Research Proposal

Exploring the Synergy between Learning Strategies and Control Theory in Robotic Deformable Object Manipulation

Chaoyue Fei
chaoyue.fei.21@ucl.ac.uk

Abstract

Deformable object manipulation (DOM) is an open question in academia that is gaining increasing attention. Robots are expected to carry out tasks involving deformable objects, with promising applications in logistics, ageing care, and robotic-assisted surgery. To make it a reality, challenges in hardware design, sensing, deformation modelling, planning, and control need to be addressed. This research proposes to explore and design a robotic system combining artificial technologies and control algorithms. The robotic system is initially expected to perform deformable object manipulation tasks using a single robot arm, a visual sensor, and low data-driven approaches.

Research Background

Deformable object manipulation (DOM) is an emerging field of research in robotics. As the name suggests, it involves manipulating objects usually composed of cloth, rubber, or soft plastics. Robots are required to manipulate objects that undergo significant deformation, ranging from delicate microsurgical procedures to complex industrial assemblies [21]. DOM, such as Folding and unfolding, are everyday and easy tasks for humans, but they can be challenging for a robot arm. With the rapid advancement of artificial intelligence, computers and robots will soon match or surpass human dexterity. Robots can replace any DOM, including tasks like "laundry folding" and "soft tissue manipulation". By optimising the design of the robotic system and increasing automation, the ease of human burden and manipulation efficiency can be further improved.

It is promising that model-free approaches such as learning from demonstration (LfD) or (deep) reinforcement learning enable the discovery and acquisition of synergies between non-prehensile actions like pushing and prehensile actions like gripping [19]. This allows robots to acquire skills and exhibit "intelligent" behaviour.

Research Aim

First, this research aims to indicate the technical requirements for addressing DOM challenges. These requirements include hardware design, sensing, deformation modelling, planning, and control. Second, calculate every required parameter of the robotic system in DOM. Third, analyse the theoretical feasibility of tackling DOM challenges by integrating neural networks and robotic control. Fourth, do simulations and experiments of DOM (holding, transporting, folding, unfolding) with different deformable objects. Finally, present the robotic system achieving generic manipulation of deformable objects.

Literature Review

To tackle DOM challenges, advancements are needed in various areas of robotics including hardware design, sensing, modelling (deformation), planning, and control [21].

Hardware Design

Deformable objects are typically handled using custom grippers, unlike rigid objects. Grippers are specifically designed based on the properties of deformable objects.

Hu et al. utilized a dual-arm robot (ABB Yumi) with a flat clip attached to each arm for holding towels [6]. Similarly, Duenser et al. [5] deployed a dual-arm Yumi robot with custom 3D-printed grippers to manipulate an elastic object. The GelSight sensor was used to detect cloth properties in a parallel robot gripper WSG 50, as described in [18]. A soft hand based on MUSHA Hand II for manipulating organs is proposed and tested on da Vinci Research Kit [9]. Regarding the robot itself, it is typically rigid in most tasks. However, in certain situations such as surgical applications, both the robot (manipulator) and object may be deformable to ensure safe manipulation [1].

Table 1: Hardware Design and Application of Robots Manipulating Deformable Objects

Authors	Year	Robot Testbed	Robot Type	Grippers	Application
Hu et al. [6]*	2019	ABB Yumi	Dual-arm	Flat Clip	Holding Towels
Duenser et al. [5]	2018	ABB Yumi	Dual-arm	Flat Clip	Elastic Object
Liu et al. [9]	2021	da Vinci	Surgical Robotics	MUSHA Hand II	Organs
Alambeigi et al. [1]	2019	da Vinci	Surgical Robotics	Snake-like Wrist	Tissues
Yuan et al. [18]	2018	UR5	Uno-arm	WSG 50	Active Clothing Perception

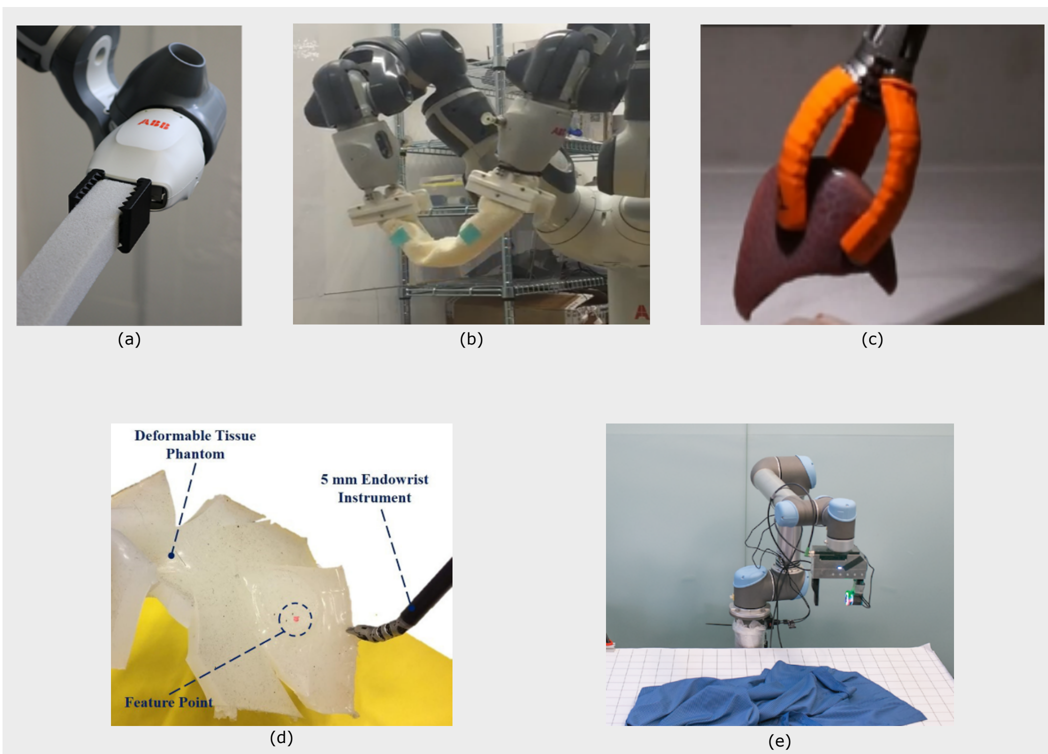

Figure 1: Various robot grippers for DOM. (a) A flat clip gripping an elastic object [5], (b) flat clips holding towels [6], (c) MUSHA Hand II manipulating organs [9], (d) a snake-like Endowrist manipulating tissues [1], (e) a robot gripper WSG 50 perceiving clothing properties [18].

Sensing

There are three common modes used to estimate the state of deformable objects: visual, tactile, and force sensing. Generally, vision provides global information on large scale, while tactile and force sensing provides local information [21].

Vision is ideal for objects that undergo significant global deformation, such as rope or cloth. In 2015, Sun et al. [15] proposed an industrial robot system that uses high-quality RGB-D images to autonomously flatten garments. Li et al. [8] utilized a Baxter robot to pick up a sweater, while employing a Kinect to capture depth images for recognizing the sweater's pose. Hu et al. [6] introduced a novel feature to describe deformable objects' deformation used in visual servoing. The feature is directly extracted from the 3-D point cloud using RGB-D camera Intel Realsense.

Tactile and Force A recent study [13] has demonstrated that a deep convolutional neural network (CNN) designed for processing vision data can also be adapted with minor modifications to process tactile data for deformable object recognition. In [18], the authors used a GelSight tactile sensor to obtain tactile data by having a robot squeeze clothes. They then applied CNN to the tactile data in order to recognize the properties of the clothing.

Modelling

In order for robots to perform deformation tasks based on sensory data, a model is required to map sensor information to robot motion. Models can be classified as either local or global, and this classification has clearer implications for control [21].

Local models commonly utilize a Jacobian matrix to approximate the perception/action relationship. This linear model can be computed in real time with minimal data and requires continuous updating during execution [21]. There are several updating methods, Broyden's method [1], receding horizon [22], QP-based optimization [7].

Global models can be approximated with FEMs [17, 5] and (deep) neural networks (D)NNs. In 2016, a first learnable physics engine named the Interaction Network (IN), that is capable of scaling up to real-world problems, was implementd by using DNNs [3]. Valencia and Payeur proposed the Batch Continual Growing Neural Gas (BC-GNG) model to estimate object state based on sensor measurements [16].

Table 2: Model Type and Method of Modeling Deformable Objects

Authors	Year	Model Type	Application
Alambeigi et al. [1]	2019	Local: Jacobian Matrix	Continuum Manipulator Control
Lagneau et al. [7]	2020	Local: Jacobian Matrix	Wires Shape Control
Zhu et al. [22]	2021	Local: Jacobian Matrix	Deformable/Rigid Objects
Yoshida et al. [17]	2015	Global: FEM	Ring-shape Object
Duenser et al. [5]	2018	Global: FEM	Elastic Objects
Battaglia et al. [3]	2016	Global: NNs	Objects Reasoning
Valencia and Payeur [16]	2020	Global: NNs	Modeling Deformable Objects

Planning

Planning involves finding a sequence of valid configurations for the robot or object. It helps address the issue of limited validity in local models [21].

McConachie et al. [10] proposed a method for integrating global planning and local control in deformable object manipulation. The approach does not require high-fidelity modeling or object simulation. The use of the Covariant Hamiltonian Optimization and Motion Planning (CHOMP) method is effective in minimizing elastic deformation during assembly tasks. In [12], authors proposed utilizing the CHOMP method for motion planning of a dual-arm manipulator handling a ring-shaped elastic object in an assembly task. A distributed receding horizon planner is used for local control [2]. It formulates a convex optimization problem in velocity space and includes constraints such as avoidance and shape maintenance. In 2021, Zhou et al. introduced LaSeSOM, a novel framework for semantic soft object manipulation that utilizes feedback latent representation [20]. The authors employed two common techniques, Principal Component Analysis (PCA) and Autoencoder (AE), to perform dimensionality transformation. The high-level semantic layer allows for performing shape planning tasks with soft objects.

Control

Control is the process of designing inputs for the robot to execute the planned motion. The choice of controller typically depends on the specific task at hand. A data-driven control approach is used, which employs a recurrent neural network to model the dynamics. This approach is applied to a Model Predictive

Controller for the task of food cutting [11]. To ensure safe interaction in minimally invasive surgery, the authors of [14] utilized a fuzzy compensator with impedance control. The system proposed by [4] achieves high accuracy in-hand manipulation. It integrates a self-identified hand-object model into a model predictive control framework, effectively closing the control loop. This is achieved through a non-parametric approach based on Gaussian Process Regression, which reduces the need for extensive online data collection. The system model utilizes just 15 data points to enable an encoderless underactuated robot hand to manipulate an unknown object and follow a reference path.

Table 3: Control Method and Highlight in Control

Authors	Year	Control Method	Highlight	Application
Mitsioni et al. [11]	2019	MPC	RNN	Food Cutting
Su et al. [14]	2019	Impedance Control	Fuzzy Compensator	MIS
Chanrungmaneekul et al. [4]	2023	MPC	Gaussian Process Regression	Rigid Object Manipulation

Research Methods

1. Literature research. Examine and summarise various aspects of addressing challenges in DOM. Pay particular attention to planning and control. Compare existing robotic systems relevant to object manipulation and use them as references for designing a new robotic system.

2. Theoretical research and calculation. It is necessary to analyse the essential components of the robotic system. These include sensors, local or

global deformation modelling methods, control methods, datasets, and network architecture.

3. Simulations and Experiments. Perform simulation experiments to collect data for training the neural network model and demonstrate the feasibility of the robotic system design. Additionally, conduct experiments to measure the time, success rate, and versatility.

Research Gap and Expectations

Several existing works in DOM have laid a foundation for future research. Based on the literature review, the following research gaps have been identified and are expected to be addressed.

1. Lack of Generality: While numerous studies have been on DOM, many focus on specific use cases and are not easily applicable to other applications. To overcome this limitation, there is a need for the development of a more generic system that can handle various tasks and types of objects.

2. Synergy between Learning and Control: Deep neural networks (NNs) have been widely integrated in modelling, planning, and controlling. However, there is still room for improvement in achieving a stronger synergy between learning strategies and control mechanisms.

3. Low-Data-Driven Approaches: Given the high cost and challenges associated with collecting extensive online data, low-data-driven approaches

have gained significant interest. These approaches prioritise model structure and parameter design, improving generalisation performance and adaptability to different data distributions and new scenarios.

There is still a long way off in achieving deformable object manipulation at the level of human dexterity, but it holds promising application prospects. I plan to utilise the research results to explore approaches for DOM using a single robot arm, visual-only sensor, and low-data-driven approaches.

References

[1] F. Alambeigi, Z. Wang, R. Hegeman, Y.-H. Liu, and M. Armand. Autonomous Data-Driven Manipulation of Unknown Anisotropic Deformable Tissues Using Unmodelled Continuum Manipulators. 4(2):254–261.

[2] J. Alonso-Mora, R. A. Knepper, R. Siegwart, and D. Rus. Local motion planning for collaborative multi-robot manipulation of deformable objects. In *IEEE International Conference on Robotics and Automation (ICRA)*, pages 5495–5502. IEEE, 2015.

[3] P. Battaglia, R. Pascanu, M. Lai, D. Jimenez Rezende, and k. kavukcuoglu. Interaction Networks for Learning about Objects, Relations and Physics. In *Advances in Neural Information Processing Systems*, volume 29. Curran Associates, Inc.

[4] P. Chanrungmaneekul, K. Ren, J. T. Grace, A. M. Dollar, and K. Hang. Non-Parametric Self-Identification and Model Predictive Control of Dexterous In-Hand Manipulation. *arXiv preprint arXiv:2307.10033*, abs/2307.10033, 2023.

[5] S. Duenser, J. M. Bern, R. Poranne, and S. Coros. Interactive Robotic Manipulation of Elastic Objects. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 3476–3481.

[6] Z. Hu, T. Han, P. Sun, J. Pan, and D. Manocha. 3-D Deformable Object Manipulation Using Deep Neural Networks. 4(4):4255–4261.

[7] R. Lagneau, A. Krupa, and M. Marchal. Automatic Shape Control of Deformable Wires Based on Model-Free Visual Servoing. 5(4):5252–5259.

[8] Y. Li, D. Xu, Y. Yue, Y. Wang, S.-F. Chang, E. Grinspun, and P. K. Allen. Regrasping and unfolding of garments using predictive thin shell modeling. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1382–1388.

[9] H. Liu, M. Selvaggio, P. Ferrentino, R. Moccia, S. Pirozzi, U. Bracale, and F. Ficuciello. The MUSHA Hand II:A Multifunctional Hand for Robot-Assisted Laparoscopic Surgery. 26(1):393–404.

[10] D. McConachie, A. Dobson, M. Ruan, and D. Berenson. Manipulating deformable objects by interleaving prediction, planning, and control. 39(8):957–982.

[11] I. Mitsioni, Y. Karayiannidis, J. A. Stork, and D. Kragic. Data-driven model predictive control for the contact-rich task of food cutting. In *2019 IEEE-RAS 19th International Conference on Humanoid Robots (Humanoids)*, pages 244–250. IEEE, 2019.

[12] I. G. Ramirez-Alpizar, K. Harada, and E. Yoshida. Motion planning for dual-arm assembly of ring-shaped elastic objects. In *IEEE-RAS International Conference on Humanoid Robots (Humanoids)*, pages 594–600. IEEE, 2014.

[13] G. Rouhafzay, A.-M. Cretu, and P. Payeur. Transfer of Learning from Vision to Touch: A Hybrid Deep Convolutional Neural Network for Visuo-Tactile 3D Object Recognition. 21(1):113.

[14] H. Su, C. Yang, G. Ferrigno, and E. D. Momi. Improved Human-Robot Collaborative Control of Redundant Robot for Teleoperated Minimally Invasive Surgery. *IEEE Robotics and Automation Letters*, 4(2):1447–1453, 2019.

[15] L. Sun, G. Aragon-Camarasa, S. Rogers, and J. P. Siebert. Accurate garment surface analysis using an active stereo robot head with application to dual-arm flattening. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pages 185–192.

[16] A. J. Valencia and P. Payeur. Combining Self-Organizing and Graph Neural Networks for Modeling Deformable Objects in Robotic Manipulation. 7.

[17] E. Yoshida, K. Ayusawa, I. G. Ramirez-Alpizar, K. Harada, C. Duriez, and A. Kheddar. Simulation-based optimal motion planning for deformable object. In *2015 IEEE International Workshop on Advanced Robotics and Its Social Impacts (ARSO)*, pages 1–6.

[18] W. Yuan, Y. Mo, S. Wang, and E. H. Adelson. Active Clothing Material Perception Using Tactile Sensing and Deep Learning. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 4842–4849.

[19] A. Zeng, S. Song, S. Welker, J. Lee, A. Rodriguez, and T. Funkhouser. Learning Synergies between Pushing and Grasping with Self-supervised Deep Reinforcement Learning.

[20] P. Zhou, J. Zhu, S. Huo, and D. Navarro-Alarcon. Lasesom: A Latent and Semantic Representation Framework for Soft Object Manipulation. *IEEE Robotics and Automation Letters*, 6(3):5381–5388, 2021.

[21] J. Zhu, A. Cherubini, C. Dune, D. Navarro-Alarcon, F. Alambeigi, D. Berenson, F. Ficuciello, K. Harada, J. Kober, X. Li, J. Pan, W. Yuan, and M. Gienger. Challenges and Outlook in Robotic Manipulation of Deformable Objects. 29(3):67–77.

[22] J. Zhu, D. Navarro-Alarcon, R. Passama, and A. Cherubini. Vision-based manipulation of deformable and rigid objects using subspace projections of 2D contours. 142:103798.