an end-effector mounted camera, rather than a fixed one. Such a combined vision/force control scheme was reported by (Baeten & De Schutter, 2003) who use both force and vision sensors mounted on the end-effector at the same time. Using this eye-in-hand camera configuration, a common global 3D framework for both force and vision control was proposed to model, implement and execute robotic tasks in an uncalibrated workspace. The method to control the orientation of the end-effector using the force/torque sensor in this framework was investigated later by (Zhang *et al.*, 2006) and it was found that the torque measurement is not accurate enough for a free-form surface, which could cause orientation control errors. To overcome this problem an automated robot path generation method was developed based on vision, force and position sensor fusion in an eye-in-hand camera configuration. The combined sensor is used to identify the line or edge features on a free form surface. A robot is then controlled to follow the feature more accurately.

In integrated multi-sensory robotic setups it is important to accurately and coherently fuse measurements of complementary sensors. Therefore, sensor fusion becomes a crucial research topic. Sensor fusion as has been investigated in several ways to increase the reliability of the observed sensor data by performing some statistical analysis, e.g. averaging sensors readings over redundant sensory measurements. A sensor fusion strategy has been proposed by (Ishikawa *et al.,* 1996) to fuse complementary information to obtain inferences that an individual sensor is not able to handle. In (Xiao *et al.*, 2000), they proposed a complementary sensor fusion strategy to fuse force/torque based and vision-based sensors, while in (Zhang *et al*., 2006), they integrated sensor fusion with an automated robot program generation method for the vision, force and position sensors. In (Pomares *et al.*, 2007), researchers were able to plan the manipulator motion in 3D by fusing data from force and vision sensors in an eye-in-hand setup. Other sensor fusion techniques were introduced by (Smits *et al*., 2006) using Bayesian filter, and by (Thomas *et al*., 2007) using particle filters.

2.2.3 Integrating Vision, Force and Tactile Sensing

To better achieve autonomy in the robotic manipulation, robots should ultimately produce similar adaptive sensorial coordinations as human beings do (i.e. vision, servo and touch capabilities) in order to be effective to work in unknown and uncalibrated environments and therefore be able to adapt their behavior to unpredictable modifications. To achieve the resemblance with human arm/hand in robotics, tactile sensors along with force sensors can be used. Tactile sensors give crucial information such as the presence of a contact with the object, its physical size and shape, the exchanged forces/torques between the object and the robot hand, the mechanical properties of the object in contact (e.g. friction, rigidity, roughness, etc), as well as the detection of slippage of the body in contact. Hence, the robot hand can be used in a variety of ways. In particular, an important function that mimics human hand, other than grasping, is the ability to explore and to probe objects with fingers. Adding such type of interactions over the ability of grasping leads to the concept of dexterity of manipulation.

While vision can guide the manipulator toward the object during the pre-grasping phase, force and tactile sensors are used to provide real-time sensory feedback to complete and refine the grasping and manipulation tasks. The measurements obtained from force and tactile sensors are used to perform grasp control strategies aimed at minimizing the grasp forces or optimizing the end-effector's posture, as well as to perform force control strategies necessary for dexterous manipulation. Based on the provided measurements about the object in contact, the corresponding control strategies can then be performed in an autonomous manner during the task execution phase.

Force sensors commercially available are devices installed mostly at the robot manipulator wrist or at hand tendons. They usually measure the forces and moments experienced by the robot hand in its interaction with the environment. In fact, the major part of these sensors is composed of transducers which measure forces and torques by means of the induced mechanical strains on flexible parts of their mechanical structure. These strains are generally measured using strain gauges which in turn change their resistance according to local deformation during the interaction with the object. This way, these sensors provide the equivalent force/torque measurements.

On the other hand, tactile sensors are mounted on the contact surface of the fingertips of a robot hand, and eventually on the inner fingers and the palm, to measure the amount of contact pressure that is exerted. They consist of a matrix or array of sensing elements. Their function is to measure the map of pressure over the sensing area. A number of force and tactile sensors have been proposed for robotic applications with different realisations. The

work of (Javad & Najarian, 2005; Tegin & Wikander, 2005) give good overviews on the technologies and implementations used for such type of sensors.
The integration of vision, force and tactile sensors for the control of robotic manipulation can be found for example, in the work of (Payeur *et al.*, 2005) using industrial manipulator setup. There are also some other research efforts reported in the literature on using haptic systems to handle robotic manipulation at the dexterous hand level in (Barbagli *et al.*, 2003; Schiele & De Bartolomei, 2006; Peer *et al.*, 2006). In such systems, where the focus is on virtual control prototyping, users interact with virtual manipulated objects in the exact same way they would interact with the physical objects. The limitation in interacting with these objects in virtual manipulation rests the same that is faced by robotic systems working in the real world. These systems also assume that an in-depth knowledge of the object characteristics is available for inclusion into the simulated environment.

2.3 Robotic Grasping and Contact Modeling

In order to perform robotic grasping, contact points should be established first between the end-effector and the object. Contact points are of different types and physically differ in the shape of the contact area, and in the magnitude and direction of friction forces. Several types of such possible contacts are identified and examined thoroughly in (Mason and Salisbury, 1986). Grasping can be seen as the resultant of the interaction with an object at these contact points, while the location of the contact points can determine the quality and stability of the grasp.
There exists a substantial research effort carried out on robotic grasping and contact modeling of rigid objects where deriving the contact and grasping model is one of the essential operations in the manipulation process. A robot end-effector or hand is usually comprised of two or more fingers that restrain object (fixturing) or act on manipulated objects through multiple contacts at the same time. A standard classification of such interaction contacts according to specific models was introduced in (Salisbury & Roth, 1983; Cutkosky, 1989; Bicchi & Kumar, 2000; Mason, 2001). These contact models, which affect the analysis of the manipulation process, can be classified mainly into hard-finger (point contact with friction or without friction) and soft-finger (constraint contacts). In (Li & Kao, 2001) the review focuses specifically on the recent developments in the areas of soft-contact modeling and stiffness control for dexterous manipulation. Other important aspects of contact modeling consider also the viscoelastic behavior during rolling and slippage conditions. Under such circumstances the static and kinetic coefficients of friction play an important role in the grasp analysis, as well as whether the contact point moves on the contacting surfaces as they rotate with respect to each other or not.
In grasp analysis, the corresponding contact ways between hand fingers and objects to perform the desired grasp are also analyzed extensively in the literature. Extensive surveys on robot grasping of rigid objects reviewing the concepts and methodologies used can be found in (Bicchi & Kumar, 2000 ; Mason, 2001). Form closure and force closure are the most widely covered topics on grasp modeling that concern the conditions under which a grasp can restrain an object. These two concepts have been originally proposed for evaluating stable grasping of rigid objects. Form closure grasp (Bicchi, 1995), which was motivated by solving fixturing problems in assembly lines, considers the placement of frictionless contact points so as to fully restrain an object and thus can resist arbitrary disturbance wrenches due to object motion. Alternatively, force closure grasp (Nguyen, 1988) is more related to the

ability of a grasp to reject disturbance forces and usually considers frictional forces. The latter can resist all object motions provided that the end-effector can apply sufficiently large forces. A survey about force closure grasp methods was presented by (Shimoga, 1996). In this survey, different algorithms are reviewed for the computation of contact forces in order to achieve equilibrium and force closure grasps. Criteria for grasping dexterity are also presented. On the other hand, power grasps (Mirza & Orin, 1990) are characterized by multiple points of contact between the grasped object and the surfaces of the fingers and palm and hence increase grasp stability and maximize the load capability. The paper (Vassura & Bicchi, 1989) proposed a dexterous hand using inner link elements to achieve robust power grasps and high manipulability. Later on, in (Melchiorri & Vassura, 1992) mechanical and control issues are discussed for realizing such dexterous hand.

In another category, the research on multi-fingered robot grasping modeling can be classified as fingertip grasp and enveloping grasp (Trinkle *et al.*, 1988) respectively. In fingertip grasp the manipulation of an object is expected to be dexterous since the finger can exert an arbitrary contact force onto the object. Alternatively, when an object is grasped using the enveloping grasp model, the grasping process is expected to be stable and robust against external disturbance since the fingers contact with the object at many points.

There has been significant work as well towards recovering good grasp point candidates on the object. In this case the focus is not only on the contact forces, but also on investigating the optimal grasp points on the manipulated object. A comprehensive review is presented in (Watanabe & Yoshikawa, 2007) where different classifications are proposed for the methods used to choose such grasp points. In their work, choosing optimal grasp points was investigated on an arbitrary shaped object in 3D space using the concept of required external force set. A graphical method is presented in (Chen *et al.*, 1993) for investigating optimal contact positions for grasping 3D objects while identifying some grasp measures. Some researchers aimed at investigating optimal grasp points or regions for balancing forces to achieve equilibrium grasp. A breakthrough in the study of grasping-force optimization was made by (Buss *et al.*, 1996), while in (Liu *et al.*, 2004) the researchers presented an algorithm to compute 3D force closure grasps on objects represented by discrete points. The proposed algorithm combines a local search process with a recursive problem decomposition strategy. In (Ding *et al.*, 2001) they proposed a simple and efficient algorithm for computing a form closure grasp on a 3D polyhedral object using local search strategy. A mathematical approach is presented in (Cornellà *et al.*, 2008) to efficiently obtain the optimal solution of the grasping problem using the dual theorem of nonlinear programming. However, these methods yield optimal solutions at the expense of extensive computation. In (Saut *et al.*, 2005) an alternative on-line solution is introduced to solve the grasping force optimization problem in multi-fingered dexterous hand by minimizing a cost function. Another real-time grasping force optimization algorithm for multi-fingered hand was introduced in (Liu & Li, 2004) by incorporating appropriate initial points.

3. Manipulation of Deformable Objects

The main challenge in developing autonomous robotic systems to manipulate deformable objects comes from the fact that there are several generic interconnected problems to be resolved. Mainly it involves the collection of deformation characteristics, the modeling and simulation of the deformable object from these estimates, and the definition and tuning of an efficient control scheme to handle the manipulation process based on multi-sensory feedback. A recent trend aims at merging measurements taken from vision, force and tactile sensors to accelerate the development of autonomous robotic systems capable of executing intelligent exploratory actions and to perform dexterous grasping and manipulation.

3.1 Deformable Objects Modeling and Simulation

Automatic handling of deformable objects usually requires that the evaluation of the deformation characteristics is carried out using simulated environments before conducting the physical experiment. Hence, the manipulation process can be successfully performed by analyzing the manipulative tasks and deriving their control strategies using deformable object models.

3.1.1 Computer Simulation of the Object Elasticity

A wide variety of approaches have been presented in the literature dealing with computer simulation of deformable objects (Gibson & Mirtich, 1997; Lang *et al.*, 2002; Terzopoulos *et al.*, 1987). These approaches are mainly derived from physically-based models that emulate physical laws to produce physically valid behaviors. Using these models to provide interactive simulation of deformable objects dynamics has been a major goal of the computer graphics community since the 1980s (Pentland & Williams, 1989; Pentland & Sclaroff, 1991). Mass-spring system simulations and finite-elements methods (FEM) are the major physically-based modeling techniques considered. Under these frameworks, it can be considered that a deformable object has infinite degrees of freedom and therefore an attempt to simplify the problem is to discretize the structure, reducing the number of its degrees of freedom to a finite countable set.

Mass-spring system techniques have widely and effectively been used for modeling deformable objects. These objects are described by a set of mass particles dispersed throughout the object and interconnected with each other through a network of springs in 3D. This configuration constitutes a mathematical representation of an object with its behavior represented according to Newton's laws which incorporates calculating forces, torques, and energies. This model is faster and easier to implement as it is based on well understood physics, than finite-elements methods. It is also well suited for parallel computation, making it possible to run complex environments in real-time for interactive simulations. On the other hand, mass-spring systems have some drawbacks. Incompressible volumetric objects and high stiffness materials, which have poor stability, require small time integration step during the simulation process. This considerably slows down the simulation. Another weakness is that most of the materials found in nature maintain a constant or quasi-constant volume during deformations; unfortunately, mass-spring models do not have this property.

In finite-elements methods, unlike mass-spring methods where the equilibrium equation is discretized and solved at each finite mass point, objects are divided into unitary 2D surfaces, or volumetric 3D elements, joined at discrete node points. The relationship between the nodal displacements and the force applied follows Hooke's law where a continuous equilibrium equation is approximated over each element. Therefore, finite-elements methods offer an approach with much higher accuracy. However, while finite-elements methods generate a more physically realistic behavior, at the same time they require much

more numerical computation and therefore are difficult to use for real-time simulations. This is due to the fact that the object discretization and calculation of a stiffness matrix are computationally expensive.
In practice the physically motivated deformable models are mostly limited to surface modeling, mainly due to overwhelming computational requirements. Therefore, for simulation of robot interaction with deformable objects, mass-spring models prove to be very efficient. On the other hand, the deformable materials are considered to be either elastic, viscous, or viscoelastic. Objects with elastic behavior have the ability to recover from deformation caused by an externally applied force. Objects with viscosity resist such applied force due to their internal forces which act as damping force. The viscoelastic objects combine the elastic and viscous behaviors together. Such objects can also be deformed to the required shape according to applied force. Therefore automating and controlling the process of casting the raw viscoelastic material is crucial in some industrial applications (Tokumoto *et al.*, 1999).
As mentioned above the mass-spring model normally describes a deformable object as a set of particles constructed from a discretized sampling of its volume using a lattice configuration where a network of interconnected particles and springs is formed. These particles are the mass points in which the body mass is concentrated and are related to each other by forces acting on the object. Springs connecting these mass points exert forces on neighboring points when the object mass is displaced from its rest positions due to interaction. Therefore, the deformation of the object can be characterized by the relationship between the applied force and the corresponding particle displacement reflecting the deformation taking place. This means that this displacement describes the movement of the particle during the process of deformation.
Deformable materials can be described by models that are essentially made of different configurations of mass-spring-damper. The basic models are determined by the Kelvin model (or Voigt model) and the Maxwell model. The Kelvin model consists of a spring and a damper which connect two mass points in parallel. The Maxwell model is a series of a spring and a damper connecting two mass points. Other models can also be derived from the combination of the basic models or elements. For example, the Standard Linear model is a combination of the Maxwell model in parallel with a spring. (Byars *et al.*, 1983) give further details on the models mentioned above and discuss further issues on deformable objects modeling and analysis from a mechanical engineering perspective. A new approach is presented in (Tokumoto *et al.*, 1999) for the deformation modeling of viscoelastic objects for their shape control. In this work, the deformable object is modeled as a combination in series of Kelvin and Maxwell models. In a later step of their experiment they introduced a nonlinear damper into the model to solve a discrepancy between an actual object and its linear model. The drawbacks of Kelvin-Voigt modeling were investigated by (Diolaiti *et al.*, 2005) proposing an alternative solution for estimating the contact impedance using nonlinear modeling.

3.1.2 Modeling and Simulating the Physical Interaction

In addition to computer modeling and simulation of deformable objects, other research efforts in robotics were dedicated to the problem of modeling the physical process of manipulation. In order to implement and evaluate the manipulative operations on deformable objects by a robotic system, an object model is indispensable to represent the

elasticity and deformation characteristics during the physical interaction. The corresponding modeling problem for 1D and 2D deformable objects was studied extensively for specific applications in (Henrich & Worn, 2000; Saadat & Nan, 2002), based on mathematical representations of their internal physical behavior.
Robotic manipulative operations for deformable objects often rely on the object deformation model. However the operations may result in failure because of unexpected deformation of the objects during the manipulation process. Thus, automatic handling of deformable objects requires that the evaluation of the deformation of these objects is performed in advance using the object models to ensure that the manipulative operation is successful in the real application. Furthermore, it is important to plan tasks and derive their strategies by analyzing the manipulative processes using deformable object models. Beyond performing only simulations, in (Shimoga & Goldenberg, 1996) a soft finger is modeled using the Kelvin model in which a spring and damper are placed in parallel. The deformation parameters were experimentally calculated in a first phase, and then used in the Kelvin model with the desired impedance parameters to successfully control the impedance of a soft fingertip. In another experiment the physical interaction between a deformable fingertip and a rigid object was modeled and controlled by (Anh *et al*., 1999) based on a comprehensive dynamical notations.
In fact, deformable objects change their shapes during manipulation and display a wide range of responses to applied interaction forces because of their different physical properties. This is due to their nonlinearity attributes and other uncertainties, such as friction, vibration, hysteresis, and parameter variations. To cope with this problem, one approach is to estimate the shape of the deformable object by calculating an internal model and simulating the object behavior. Such internal model could be static or dynamic (Abegg *et al.*, 2000). As examples from the work on static and dynamic modeling, in (Hirai *et al.*, 1994) they calculated a static model for the object and obstacle in 2D, while in (Wakamatsu *et al.*, 1995) they calculated the same but in 3D. In (Zheng & Chen, 1993) they emphasized on trajectory generation based on a static model for a flexible load. Using a similar static modeling approach, the problem of insertion tasks is tackled in (Zheng *et al.*, 1991) with a flexible peg modeled as a slender beam. In the work presented in (Kraus & McCarragher, 1996), they followed the same static modeling guidelines such that no dynamic analysis is considered. However, in contrast to other works on static modeling they considered the use of force feedback to control manipulator motions. In the paper of (Wakamatsu *et al.*, 1997), they extended the ideas employed in static modeling to derive a dynamic model of a deformable linear object. Other modeling techniques were also reported in the literature, for example, in (Nguyen & Mills, 1996) they considered using lumped parameter model. In (Wu *et al.*, 1996; Yukawa *et al.*, 1996) they investigated the problem with a distributed parameter model solution.
However, it is difficult to build an exact model of deformable objects. Thus, for some researchers modeling can be highly depending on imitating and simulating the skills of human expertise when dealing with such objects. In this case the robot motion during task execution can be divided into several primitives, each of which has a particular target state to be achieved in the task context. These primitives are called skills. An adequately defined skill can have enough generality to be applied to various similar tasks. Accordingly, different control strategies are required for the robot arm to manipulate in an autonomous manner the different kinds of objects according to the specified application. Most of the

previous research works on deformable objects involve the modeling and controlling of 1D deformable linear objects, such as beams, cables, wires, tubes, ropes, and belts. Some of the skill-based modeling and manipulation for handling deformable linear objects has been reported, for example, by (Henrich *et al.*, 1999) where they analyzed the contact states and point contacts of a deformable linear object with regard to manipulation skills. The problem of picking up linear deformable objects by experimentation is discussed in (Remde *et al.*, 1999a). The problem of inserting a flexible beam into a hole is examined in (Nakagaki *et al.*, 1995) using a heuristic approach to guide the manipulator motion.
Finite-elements modeling techniques were also used to model deformable objects characteristics and to simulate the physical interaction. A framework is described in (Luo & Nelson, 2001) based on FEM modeling that fuses vision and force feedback for the control of highly linear deformable objects in form of active contours, or snakes, to visually observe changes in object shape during the manipulation process. The elastic deformation of a sheet metal part is modeled in (Li *et al.*, 2002) using FEM and a statistical data model. The results from this model are used to minimize the part's deformation. In (Kosuge *et al.*, 1995), they used FEM modeling to examine the problem of controlling the static deformation of a plate when handled by a dual manipulation system. In one of the recent efforts, a finite-elements modeling technique was reported by (Garg & Dutta, 2006), where a model is developed to control the grasping and manipulation of a deformable object based on internal force requirements. In this model the object deformation is related to fingertip force, and based on impedance control of the end-effector.
However, modeling of 3D deformable objects for robotic manipulation has not been widely addressed in the literature so far. This results from its inherent complexity and the fact that a majority of researchers hope to tackle the simpler 1D modeling problem before generalizing it to a 3D modeling solution. Among the very few research efforts on 3D modeling of deformable objects is the pioneering work reported by (Howard & Bekey, 2000) who developed a generalized solution to model and handle 3D unknown deformable objects. This work benefited from a dynamic model originally introduced by (Reznik & Laugier, 1996) to control the deformation of a deformable fingertip. The model used in (Howard and Bekey, 2000) to represent the viscoelastic behavior is derived from dividing the object into a network of interconnected particles and springs according to the Kelvin model. Then by using Newtonian equations, the particles motion is used to calculate the deformation characteristics based on neural networks. Other interesting methods for modeling 3D deformable objects are based on probing the object to extract the deformation characteristics with the aid of vision. One of these methods was developed in (Lang *et al.*, 2002) to acquire deformable models of elastic objects in an interactive simulation environment where an integrated robotic facility was designed to probe the deformable object in order to acquire measurements of interactions with the object. Another method of probing and vision tracking was proposed in (Cretu *et al.*, 2008) to model deformable objects geometric and elastic properties. The approach uses vision and neural networks to select only a few relevant sampling points on the surface of the object and guides the acquisition of deformation characteristics through tactile probing on these selected points. The measurements are combined to accurately represent the 3D deformable object in terms of shape and elastic behavior.

3.1.3 Deformable Object Grasping and Contact Modeling

Nowadays, an important goal of robotic systems is to achieve stable grasp and manipulation of objects whose attributes and deformation characteristics are not known a priori. To establish contact and grasp modeling for deformable objects, the concepts of rigid force and form closure, as well power grasp, were extended to accommodate deformable objects. In (Wakamatsu *et al.*, 1996) the effort was to extend the concept of force closure for rigid objects with unbounded applied forces to deformable objects with bounded applied forces. Wakamatsu *et al*. introduced the concept of bounded force closure, which is defined as grasps that can resist any external force within the bound. They considered a candidate grasp and external forces within a bound that can deform and displace the deformed part. In (Prattichizzo *et al.*, 1997) the focus is on the dynamics of the deformable objects during the process of power grasp. A geometric approach is adopted to derive a control law decoupling the internal force control action from the object dynamics. More recently, a new framework for grasping of deformable parts in assembly lines was proposed in (Gopalakrishnan & Goldberg, 2005) based on form closure for grasping deformable parts. In this framework a measure of grasp quality is defined based on balancing the potential energy needed to release the part against the potential energy that would result in plastic deformation. Other attempts were reported on grasping using soft fingers, such as the work in (Shimoga & Goldenberg, 1996), to design systems with force control based on grasping with soft fingers. In (Tremblay & Cutkosky, 1993) they also used a deformable fingertip but equipped with a dynamic tactile sensor which was able to detect slippage. The paper of (Inoue & Hirai, 2008) is an up-to-date reference on soft finger modeling and grasping analysis.

3.2 Robotic Interaction Control with Deformable Objects

In early robotic systems designed to manipulate deformable objects, the problem of interaction control was solved mainly in two different ways. The robotic system to handle deformable object was either designed based on force and grasp stability control, or force control versus deformation control. A control strategy based on PID control was proposed in (Mandal & Payandeh, 1995) to maintain stable contact against a compliant 1D surface. In (Meer & Rock, 1994) they used impedance control to manipulate flexible objects in 2D. A force and position control scheme was developed in (Chiaverini *et al.*, 1994) capable of regulating a manipulator in contact with an elastically compliant surface using PID control. In the paper of (Patton *et al.*, 1992) they used an adaptive control loop to generate correct tension on a 2D deformable object where stiffness is designated as the adaptive variable. In (Luo & Ito, 1993) the researchers developed an adaptive control algorithm such that the robot manipulator was able to maintain continuous interaction with a 1D deformable surface. In the work of (Seraji *et al.*, 1996) a dual-mode control scheme using both compliance and force control was applied to establish a desired force on a 1D deformable surface. In the research effort of (Yao & Tomizuka, 1998) they used a robust combination of force and motion control to enable a robot manipulator to apply a force against a 1D nonlinear compliant surface. A feedback regulator was developed in (Siciliano & Villani, 1997) which only required force and position measurements to be fed into the control loop to handle a compliant surface. In another framework handling compliant surfaces with unknown stiffness, (Chiaverini *et al.*, 1994) introduced a parallel force/position control solution. In (Li *et al.*, 2008) researchers investigated solving the problem of interaction with unknown deformable surface within an adaptive compliant force/motion control framework. The deformable object elasticity parameters were identified as a mass-spring system. Based on an intelligent setup for dynamic modeling introduced in (Katic & Vukobratovic, 1998) a PD controller was developed which allows a manipulator to apply a constant force on a 1D deformable object without having prior knowledge of its deformation. In the work reported by (Al-Jarrah & Zheng, 1998) a controller is set initially to command the manipulator to bend a 1D deformable object into a desired configuration in an intelligent compliant motion framework. In the work of (Venkataraman *et al.*, 1993), a neural network was used to address the problem of deformation parameters identification. Similarly, a fuzzy logic based control system was introduced by (Tarokh & Bailey, 1996). In (Arai *et al.*, 1993) the problem of deformable object manipulation in terms of both positioning and orientation of 2D objects was addressed. In their work, the desired trajectory was produced by controlling the torque. This control scheme was improved later in (Arai *et al.*, 1997) by using recurrent neural network as a forward model. The focus in (Kim & Cho , 2000) was on solving the misalignment problem in flexible part assembly using neural networks. Finally, a real-time eye-in-hand system was introduced by (Terauchi *et al.*, 2008) in which impedance control is used to cope with the flexible interaction and a neural network is used to learn the impedance parameters. A review of the intelligent control techniques applied for deformable object cases can be found in (Katic & Vukobratovic, 2003).

Overall, these systems require explicit models of the object which include in-depth knowledge about mass/object dynamics and deformability, and therefore, a complex force sensory system is required to measure the position and force on the object. However, dexterous grasping and manipulation of a deformable object must be performed robustly despite uncertainties in the robot environment where deformable objects are neither exactly located nor modeled. This leads to higher flexibility, and can improve speed and precision of the task execution. A number of recent research efforts focus on improving both the task quality and its range of feasibility by using integrated vision and force based control schemes. In such dexterous manipulation it is important to consider the difference between the way of handling rigid and deformable objects. This leads to a major distinction between the definitions of grasping and manipulation respectively (Hirai *et al.*, 2001). While the manipulation of a rigid object requires only the control of its location, the manipulation of a deformable object requires controlling both the location of the object and its deformation. In the handling process of rigid objects, grasping and manipulation can be performed independently. Grasping of a rigid object requires the control of grasping forces only, while manipulation of a freely moving rigid object results in the change of its position and orientation. On the other hand, grasping and manipulation interfere with each other in the handling of deformable objects. Grasping forces yield the deformation of a non-rigid object, which may simultaneously change the shape and location of the object. Hence contact between fingers and the object may be lost and grasping may be compromised due to the deformation at the fingertips. Therefore, in the handling of deformable objects, grasping and manipulation must be performed in a collaborative way.

3.3 Interaction under Combined Vision, Force and Tactile Feedback

The way of automating robotic manipulators to handle deformable objects in an unknown configuration typically involves an initial exploratory action by vision sensors to guide the robot arm toward the object, then visual information must be complemented by force/tactile measurements collected when a tactile probe or a dexterous hand comes in contact with the surface of the object. This supplementary data refines the knowledge about the position and orientation of the object and can provide an estimate of its elasticity or viscosity characteristics. All available information must be merged into a coherent model in order to allow the tuning of the feedback control loop that will guide the dexterous grasping and manipulation processes. Finally, tactile probing should continue during the operation using tactile sensors mounted on the fingertips to provide the necessary tactile sensitivity and sufficient dexterity to perform skillful manipulations of the deformable objects which may be of irregular shape and composition. Furthermore, visually monitoring of the task provides the necessary feedback to gauge how well the manipulator performed the task, or if an error has occurred, such as slippage. It is generally recognized that employing a multi-sensory system is the most effective way to model the deformation and estimate the object's shape and its attributes during the manipulation.

Vision systems can be used to detect the shape as well as to select proper picking points. Force/tactile sensors can also detect the shape or the contact. The contact state transitions based on force and vision sensors was studied in (Abegg *et al.*, 2000). They presented a systematic approach to manipulating a deformable linear object by capturing the transition graph representing the possible poses of a linear deformable object in contact with a convex polyhedron. Neurocomputing was used on tactile data in (Molina *et al.*, 2007) to model in real-time the stiffness of unknown deformable objects in the form of an anthropomorphic finger. Earlier attempts using vision systems for guiding a manipulator motion were concerned about making a knot with a rope (Inoue & Inaba, 1983), about estimating the 3D pose of deformable object using stereoscopic vision (Byun & Nagata, 1996), or about estimating the shape of a flexible beam while inserting it into a hole (Nakagaki *et al.*, 1996). Force/torque sensors were used also in (Kraus & McCarragher, 1997) to estimate the buckling of a linear deformable object when being inserted into a hole.

In recent efforts to solve the interaction control problem using multi-sensory feedback, a robust control law was developed in (Hirai *et al.*, 2001) for manipulation of 2D deformable parts using tactile and vision feedback to control the motion of a deformable object with respect to the position of selected reference points. Following this positioning approach, multiple points on a deformable object are guided to the final position. In a later study (Huang *et al.*, 2005), a position/force hybrid control method that incorporates visual information with force control was introduced to enable a robot arm with a flexible tool in the form of a hose to perform the contact process with the unknown 2D deformable object. Recent developments in (Foresti & Pellegrino, 2004) focused on automating the way of handling deformable objects using vision techniques only. Their vision system works along with a hierarchical self-organizing neural network to select proper grasping points in 2D.

3.4 Deformable Objects Manipulation in the Industry

In the recent years, robotic manipulation of deformable objects has been demonstrated in a variety of biomedical applications as well as in various manufacturing processes, especially in the electronic and electrical industry, as well as in the automotive, the aerospace, the leather, textile and garment, and in the food processing industries. In biomedical and industrial applications, there exist many manipulative operations that deal with different types of deformable objects ranging from viscoelastic objects, such as in a tele-surgery