Robotic Picking of Tangle-prone Materials (with Applications to Agriculture).

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Robotic Picking of Tangle-prone Materials

with Applications to Agriculture

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To my grandparents, Leela and Sheel Narayan Ray

Copyright Statement

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and acknowledgements.

Prabhakar Ray
October 2023

Covid-19 Impact Statement

The covid-19 pandemic continues to impact many aspects of human lives. The below outlines the impact of the pandemic on the research work presented in this thesis. The statement provides specific details of (i) the impact of disruption, (ii) planned work that could not be completed because of the disruption and (iii) the mitigating actions that were considered to abate the overall impact of the covid-19 pandemic.

Impact of disruption

- **Removal of access to labs/research facilities:** Removal of access to engineering labs meant that lab-based experimental research requiring specialist equipment, on which this thesis is primarily based, had to be paused.

- **Restricted access to labs/research facilities:** When access to engineering labs was restored after 6 months, progress was hindered because of prevailing restrictions (*e.g.,* travel, health and safety, reduced availability of the lab spaces).

- **Onsite/human-participants experiments:** Onsite experiments and experiments with human participants were suspended.

Planned work

- **Onsite experiments:** After publishing results from the first phase of research in March 2020, it was originally planned to conduct large-scale onsite experiments at the packaging lines of the industry partner Vitacress. These experiments would have proved valuable for developing new methods by which robotic systems can be programmed by non-expert users in the context of the industrial production and packaging of fresh herbs/salads for the retail market.

- **Human-participants-based experiments:** Picking experiments involving human participants were also planned for developing new methods for data-driven analysis of human hand motions associated with untangling bunches of tangling-prone mate-

rials (TPs) such as herbs and salads from larger bins.

– **TPs:** Picking experiments involving a wide variety of tangling-prone materials (*e.g.,* rosemary, coriander, dill, basil) were planned to further test the efficacy of the entanglement reduction method proposed in this thesis.

Mitigating actions

– Small-scale research equipment safe for home operation was specially acquired for running experiments at home. However, this equipment required additional hardware modifications requiring other specialist equipment (*e.g.,* 3D printer), to be able to continue the planned experiments. Additionally, home conditions did not prove favourable for running robotic experiments.

– Different simulation platforms (*e.g.,* gazebo, unity, MuJoCo) were explored and evaluated to be able to simulate the research problem considered in this thesis. However, these simulation platforms were found not sufficient for simulating the challenging TPs considered in this thesis at that time.

Abstract

The picking of one or more objects from an unsorted pile continues to be non-trivial for robotic systems. This is especially so when the pile consists of individual items that tangle with one another, causing more to be picked out than desired. One of the key features of such *tangling-prone* materials (*e.g.,* herbs, salads) is the presence of *protrusions* (*e.g.,* leaves) extending out from the main body of items in the pile.

This thesis explores the issue of *picking excess mass due to entanglement* such as occurs in bins composed of tangling-prone materials (TPs), especially in the context of a one-shot mass-constrained robotic bin-picking task. Specifically, it proposes a human-inspired entanglement reduction method for making the picking of TPs more predictable. The primary approach is to directly counter entanglement through *pile interaction* with an aim of reducing it to a level where the picked mass is predictable, instead of avoiding entanglement by picking from collision or entanglement-free points or regions. Taking this perspective, several contributions are presented that (i) improve the understanding of the phenomenon of entanglement and (ii) reduce the picking error (PE) by effectively countering entanglement in a TP pile.

First, it studies the mechanics of a variety of TPs improving the understanding of the phenomenon of entanglement as observed in TP bins. It reports experiments with a real robot in which picking TPs with different protrusion lengths (PLs) results in up to a 76% increase in picked mass variance, suggesting PL be an informative feature in the design of picking strategies. Moreover, to counter the inherent entanglement in a TP pile, it proposes a new Spread-and-Pick (SnP) approach that significantly reduces entanglement, making picking more consistent. Compared to prior approaches that seek to pick from a tangle-free point in the pile, the proposed method results in a decrease in PE of up to 51% and shows good generalisation to previously unseen TPs.

Keywords: Robotic bin-picking of tangling-prone materials, Entanglement reduction, Robotics in Agriculture and Forestry, Agricultural Automation, Computer Vision for Automation.

Acknowledgements

A PhD changes one in many ways. As a first-generation PhD student, I have gone through innumerable positive professional and personal changes over these four years. Like the proverb—It takes a village to raise a child, my PhD is also a result of unfaltering support and dedication from a long list of people. I cannot thank this amazing group of people [1] enough for their support, especially during a raging pandemic.

I would like to start by expressing my heartfelt gratitude and appreciation to my advisor, Dr Matthew Howard. Throughout my PhD, your exceptional support, feedback and advice remain the cornerstone of my research. Apart from the academic front, your understanding always helped me in tricky life situations. I would not be exaggerating to mention that you have played an important role in helping me develop core life and research skills.

Although being an international student brings in other social and cultural challenges, continuous support from my family members made things much easier to deal with. Infinite sacrifices by my parents—Pramila and Prakash Ray are the only reason I was able to even begin my PhD. I will be forever indebted to you both for making me what I am today. My uncle and aunt—Jyoti Narayan Ray and Nirmala Ray were also always there to help me with anything and everything. I certainly would not have reached the end of my PhD without your support. I also would like to thank my brother—Prakanshu Ray for keeping me sane during these challenging times. Furthermore, I would like to thank my cousins—Ravi Ray, Rashmi Ray, Deepak Ray, Roshan Ray, Roshni Verma and their partners for all their help during my PhD. Especially, my sister-in-law—Shubhra's biryani is the only reason I did not lose a single pound even during these stressful years. I also thank my nephews and nieces—Raghav, Krishna, Aditya, Nandini, Samarth, Aashna and Ayush for not letting me lose touch with my inner child during my PhD.

Finally, a special thank you to my partner—Pooja Shankar, who has put up with a long-distance relationship with me for far too long. You were always there to listen to my blabbering and I am sure, by now, you understand my research better than I do. I hope you will forgive me for unexpectedly taking you with me on this strenuous PhD journey.

[1] This work has been supported by the Professor Richard Trainor PhD Scholarship. This thesis is also supported in part by our industry partner—Vitacress Herbs Ltd.

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List of Notation and Abbreviations

Unless otherwise stated, scalar values are represented by lower case letters, column vectors are represented by bold lower-case letters and matrices are represented by bold upper case letters.

Symbols

$\mathbf{G}$	Graspability map
$\mathbf{X}$	Gaussian
$\mathbf{G_c}$	Gripper contact region
$\mathbf{G_{c'}}$	Gripper collision region
m	Picked mass
m_n	Picked mass for trial n
m_t	Target Mass
$\mathbf{O_c}$	Object contact region
$\mathbf{O_{c'}}$	Object collision region
p	Pile mass
δ	Pick parameter
r_θ	Gripper orientation around z-axis
r_x	X-coordinate
r_y	Y-coordinate
r_z	Z-coordinate
w	Gripper aperture

$\mathbf{W_c}$ Gripper-Object contact region

$\mathbf{W_{c'}}$ Gripper-object collision region

d Staple width

l Protrusion length

Abbreviations

ASC Agri-Food Supply Chain

CAD Computer-aided Design

CNN Convolution Neural Network

DEM Discreet Element Method

DoF Degree of Freedom

FP Fixed-Point

GI Graspability Index

GM Granular Material

PE Picking Error

PL Protrusion Length

RAS Robotics and Autonomous Systems

SnP Spread-and-Pick

TP Tangling-prone Material

Chapter 1

Introduction

Today, *large* scale industries such as agriculture and construction are facing acute constraints such as low production efficiency, human errors and labour shortages [1, 2]. Robotics and autonomous systems (RAS) are a vital tool for tackling such issues. However, industry-specific complications pose further challenges, given the scale and variety of materials involved, inhibiting automation.

Tangling-prone materials (TPs) such as salads, herbs, and staples are a special class of materials appearing frequently in large-scale industries. Formally, granular materials (GMs) are defined as *large* conglomeration of discrete solid, macroscopic particles that interact through contact forces and flow as one when piled together [3]. Although, tangling-prone materials (TPs) utilised in this research can display certain granular-like properties such as flow and compaction, all of them cannot be strictly classified as GMs. The definition of GMs is still a subject of research and lacks clear distinction [4]. However, this research draws some inspiration from GMs. Labour-intensive and error-prone tasks involving TPs such as herb/salad packaging requiring controlled dexterous manipulation can benefit from the advancements in RAS. However, TPs exhibit a complex range of physical properties such as entanglement, making the application of RAS for manipulating such objects exceedingly challenging.

RAS have come a long way in emulating a human's ability to grasp, grip and manipulate different objects. Today, robots have learned to push [5], poke [6], pivot [7], slide [8] and throw [9], just like humans. They have transformed from non-adaptive systems working in a fully deterministic environment to adaptive systems that can recognise, choose and manipulate objects from a highly stochastic environment such as an arbitrary unsorted bin/pile. However, a contact-rich cluttered environment presents many challenges such as object occlusion, gripper-object collision and object entanglement, making manipulation in such environments non-trivial. These issues are further aggravated for a pile composed of TPs, owing to the highly variable handling properties.

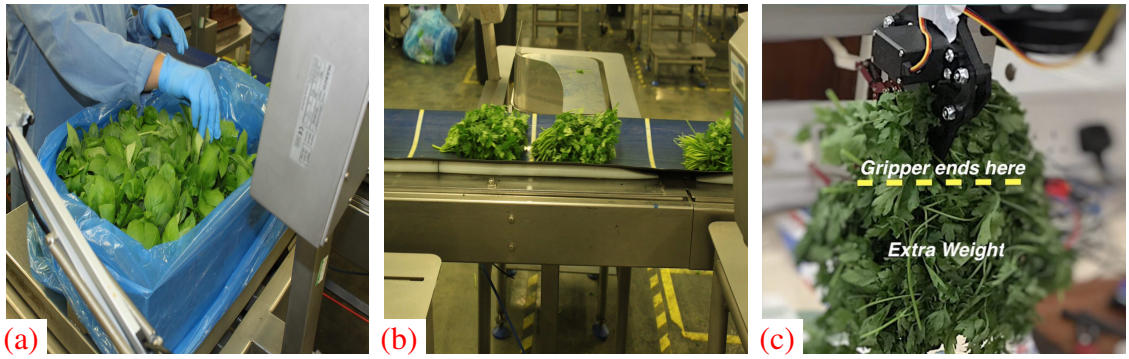

Figure 1.1: Handling fresh salads and herbs. (a) Plant material enters the packaging centre as a tangled mass in crates or boxes. (b) Smaller, fixed-mass portions must be extracted and fed via conveyor belt for packaging. (c) Tangling makes the mass lifted in a simple pick operation difficult to predict.

Consider, for example, the task of processing a TP pile—fresh horticultural produce consisting of many protrusions in the form of leaves, extending out from the main stem, as shown in Figure 1.1. The word protrusion from the English vocabulary is derived from the Latin word *protrudere*. In general, *protrudere* means an extension beyond the normal line or surface [10]. For the purpose of this work, protrusion length PL is defined as the length of these extensions. Specifically, this research utilises different objects with protrusions in their *natural form* only and does not consider other notable factors such as deformations. The suppliers of fresh herbs and salads grow stock under glass or in fields and then must transport them to packaging stations and pack them as per the mass requirements of retailers. The manual packaging process involved is not only costly in terms of labour but also suffers from wastage, labour shortage, human errors and low production efficiency. A more scalable approach could be automation through adaptive RAS, however, their deployment presents several challenges. Fresh horticultural produce can be highly variable in terms of its handling properties, even within a single plant variety, making it difficult to design robotic controllers for their manipulation. Herbs and salads in particular, tend to present as a highly stochastic, tangled mass (see Figure 1.1(a)), making it difficult for a robotic system to extract a uniform quantity suitable to be fed via conveyor belt for packaging (see Figure 1.1(b) and (c)). These problems are exacerbated when the robot must adaptively handle multiple types of herbs (*e.g.,* parsley, dill, coriander), and do so in a way that does not damage them (herbs and salads are highly prone to bruising, which adversely affects both shelf-life and appearance).

This thesis analyses a TP pile, specifically in the context of a one-shot mass-constrained picking task. Given the inherent entanglement in a TP pile, the thesis focuses on *entanglement reduction* before attempting the pick, with an aim of improving the picking accuracy.

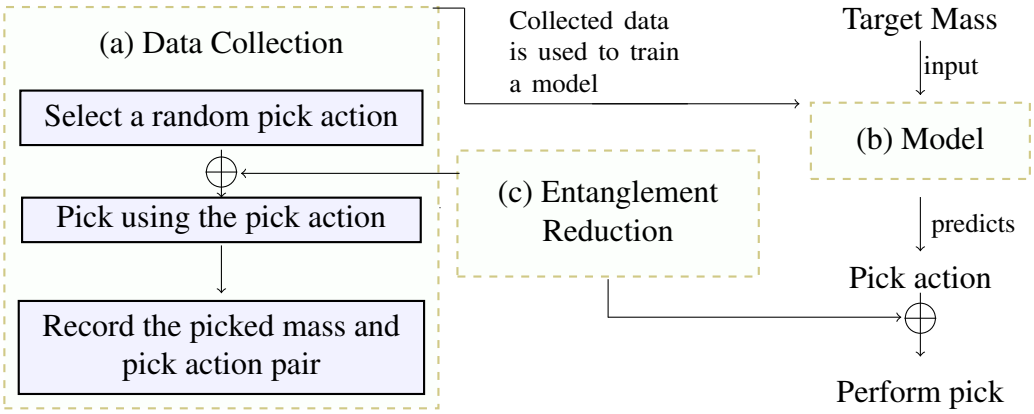

Figure 1.2: Example framework for learning a one-shot mass-constrained picking skill for a tangle-prone material pile.

The objective of this work is to enable a robot to grasp multiple objects as per user-specified mass simultaneously as opposed to a single object and the term "entanglement" in this work only refers to ungripped objects getting attached to gripped objects (see Figure 1.1(c)). Firstly, real robot experiments involving a variety of TPs are conducted to identify a common informative feature that could assist in developing generalised picking strategies. Then it proposes a human-inspired method for *entanglement reduction* through *pile interaction*, assisted by vision-based techniques. The proposed method is evaluated experimentally involving a real robot and TPs to demonstrate its effectiveness in improving the picking accuracy and a final evaluation through an industrial herb and salad picking task conclude the thesis.

1.1 Motivation

The primary motivation of this thesis is to provide a method for *entanglement reduction* in a TP pile, such that the challenging task of one-shot mass-constrained picking can be made more predictable in terms of picked mass. It has vast potential applications in many sectors, especially in the food and farming sector, where previously fruits, vegetables, and flowers have been left to rot because of the declining availability of farm workers [11]. Thus, RAS capable of manipulating bins of challenging food materials may play a considerable role in safeguarding food security. However, to acquire a one-shot mass-constrained picking skill, such systems should be able to effectively counter the entanglement present in bins composed of TPs such as herbs and salads.

Learning such a skill would require data for training which can be obtained by running picking experiments with the robot. Generally, the data collection process would consist of three main steps: (i) selecting a random pick action, (ii) picking using the chosen pick

action and finally, (iii) recording the picked mass and picking action pair (see Figure 1.2 (a)). The collected training data can then be used to train a model (see Figure 1.2 (b)). However, the entanglement in a TP pile leads to a high picking mass variance even for a fixed pick action, introducing significant uncertainty in the training data, which can considerably impact the prediction of any meaningful observation.

Alternatively, a target mass could be picked out from a tangled pile using approaches that avoid picking from a tangled region. However, the tangle-prone nature of TPs makes avoiding entanglement extremely challenging. Instead, countering the entanglement through *pile interaction* is more effective in reducing it to a level where the picked mass is predictable. To this end, this thesis demonstrates that the accuracy of a one-shot mass-constrained picking skill can be improved using an *entanglement reduction* step (see Figure 1.2 (c)) without directly estimating the overall degree of entanglement in a TP pile.

1.2 Contributions

The main goal of this thesis is to address the largely unexplored issue of *picking excess mass due to entanglement*, such as occurs in bins composed of TPs. To this end, a human-inspired *entanglement reduction* method is proposed. As it is not practical to design a separate picking strategy for all individual TPs, a variety of TPs are studied to identify a common informative feature necessary for developing generalised picking strategies. Specifically, the main contributions of this work are as follows:

1. *Protrusions play a crucial role in making picking inconsistent*

   In experiments where a 7-degree of freedom (DoF) robot with a parallel gripper is used to pick pre-set quantities from tangled bins of TPs, a significant increase (76%) in the picked mass variance is observed for TPs with protrusions, suggesting protrusions play an important role in causing tangling and making picking inconsistent. This work is under peer review and available on arxiv [12].

2. *PL is an informative indicator of entanglement*

   Results from picking experiments reported in this work characterise the propensity of a TP to tangle in terms of a measurable quantity. Experimental results suggest that PL is an informative feature for achieving better generalisation. Additionally, it is observed that the interplay between the *ability to pack* and the *ability to entangle* gives rise to a non-monotonic relationship between PL and entanglement in a TP

pile. This work is under peer-review and available on arxiv [12].

3. *Picking accuracy can be improved by reducing tangling in a TP pile*

   A Spread-and-Pick (SnP) strategy is proposed to mitigate the effect of tangling to achieve a level of predictability in robotic picking. Compared to the approach of avoiding tangling by seeking to pick from a collision-free point in the pile, Spread-and-Pick (SnP) results in a decrease in picking error (PE) of up to 51%, and shows good generalisation to previously unseen TPs. This highlights the benefit of using SnP as a practical tool for deploying RAS for a variety of challenging picking tasks involving TPs, such as mass-constrained herb packaging. The proposed approach does not require estimating the overall degree of entanglement in the pile, is applicable for use with a variety of different hand mechanisms, including parallel, multi-finger and vacuum grippers and is unaffected by colour variation (that may occur between different plants). This work has been published in [13, 14]. A part of this work is under peer-review and available on arxiv [12].

1.3 Outline

The thesis is organised as follows:

- Chapter 2 formally defines the problem in the context of a one-shot mass-constrained picking skill. It further presents details of the relevant background and the materials used in this work. Intriguing insights from human pickers are discussed, considering the human inspiration this research builds on. The detailed mechanics of the proposed untangling manoeuvre is also presented. Additionally, it extensively discusses the TPs considered in this thesis, providing details of the challenges, considerations and assumptions respective to each TP.

- Chapter 3 provides a detailed review of the state-of-the-art in robotic bin-picking and relevant works which consider the largely unexplored issue of *picking excess mass due to entanglement*. Firstly, the current state of RAS in agriculture is discussed, with particular emphasis on how this work fits in the agri-tech space. It then provides a comprehensive overview of relevant works that focus on robotic manipulation in clutter. Finally, it discusses robotic bin-picking literature specifically in the context of bins composed of (i) large objects, (ii) non-tangling materials and,

(iii) tangle-prone materials.

– Chapter 4 explores the phenomenon of entanglement in a TP pile. It presents robot picking experiments involving homogeneous pile of plastic herbs, identifying the role protrusions play in causing entanglement in a TP pile. Picking experiments involving homogeneous bins composed of staples with different PLs are reported, characterising the tangling propensity of a TP in terms of a measurable quantity.

– Chapter 5 proposes a human-inspired method of entanglement reduction in a TP pile. The effectiveness of the proposed SnP method in reducing the tangling in a TP pile and consequently improving the picking accuracy is demonstrated through robotic picking experiments. A robotic picking experiment with staples is presented to evaluate the usefulness of SnP in reducing the entanglement in a TP pile and making picking consistent. Furthermore, picking experiments involving plastic and real plant materials evaluate the efficacy of SnP through an industrial herb and salad picking task. The experiments specifically compare fixed-point (FP) and collision-free point *i.e.,* Graspability index (GI)-based picking strategies with picking following SnP.

– Chapter 6 provides the conclusions to this thesis with some limitations, future work and directions of the research proposed in the thesis.

Appendices

– Appendix A presents the list of academic publications resulting of this thesis.

– Appendix B presents the data and software supporting this thesis.

Chapter 2

Background and Materials

This chapter presents an overview of the background and materials relevant to this thesis. Specifically, it discusses the human inspiration behind the untangling manoeuvre proposed in this thesis. The detailed mechanics of the proposed manoeuvre is discussed. Additionally, it describes the nature of TPs utilised in this thesis with a particular emphasis on the challenges, considerations and assumptions associated with each TP.

2.1 Problem Definition

This work considers the problem of picking a target mass from a pile of TPs such as L-hooks, cup hooks, staples and herbs. In the context of mass-constrained bin-picking, the primary objective of the robot is to pick a target mass accurately. The picking error (PE) is expressed as

$$PE = |m_t - m_n|, \tag{2.1}$$

where m_t is the target mass and m_n is the picked mass for trial n. The objective is to learn to pick in a way that minimises mean and standard deviation of (2.1) for any given m_t. The desired picking skill is expressed as

$$\delta = f(m_t), \tag{2.2}$$

where $f(m_t)$ maps the target mass $m_t \in \mathbb{R}_{>0} = \{x \in \mathbb{R} \mid x > 0\}$ to pick parameter $\delta = (\mathbf{r}, w)^\top$ comprising of a picking location $\mathbf{r} = (r_x, r_y, r_\theta)^\top$ with gripper orientation r_θ around the vertical (z) axis and gripper aperture w, enables the selection of δ such that (2.1) is minimised for the target mass m_t. However, the highly stochastic nature of pile composed of TPs makes such minimisation non-trivial. For example, for a fixed pile mass, container volume and pick parameter δ as estimated for a target mass m_t, a consistent mass

($m_1^\delta = m_n^\delta$) is expected to be picked across trials but instead the pile entanglement leads to a high PE.

Considering the simplest case of picking using a fixed picking parameter δ for a target mass m_t, (2.1) can be reduced simply by adjusting the gripper aperture w based on the degree of pile entanglement. However, estimating the degree of entanglement in a TP pile is non-trivial. Additionally, to improve the consistency and predictability of picking, PE variance arising out of pile entanglement should be reduced as far as possible. A lower degree of pile entanglement will reduce PE variance, making picking more predictable. To this end, this work proposes a SnP strategy to effectively reduce PE without directly estimating the degree of entanglement in a pile for efficient mass-constrained robotic bin-picking for bins composed of TPs.

2.2 Insights from Human Pickers

The human body is a complex machine, able to carry out various complicated manipulation tasks with dexterity. Research in robotics frequently draws inspiration from the human way of manipulating objects [15, 16]. Specifically, human hands are a product of millions of years of evolution and can perform highly dexterous skills such as precision gripping and in-hand manipulation. The ability of human hands and fingers to work in synergy makes us capable of achieving non-trivial objectives with relative ease and high precision. A variety of grippers have been developed over the years, emulating the design of the human hands [17]. However, no man-made gripper can currently achieve the full range of abilities possessed by the natural human hand. This highlights the knowledge potential

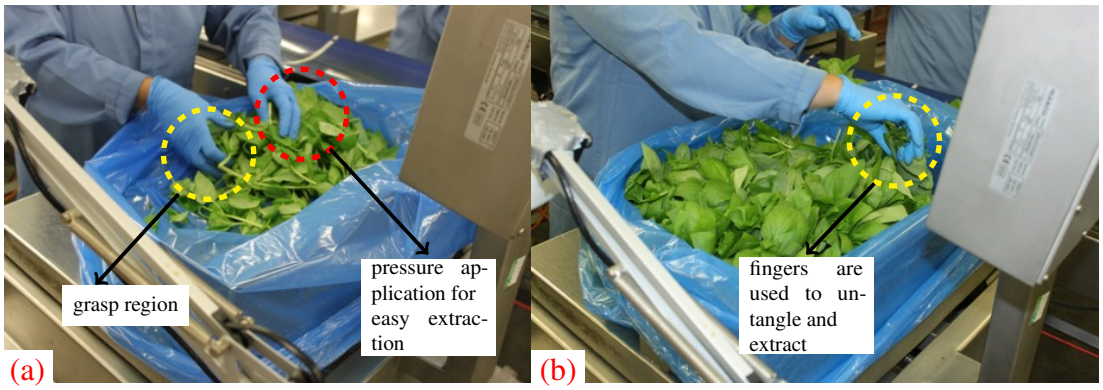

Figure 2.1: Human pickers can efficiently use (a) both or (b) just one hand for untangling and extracting a smaller mass from a bigger pile of tangled plant material. The dashed yellow and red circles represent the right and left hand respectively.

of human hands and the importance of drawing inspiration from the ultimate machine for building truly cognitive robotic systems.

The ability to manipulate complex shaped objects in hand enables humans to perform many tasks using just one hand. Consider, for example, the task of untangling and extracting a small bunch of plant materials from a tangled pile, as shown in Figure 2.1. Humans can efficiently perform this task using both or just one hand. In the case of dual-hand manipulation, first, one hand is used to grasp the plant material to be extracted based on factors such as ease of reach. Then, the other hand is utilised to apply pressure on the area surrounding the grasp region assisting in untangling and easy extraction of the grasped bunch (see Figure 2.1(a)). Dual-arm manipulators have been explored in the context of challenging robotic tasks such as laundry [18], elderly care [19], cooking [20] and space exploration [21]. A dual-arm manipulator might simplify performing complex tasks, however, it adds further complexities and requires advanced system integration, high-level planning and reasoning and efficient control approaches compared to single manipulators [22]. Additionally, in terms of industrial automation, it leads to a higher financial cost, inhibiting adoption.

As humans are able to perform a variety of tasks using just one hand in many instances, single manipulators have also received great attention from the robotics research community. When working with one hand, humans frequently use their fingers for reorienting or repositioning different objects (see Figure 2.2) and decluttering (see Figure 2.3). Robotics

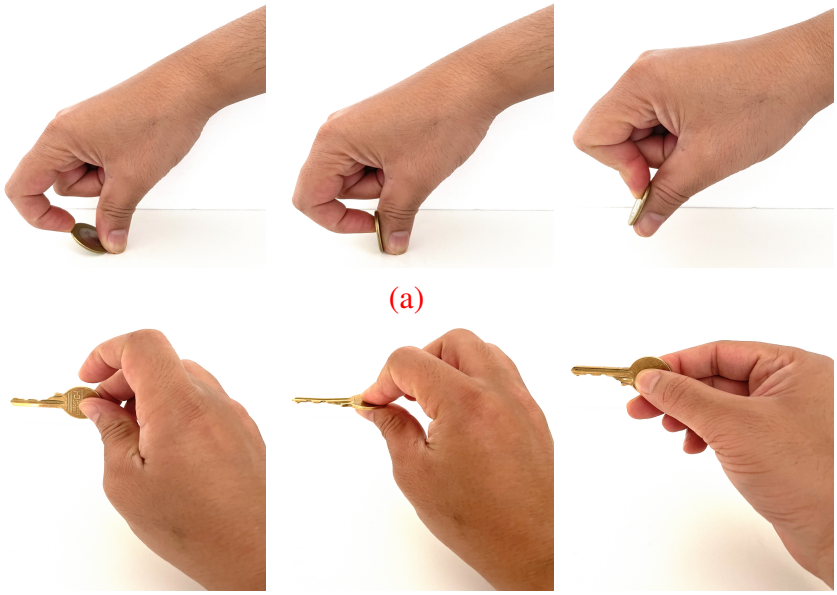

Figure 2.2: Example in-hand manipulation scenarios depicting (a) coin flipping for acquiring a pinch grasp and (b) key reorientation.

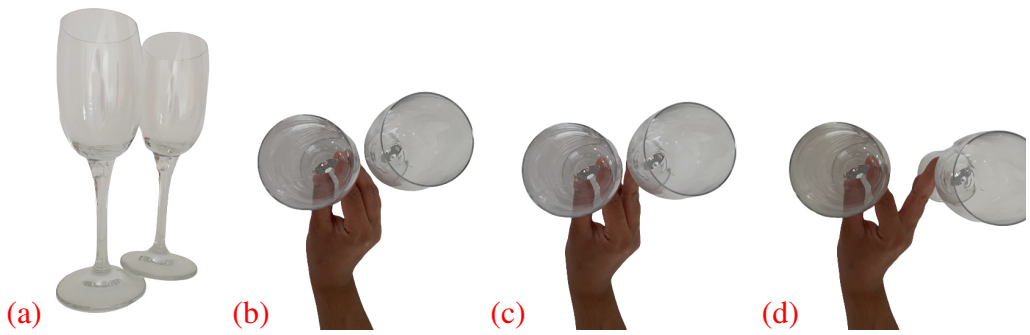

Figure 2.3: Example decluttering scenario depicting (a) front view of the cluttered scene consisting of two wine glasses. When working with one hand, (b) after grasping one of the glasses, (c) humans generally use fingers to push (d) the other glass out of the way.

researchers have leveraged the usability of fingers for a variety of in-hand manipulation tasks [23–26]. For the task of picking from a bin composed of tangled plant material, humans are also able to untangle and extract a smaller bunch by using just one hand—fingers are frequently used in synergy for untangling and extraction of the grasped bunch (see Figure 2.1(b)).

The untangling manoeuvre proposed in this thesis takes inspiration from this aspect of the human hand. In the next section, an overview of the mechanics of the proposed untangling manoeuvre is presented.

2.3 The Mechanics of Spreading

Picking a target mass or number of TPs is highly challenging due to the variability induced by the tangling. Although some level of tangling is unavoidable in the materials considered here, it is proposed to *reduce this through a SnP strategy*.

Figure 2.4 illustrates the mechanics behind the proposed approach. In the first step, the location of a *collision-free point* is estimated from a RGB-D image of the grasping scene as a picking location. When picking a target object from a bin, the collision-free point refers to the point in the scene where there is no collision between the gripper and the other objects in the bin. This helps to reduce the risk of damage to the plant material by minimising contact with the gripper, but usually still leads to variable picking mass due to tangling. Therefore, in the second step, the peak *entanglement point* is estimated and used to perform a spreading action such that the target mass is separated from the rest of the pile. Section 5.2 further describes how these points are estimated through a vision-based approach.

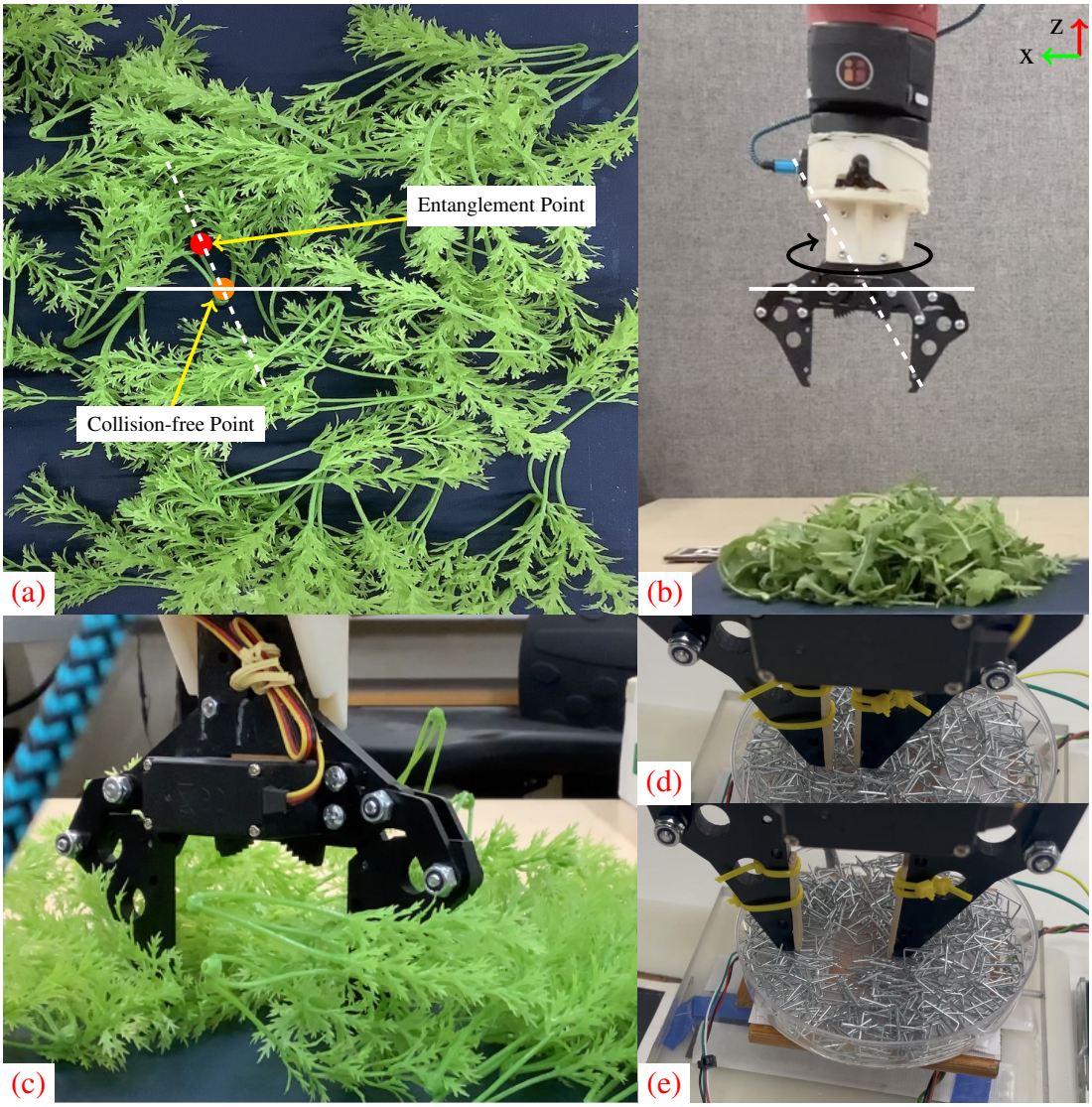

Figure 2.4: Overview of the proposed SnP approach. (a) Top view of the pile. (b) Front view showing the gripper. The solid white line represents the initial orientation of the x-axis of the gripper. The dashed white line represents the *line of entanglement*. The black curved arrow represents the direction of rotation. Once the collision-free and entanglement points are identified, the gripper is rotated around the z-axis before lowering down on the pile such that it aligns with the line of entanglement. (c) Finally, gripper plates are opened along the line of entanglement to spread the tangled pile. A pile of staples (d) before and (e) after the spread manoeuvre.

2.4 Considered tangling-prone materials (TPs)

This thesis mainly considers materials that are *tangle-prone* in nature. For comparison, picking experiments are also conducted for a pile composed of a non-tangling material. One of the key features of TPs is the presence of *protrusions* extending out from the main

body. Picking a target mass or number of TPs is highly challenging due to the variability induced by the entanglement. This section presents the challenges, considerations and assumptions associated with each TP considered in this work in the context of a one-shot mass-constrained picking skill.

2.4.1 Staples

General-purpose office staples manufactured by Rapesco Office Products (923 type staples) are chosen as one of the TP (see Figure 2.5). These are manufactured in different sizes and thus provide the flexibility of varying the protrusion lengths (PLs) l in a controlled manner while ensuring homogeneity (each staple in the pile is identical).

Challenges

- **Gripper-object collision:** Entanglement in the pile obstructs the gripper's movement leading to failure scenarios (*e.g.,* gripper failing to penetrate the pile or gripper plates failing to close completely).

- **Formation of Heaps/Craters:** Repeatedly picking and dropping from a pile of staples for data collection leads to the formation of heaps/craters.

- **Grasp instability:** Instability of the picked mass causes some staples to fall back in the container before the pick operation is complete.

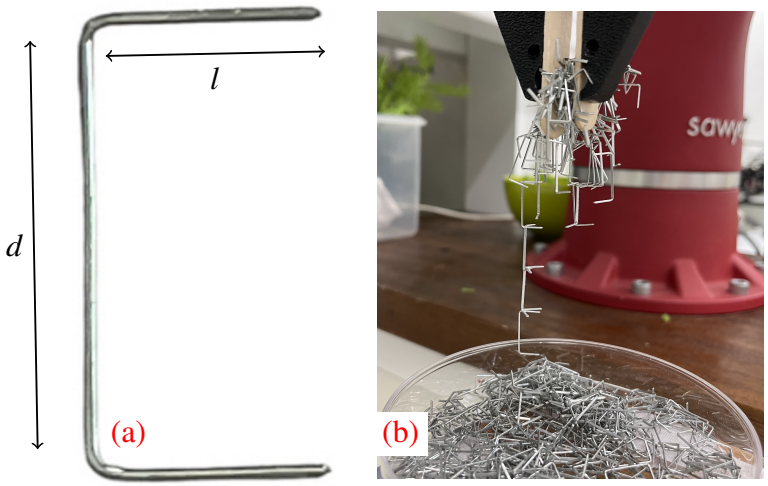

Figure 2.5: Considered TPs: Staples (a) with constant staple width $d = 12\,\text{mm}$ and variable PL l. (b) Tangling makes the mass lifted in a simple pick operation difficult to predict.

Considerations and assumptions

Given the challenges associated with picking from a pile of staples, some considerations and assumptions are required for designing robust experimental protocols. Firstly, for a suitable container, pile mass is selected accordingly such that the pile is uniformly distributed and is not severely tangled, allowing the gripper plates to penetrate and close/open without severe resistance. Additionally, a sufficiently large gripper aperture w is used and the picking trial is discarded when the picked mass $m_n = 0$ for any trial n. A coin micro vibrator with rated voltage 3 V and rotating speed 12 000 RPM is employed to vibrate the pile of staples for a fixed duration after each trial to eliminate the formation of heaps/craters, ensuring consistent packing across trials. Finally, to counter the loss of staples during the pick, the picked mass is only recorded when the robot has reached a fixed height above the pile after the pick operation. Detailed experiments involving staples with varying PLs are presented in sections 4.4 and 5.3.1.

2.4.2 Plastic Herbs

Two varieties of plastic herbs: one having many protrusions of varied lengths extending from a central stem and the other with no protrusions (see Figure 2.6(a) and (b), respectively) are also selected as a TP. Compared to staples, plastic herbs allow the proposed method for entanglement reduction to be evaluated in a more unstructured environment. Additionally, they are a reasonable mock-up of real herbs/salads and offer some degree of control against natural variations in the real plant material (see section 2.4.3).

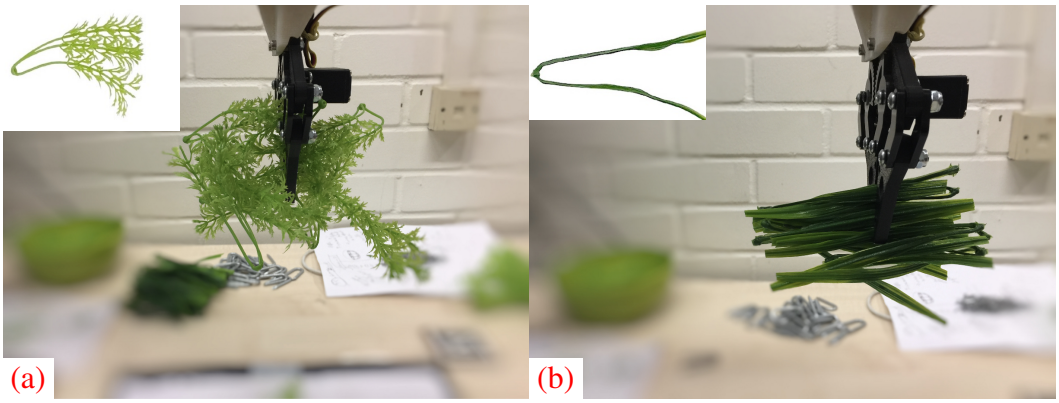

Figure 2.6: Considered TPs: Plastic herbs (a) with many protrusions of varied lengths extending from a central stem and (b) the other with no protrusions. Inset show single strand for each type of plastic herb.

Challenges

- **Restricted PL control:** Reducing/Increasing PL is a manual and error-prone process.

- **Uncontrolled variation in protrusions:** Reducing/Increasing the number of protrusions is a manual and error-prone process.

- **Deformable:** The deformable nature of plastic herbs makes them susceptible to wear-and-tear.

- **Low vibration sensitivity:** Compared to staples, plastic herbs respond less to vibrations produced by a coin micro vibration motor, making it difficult to maintain consistent packing across trials.

- **Gripper-object collision:** Entanglement in the pile obstructs the gripper's movement leading to failure scenarios (*e.g.,* gripper failing to penetrate the pile or gripper plates failing to close completely).

- **Grasp instability:** Instability of the picked mass causes some herbs to fall back in the container before the pick operation is complete.

Considerations and assumptions

Firstly, it is assumed that individual strands of respective plastic plant material are identical, inline with the product information provided by the manufacturer. To ensure a similar physical arrangement of the plant material between trials, any material picked is returned to the picking area, and the entire quantity is transferred to a container of fixed dimension before being returned to the picking area for the next pick. Similar to staples, to counter the loss of herbs during the pick, the picked mass is only recorded when the robot has reached a fixed height above the pile after the pick operation. Deformability of the chosen plastic material introduces several other challenges. Although interesting, it falls out of the scope of this thesis. Picking experiments involving plastic herbs are presented in sections 4.3 and 5.3.4.

2.4.3 Real Herbs/Salads

Finally, to evaluate the real-world effectiveness of the proposed method of entanglement reduction, one commonly available herb (see Figure 2.7(a)) and a salad variety (see Figure 2.7(b)) are chosen. Both of the selected real plant material exhibit entanglement and consists of many protrusions in the form of leaves extending out from the main stem.

Challenges

- **Natural variations:** Spurious effects arising from natural variations, or changes in their physical properties (e.g., due to plant material drying out, or becoming damaged over successive picks) contributes to the stochasticity of a herb/salad environment. Additionally, the presence of moisture in the herb/salad pile often leads to strands sticking to the gripper plates.

- **Non-Homogeneity:** Uncontrolled individual variation in mass, number of protrusions and PL inhibits designing controlled picking experiments. Reducing/Increasing the PL and number of protrusions is a manual and error-prone process.

- **Low vibration sensitivity:** Similar to plastic herbs, real herbs/salads respond less to vibrations produced by a coin micro vibration motor, making it difficult to maintain consistent packing across trials.

- **Gripper-object collision:** Entanglement in the pile obstructs the gripper's movement leading to failure scenarios (*e.g.,* gripper failing to penetrate the pile or gripper plates failing to close completely).

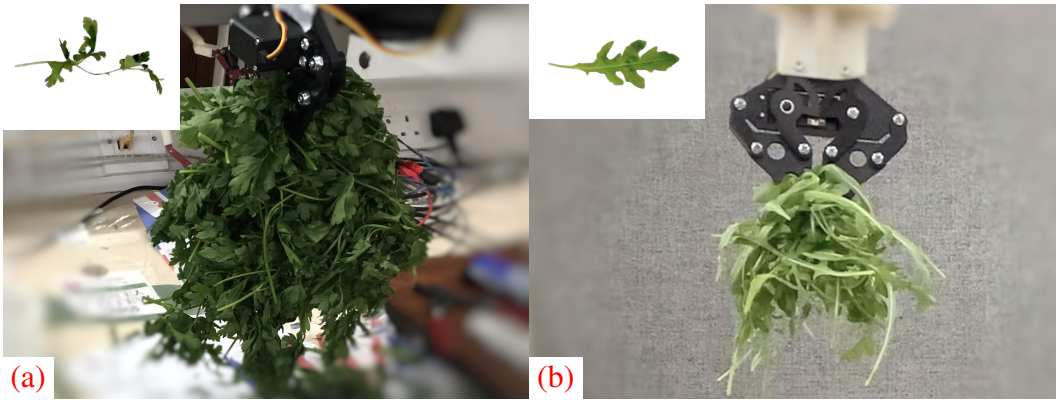

Figure 2.7: Considered TPs: (a) Flat-leaf parsley as a herb and (b) wild rocket as a salad variety are chosen. Inset show single strand for each type of real plant material.

– **Grasp instability:** Instability of the picked mass causes some real plant material to fall back in the container before the pick operation is completed.

Considerations and assumptions

When using real plant material, for each set of control factors, a fresh batch of herbs or salad leaves is used to try to minimise effects occurring as a result of natural variations. To ensure a similar physical arrangement of the plant material between trials, any material picked is returned to the picking area, and the entire quantity is transferred to a container of fixed dimension before being returned to the picking area for the next pick. Similar to plastic herbs, to counter the loss of plant material during the pick, the picked mass is only recorded when the robot has reached a fixed height above the pile after the pick operation. An industrial herb and salad picking task involving real plant materials is presented in section 5.3.4.

Chapter 3

Literature Review

This chapter presents an overview of robotic manipulation in clutter, and specifically looks at prior work that addresses the issue of object entanglement for bins composed of TPs. It consists of six parts. (i) First, it provides a general overview of the application of RAS in agriculture to help position the utility of the current research. (ii) Second is a review of the issue of robotic manipulation in clutter, focusing on how it has been addressed in prior work and how it affects object manipulation. (iii) Next is a review of work that specifically consider the robotic bin-picking problem in the context of key issues. (iv) Approaches to robotic bin-picking involving bins composed of non-tangle prone materials are discussed next to provide insights into the primary challenges and how these have been addressed. (v) A review of prior work that consider bins composed of TPs is discussed next to provide details regarding the nature of challenges that have been considered. (vi) Finally, GM studies from the natural sciences community are discussed to provide more insights into the directions GMs have been explored in the past.

3.1 Robotics and autonomous systems (RAS) in Agriculture

Robotics and autonomous systems (RAS) have transformed many industries in a short span. Similar to other large-scale industries such as manufacturing, the need for collaborative

Figure 3.1: Primary components of the ASC.

and robust RAS in agriculture is seen more evidently than ever before. World hunger is becoming a global catastrophe—between 720 and 811 million people globally experienced hunger in 2020 [27]. Reduction in available labour and arable land, with an increasing population, is threatening global food security [28–31]. If not a panacea, RAS deployed to assist in various activities in the agri-food supply chain (ASC) are seen as a potential solution to some problems plaguing the agriculture sector and are expected to contribute more than $50 billion to global gross domestic product [32].

In general, ASC can be categorised as supply chains for (i) processed food products such as breakfast cereals, bread, and canned products and (ii) fresh agricultural produce such as herbs, salads, and fruits. The latter, the focus of this research, suffers from additional issues such as short shelf life, making a timely progression of the fresh produce through the supply chain critical for minimising food wastage [33, 34]. Figure 3.1 presents the main components of the ASC for fresh agricultural produces [35]. Different RAS tailored to specific components of the ASC have been explored in the past. However, all such systems are designed to cater to the production stage, and only 35.48% are equipped with a robotic arm [36]. The application of RAS still remains effectively unexplored for other manual intensive components of the ASC such as packaging where a robotic arm with manipulation skills is generally necessary.

Today, commercially available RAS are able to carry out various land preparation activities such as fertilising [37, 38], seeding and ploughing [39]. RAS have also been designed for sowing and planting tasks [40–42]. Crop maintenance activities such as weeding [43–49], pruning [50, 51] and disease identification [52, 53] along with the laborious task of harvesting, have also received much attention from the robotics research community. Specifically, RAS have demonstrated reasonable success in harvesting *non-tangling* and *large* fresh produce such as strawberries [54–56], green asparagus [57], lettuce [58], aubergines [59], apple [60], sweet pepper [61, 62] and coconut [63]. However, in general, such fresh produces are identified and harvested one at a time and are not encountered as granular materials (GMs) while being harvested. In contrast, for the task of packaging, the harvested fresh produce is presented as a GM bin—after harvesting, the fresh produce is generally collected in trailer bins and transported to the packaging stations as a large mass. Picking from a container of fresh produce introduces non-trivial challenges (*e.g.,* object occlusion, gripper-object collision) for a robot. Furthermore, if the harvested produce is tangle-prone in nature, pile entanglement leads to the issue of *picking excess mass*, making packaging as per different requirements of retailers challenging.

Figure 3.2: Example manipulation scenarios in clutter. Extracting an object from a (a) refrigerator shelf (planar manipulation) and (b) a drawer (top-down manipulation).

3.2 Robotic Manipulation in Clutter

The challenge of efficient grasping remains at the forefront of robotics research even after many decades of interest [64]. Today, robots can grasp and manipulate many isolated and previously unseen objects [65–71]. However, challenges arise when the environment is cluttered—when the target object is close to or occluded by other objects [72, 73]. Based on the task majority of robotic manipulation in clutter strategies approach the manipulation surface in two primary ways: (i) planar and (ii) top-down manipulation [74]. Consider, for example, the task of extracting an object from a refrigerator shelf as shown in Figure 3.2(a). In this case, humans generally prefer approaching the shelf from a plane parallel to it. However, for extracting cutlery from a drawer, approaching from a plane orthogonal to the drawer is the most preferred trajectory (see Figure 3.2(b)). The latter, the focus of this thesis, is frequently termed the *bin-picking problem* and has a long history in the robotic automation literature.

Planar manipulation in clutter has also received significant attention from the robotics community and offers essential inspirations for a bin-picking task considered in this thesis. Early works considering planar manipulation in clutter focus on generating kinematically feasible candidate grasps that avoid collision with objects in the clutter [75, 76]. However,

in real world, a collision-free path to reach and grasp the target object is frequently not available. In such cases, a prehensile action (*e.g.,* grasping) is not enough, and the robot should be able to execute a non-prehensile action (*e.g.,* pushing) for manipulating the environment without violating the safety constraints [77]. Omrčen et al. [78] explore the utility of pushing actions in supporting robotic grasping. Through exploratory movements on objects, the robot first gains manipulation knowledge related to the act of pushing. The acquired manipulation knowledge is then used to support grasping when the target object cannot be grasped without explicit rearrangement. Dogar and Srinivasa [79] utilise a library of actions inspired by human strategies (*e.g.,* push, pull, slide, sweep) for proposing a push-grasping framework for manipulation in clutter. The authors demonstrate that using more natural human-inspired strategies instead of traditional rigid robot grasps proves advantageous for robotic operations in highly stochastic scenarios. Lindzey et al. [80] propose a push-planning method for rearranging cluttered objects using multiple robots. Dogar et al. [81] propose a computationally fast physics-based approach for grasping in a cluttered environment. The authors leverage controlled pushing for clearing the path to the target object in a constrained environment. Recently, Zeng et al. [82] propose learning synergies between pushing and grasping to improve grasping success rates. Using a set of primitive non-prehensile actions in a sequence has also been explored for achieving long-term objectives [83, 84].

Because of the nature of TPs considered in this thesis, a collision-free grasping point is not available in many instances. The SnP method proposed in this thesis counters entanglement in a bin composed of TPs through *pile interaction*, taking inspiration from the use of human-inspired non-prehensile actions in planar manipulation methods for resolving clutter.

Figure 3.3: (a) Traditional bin composed of non-granular (large) objects. (b) A granular, non-tangling material (rice grains). Examples of TPs include (c) herbs (wild rocket) and (d) staples.

3.3 Traditional Robotic Bin Picking

Traditionally, bins composed of large, generally household objects (see Figure 3.3(a)) have received much more attention than tangling-prone materials (TPs). With over ten decades of research, learning to pick from a bin has led to the rise of various intriguing research themes, such as scene analysis, object recognition, pose estimation, and grasp planning [85]. A large number of methods tailored to specific themes have been developed, which, when integrated, contribute to the central problem of robotic bin-picking. The bin-picking process generally starts with acquiring the scene information in some form (*e.g.,* vision, tactile). Next, the target object is identified by applying object recognition methods to the acquired scene data. Pose estimation methods are then used to estimate the orientation of the target object, and finally, an optimal grasp strategy is approximated such that the target object can be grasped and extracted without the robot colliding with other objects inside or outside the bin. However, when the bin is cluttered, contact-rich interactions further aggravate the complexity of the bin picking task. Additionally, when the bin is composed of tangle-prone materials, the focus of this thesis, the issue of object entanglement, hinders the successful extraction of the target object(s).

3.3.1 Gripper-Object Collision

The inability of robots to manipulate objects in a bin of mixed parts because of challenges such as gripper-object collision has long been considered one of the main obstacles to the broader application of robots in industry [86].

Approximately 39 years ago, Ikeuchi et al. [87] proposed a hand-eye robotic bin-picking system capable of picking objects at the top of a bin composed of homogeneous and fully deterministic (known shape and surface material) doughnut-shaped objects using a photometric stereo system, LED sensors and a PUMA 600 arm. They first segmented a scene into isolated regions using a needle map (*i.e.,* surface normals) obtained from the photometric stereo system. Target areas are then acquired from these isolated regions using an object-specific heuristics-based decision-making module. Finally, a 3D grasping point free of collision is estimated using a proximity sensor and the position of the target region in the image. For extending the bin-picking methods to different objects, Schraft and Ledermann [88] propose a collision avoidance method using an offline generated database consisting of the relevant object information. However, this does not guarantee a collision-free extraction, considering the objects not detected in the scene. Buchholz et al. [89] present a bin-picking system for picking from a scrambled bin consisting of objects (common industrial parts such as piston rods, plug gauge and joist hanger) with known geometry. They use an expensive commercial laser scanner to obtain the scene information

in 3D as a point cloud. Regions in the scene point cloud not in the gripper model are then identified as collision-free regions. Experimental results demonstrate the usefulness of the proposed approach, however, objects with complex geometries (*e.g.,* herbs) will prove challenging for such an approach.

Spenrath et al. [90] attempt to reduce the dependence of bin-picking methods on object geometry by simplifying the use of computer-aided design (CAD) models of the objects. Specifically, for improving computation time and generalising to different gripper types, authors propose a manual simplification process for obtaining simplified CAD gripper models. A gripper point calculation module generates and rates several potential gripping solutions using the scene point cloud and the simplified CAD gripper model of the used gripper. However, the method is challenging to configure and the exhaustive search through possible gripping solutions can be time and memory intensive. This consequently led to the proposal of a tree-based heuristic search instead of the exhaustive search [91]. For a truly automated bin-picking method, it is necessary to deal with unknown objects quickly and efficiently without depending on CAD models in any way. Domae et al. [92] propose Graspability index (GI), a vision-based measure for evaluating candidate grasping poses, which has proved useful in industrial pick and place settings. It uses a single depth map of the scene to estimate the optimal gripper position and orientation for picking an object without any collision. It can also be applied for use with different hand mechanisms, including parallel, multi-finger and vacuum grippers. A vision-based algorithm is proposed in [93] to resolve gripper-object collision by identifying and picking the topmost object in a pile composed of surgical instruments. Schwarz and Behnke [94] propose a deep learning approach for extracting large individual objects from a cluttered bin.

3.3.2 Object Entanglement

The issue of object entanglement has only received limited attention for bins composed of large objects such as industrial parts. Kaipa et al. [95] use CAD models for estimating a singulation plan for tangle-free extraction of individual objects from a heterogeneous tangle-prone pile. Singulation plans encountering object entanglement are discarded. A human-robot collaboration approach is proposed in [96] for resolving grasping errors due to issues such as occlusion and random object postures, including entanglement. Moosmann et al. [97] propose a method for increasing the robustness of bin picking by avoiding grasps of entangled objects. Although the methods here consider tangling directly, their objective is to extract a single individual object by avoiding entangled scenarios. Matsumura et al. [98] explicitly consider entanglement when seeking ways to extract individual items from a tangled pile. In their approach, a convolution neural network (CNN) is trained to detect when the picking of individual items is likely to be unsuccessful due to entanglement.

Their approach can be considered complementary to that considered here: while they avoid picking objects where there is tangling, here it is acknowledged that entanglement is unavoidable for the plant material considered. The aim instead is to reduce entanglement to a level where the picked mass is predictable. Specifically, this work considers extracting a uniform quantity of TPs consistently, especially when tangling cannot be avoided.

3.4 Robotic Bin Picking for non-tangling GMs

Non-tangling GMs (see Figure 3.3(b)) are ubiquitous in our daily lives. Humans frequently and, in many instances, involuntarily use the knowledge of the mechanics of the GMs to carry out complicated tasks such as pouring and scooping.

GMs have been studied by the robotics community in various scenarios (*e.g.,* locomotion, manipulation, gripper design). Locomotion has received great interest compared to manipulation [99–103]. In terms of robotic manipulation, non-tangling GMs have been studied in the context of (i) scooping [104–106] and (ii) pouring [107–109]. Kanai et al. [104] propose a disturbance observer module for autonomous scooping of rock piles. Before and after pile insertion reaction forces are compared, enabling the robotic system to adapt to various loads. Takei et al. [105] present a path planning algorithm for optimising scoop and load operation for a mining wheel loader. Cakmak and Thomaz [107] propose a human-robot interaction-based method for quickly programming new robot skills such as adding salt. Yamaguchi and Atkeson [108] propose a model-based reinforcement learning approach for pouring liquids. Schenck et al. [109] explore the manipulation of a GM, specifically pinto beans, with the aim of extracting a small quantity from a bigger pile and dropping it into a container. Kuriyama et al. [110] present a soft pneumatic gripper for packaging non-tangling food materials such as kernel corn. The authors report that although the amount (mass) of material picked using the gripper can be controlled by varying the insertion depth, the variation among trials is significant—due to the bending of the soft gripper material. The specific tasks considered by such studies involve non-tangling GMs. However, the mechanics of the GMs is not the focus, and the physics responsible for their complex behaviour remain unexplored.

Understanding the mechanics is critical for enabling tangible reasoning of how different GMs may behave in stochastic scenarios while dynamically interacting with robots. Several studies focus on understanding and leveraging the mechanics of GMs for automating complex tasks involving robotic manipulation. Clarke et al. [106] study five different non-tangling GMs (pellets, pasta, rice, coffee and soil) through shaking and pouring robotic experiments. The authors demonstrate that when manipulated GMs produce audio-frequency mechanical vibrations in air and structures. Additionally, experimental results

identify audio as an informative sensor modality for accurately estimating flow and amount. The mechanics of GMs have also been leveraged to design efficient robotic manipulators. Brown et al. [111] note that when pressed against an object GMs tend to flow around it, conforming to its shape. The authors utilise this property of a GM for enabling robotic grasping of complex objects without the need of sensory feedback. Cianchetti et al. [112] propose a soft and stiffness-controllable modular surgical manipulator that make use of the jamming properties of GMs. Thompson-Bean et al. [113] utilise granular jamming for developing a soft robotic exoskeleton. Along the same lines, this thesis investigates the *tangling* properties of TPs. However, because of the intricacies of granular mechanics, the robotics research community has preferred utilising simulation for modelling the interaction between GMs and a robot.

Traditionally, researchers in physics have relied on discreet element method (DEM) for simulating a variety of GMs [114–116]. These simulations allow observing hard-to-measure physical parameters (*e.g.,* frictional coefficient of a rice grain) from their macroscopic behaviour as a GM. Robotics community has also leveraged DEM to study GMs for a variety of robotic applications [101, 102, 117]. However, simulating a GM using DEM is a manual and complicated process [118]. Matl et al. [119] propose a likelihood-free bayesian inference method for resolving this bottleneck for robotic tasks. Real-world depth images of GM piles and rings are first used to infer physical parameters (*e.g.,* sliding friction, rolling friction). The inferred parameters are then used to simulate the GM. Once automatically calibrated, the proposed physics simulator is utilised to predict the behaviour of a GM while performing complex robotic tasks such as pouring a GM in a bowl.

However, majority of studies in the context of robotic manipulation of GMs consider non-tangling GMs. Currently, only a limited number of studies consider *robotic manipulation of TPs* (see Figure 3.3(c) and (d)) explicitly. Specifically, robotic picking of TPs under external constraints such as mass or number of items as considered in this thesis remains largely unexplored.

3.5 Robotic Bin Picking for tangling-prone materials

In terms of objective, perhaps the closest work to the present study is that of Takahashi et al. [120] where a pre-grasping motion is proposed for countering issues such as adhesion and object entanglement in bins composed of food materials such as shredded cabbage and bean sprouts. The pre-grasping motion consists of a sequence of actions where the food is picked up and dropped before repeating the pick from the same point. The proposed method to grasp a user-specified target weight of entangled foods such as shredded cabbage and bean sprouts consists of the following main steps: (i) A mass estimation neural network

is trained to predict the grasped mass for a cropped-patch of the RGB-D image and a specific insertion depth. (ii) A grasp point selection process is used to select the best grasping point from a set of candidate grasping points such that the mass as estimated by the mass estimation network is close to or slightly more than the target mass. (iii) Once a suitable point has been chosen, the pre-grasping step is used to reduce the entanglement in the pile such that the amount picked can be easily adjusted to match the target mass in the post-grasping step next. However, the work presented here specifically focuses on entanglement reduction through a separation strategy without having to repeat the pick.

3.6 Insights from Natural Sciences

The diverse variety of object interactions have intrigued researchers in physics for a long time. Specifically, knot formation has been extensively studied. Molecular biologists study knotting and unknotting of living cells and virus DNA molecules [121], [122], [123]. Knot theory is also a well-established topic of research in the area of mathematics [124], [125]. Spontaneous knotting and unknotting of a GM such as ball chains have also been studied [126]. Dorian *et al.* [127] report a simple experiment on knot formation, where a string was placed in a box and rotated at constant angular velocity. It was found that string interpenetrated itself and complex knots were formed almost immediately. No knots were formed for string length $< 0.46\,\mathrm{m}$, but probability of knot formation increased sharply for string length between $0.46\,\mathrm{m}$ and $1.5\,\mathrm{m}$, and saturated at 50% when string length was increased from $1.5\,\mathrm{m}$ to $6\,\mathrm{m}$.

GMs have also been studied in the context of entanglement and pile stability. Barabási et al. [128] propose stability criteria for calculating the maximum angle of stability for homogeneous GMs composed of 3D spherical particles and 2D circular discs. Bocquet et al. [129] explore the relationship between cohesion forces and maximum avalanche angle for rough spherical beads. Penetration studies involving soil and sand also provide valuable insights into the physical dynamics of GMs [130]. However, most studies involve approximately spherical (convex) GMs, and the shape of the particles has not received much attention [131].

3.7 Summary

The prior works relevant to the issues addressed in this thesis were presented in this chapter. From the discussion of the ASC and its components, it is evident that some components have received only limited attention from the robotics research community. The discussion further highlights the need to develop efficient RAS targeting other critical components

such as packaging. The majority of works considering robotic manipulation in clutter can be classified as: (i) planar and (ii) top-down *i.e.,* bin-picking manipulation. A detailed overview of prior works countering the challenges arising from planar manipulation in clutter demonstrates the benefits of human-inspired non-prehensile motions (*e.g.,* push, pull, slide). Prior works that propose methods for dealing with clutter in a traditional bin-picking scenario are also discussed, specifically in the context of bins composed of large objects, non-tangling GMs and TPs, respectively. It is observed that the majority of traditional bin-picking studies consider large objects (*e.g.,* screwdriver, cereal box, pen, scissor). Several studies also consider bins composed of non-tangling GMs (*e.g.,* coffee beans, grains, soil). However, the mechanics of GMs important for developing more efficient picking strategies, is not the focus. Only a small number of studies consider robotic bin-picking of TPs (*e.g.,* shredded cabbage, bean sprouts) and the issue of *picking excess mass due to entanglement* such as occurs in *TPs*, has not received much attention. This work is the first to (i) characterise the propensity of a TP to tangle in terms of a measurable quantity, and (ii) present strategies to mitigate the effect of tangling to achieve a level of predictability in robotic bin-picking of TPs such as herbs and salads.

Chapter 4

Entanglement in a TP pile

This chapter presents two experimental studies with an aim to (i) examines the role protrusions play in causing entanglement in a TP pile and (ii) identify a common informative feature of TPs, necessary for developing generalised picking strategies. One of the distinctive features of such TPs is the presence of protrusions extending out from the main body (see figs. 2.5 to 2.7). The first experiment studies the role protrusions play in causing entanglement in a TP pile. The second experiment examines the propensity of a TP to tangle in terms of a measurable quantity, *i.e.,* the Protrusion length (PL).

4.1 Introduction

Bins composed of TPs are highly stochastic environments—entanglement in the pile leads to excess picked mass making the mass lifted in a simple pick operation difficult to predict.

A picking model (see Figure 1.2 (b)) that can predict a pick action for a target mass considering the inherent entanglement in a TP pile requires informative and discriminating features providing information pertaining to tangling propensity. However, the phenomenon of entanglement in a TP pile remains largely unconsidered in the context of robotic picking. To this end, two experimental studies, where a 7-DoF robot is used to pick from bins composed of different TPs are presented to (i) examine the role protrusions play in causing entanglement in a TP pile and (ii) characterise the propensity of a GM to tangle in terms of a measurable feature—PL, common among a variety of TPs.

In the first experiment, separate homogeneous bins of plastic herbs (i) with many protrusions (see Figure 2.6(a)) and (ii) without protrusions (see Figure 2.6(b)) are used. Since plastic herbs offer restricted PL control (see section 2.4.2), the second experiment utilises staples with varying PLs as separate homogeneous TP bins. Each experiment offers insights into the role protrusions play in causing entanglement in a TP pile and highlights the benefit of PL as an informative feature.

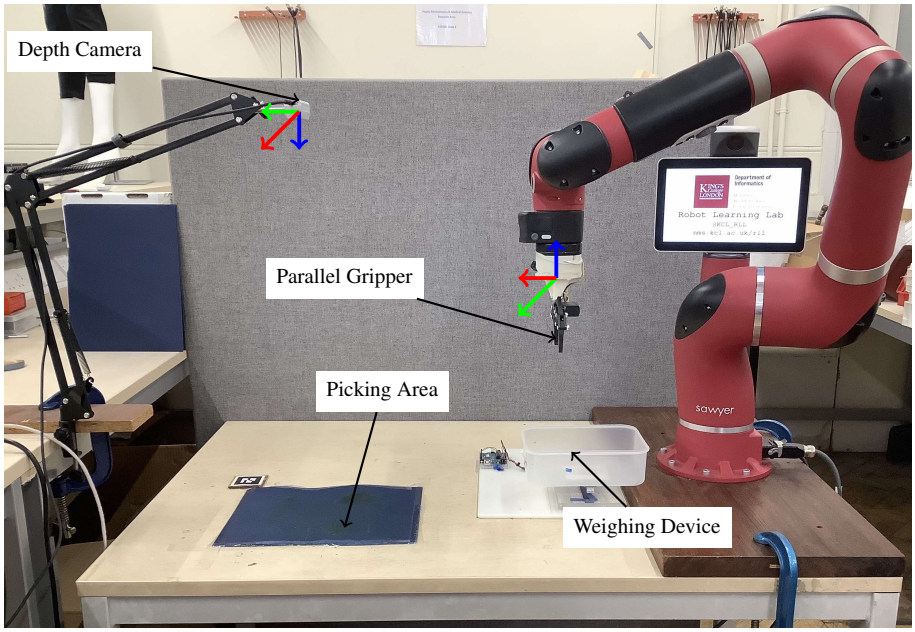

Figure 4.1: Overview of the experimental set up. Red, green and blue arrows represent x-, y- and z-axes, respectively. The coordinate frame attached to the robot is used as the frame of reference.

4.2 Setup

The experimental set up is a mock-up of the packaging workstation of a large fresh herbs and salads producer equipped with a robotic manipulator (see Figure 4.1). As the robotic platform, a 7-degree of freedom (DoF) Rethink Robotics Sawyer is used, with a maximum reach of ± 1260 mm and precision of 0.1 mm. For simplicity and lower cycle-time, 3-DoF of the robot are used for picking movements. The robot is equipped with a parallel gripper from Actobotics (product code: 637092) as its end-effector. The latter has maximum opening aperture of $w = 71.12$ mm and is controlled using a Hitec HS-422 Servo Motor with operating voltage range 4.8 V-6.0 V. As the vision module, the platform uses an Intel realsense d435i depth camera mounted on a stand at a fixed position and orientation with respect to the robot. For simplicity of image processing, the camera position is chosen such that its field of view exactly covers the picking area and it records depth data at a frequency of 15 Hz. The mass picked is recorded using a parallel beam type load cell with a combined error of $\pm 0.05\%$ and maximum weighing capacity of 10 kg. A HX711 amplifier combined with an Arduino microcontroller is used for data acquisition from the load cell. Using this experimental set up, a series of robotic picking operations are conducted.

4.3 Protrusions and Entanglement

The first experiment considers a simple picking task to compare the picking mass variance for TPs with and without protrusions. Two varieties of plastic herbs are chosen as the TP for this experiment: one with no protrusions and the other having many protrusions of varied lengths extending from a central stem. This experiment tests the following hypothesis.

4.3.1 Hypothesis

H$_1$ *The presence of protrusions leads to entanglement.*

Homogeneous bins of plastic herbs are chosen as the TP for this experiment. As discussed in section 2.4.2 each herb strand is identical with (i) fixed number of protrusions, (ii) fixed protrusion length and (iii) fixed volume, shape and density.

4.3.2 Procedure

During the experiment, a fixed mass of plastic herbs are placed in a pile in an open picking area of dimension $30\,\text{cm} \times 25\,\text{cm}$. Each picking operation consists of the robot reaching into the pile as per the pick parameter δ, closing its gripper, and lifting what is grasped free of the surface. In detail, in each pick, the gripper orientation is initialised to $r_\theta = 90°$, target picking location (r_x, r_y) is fixed as the center of the pile and the insertion depth r_z is set such that the tips of the gripper just touch the surface of the picking area. The robot moves its end-effector to a fixed position above the picking area, sets the gripper aperture w to the chosen width and lowers it into the pile. There, it closes the gripper plates, moves its end-effector vertically upwards to a fixed position, and drops what has been picked into the weighing device to record the mass. To ensure a similar physical arrangement of the plant material between trials, any material picked is returned, the entire quantity is manually transferred to a $18\,\text{cm} \times 13.5\,\text{cm} \times 7\,\text{cm}$ cuboid container and then replaced onto the picking area for the next pick. For each type of plant material used, picking is conducted 30 times for gripper aperture $w \in \{20, 30, 40, 50, 60\}$mm and pile mass $p = 30$g. The pile mass p is chosen such that the container is fully filled without any compaction.

4.3.3 Results

Figure 4.2 reports the picked mass as observed for the TP with and without protrusions. As can be seen, average picked mass for the TP with protrusions is higher for all w as compared to TP without protrusions. This is attributed to the fact the herbs with protrusions

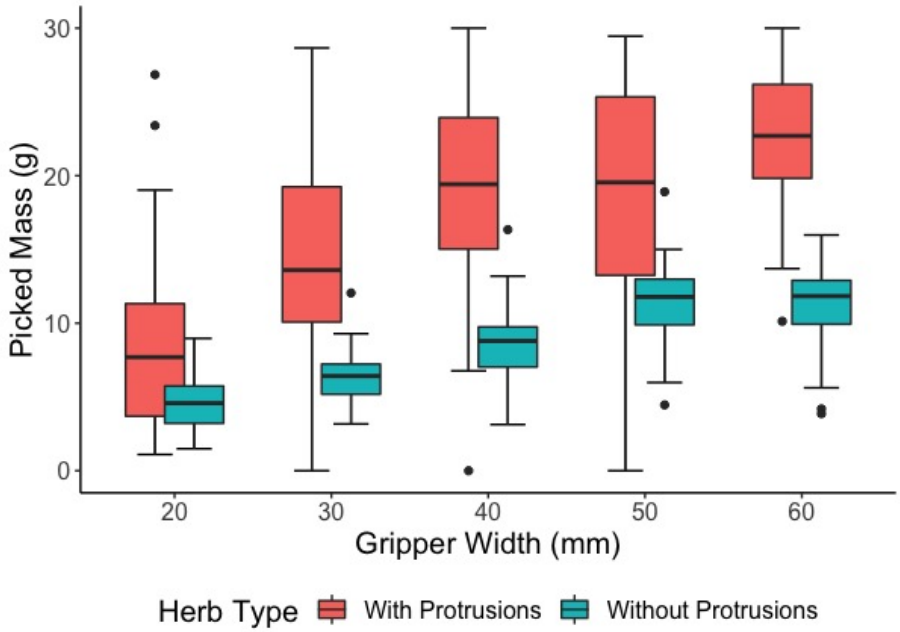

Figure 4.2: Results from fixed-point (FP) picking experiments involving plastic herbs with pile mass $p = 30\,\text{g}$, reporting *picked mass* across 30 trials. Herbs with protrusion and without protrusion weigh 1.08 g and 0.68 g respectively.

are heavier compared to the herbs without protrusions. Additionally, the picked mass variance for the TP with protrusions is considerably higher, than for those without for all w, confirming $\mathbf{H_1}$ as the presence of protrusion leads to higher pile entanglement introducing a higher picking uncertainty.

4.4 Protrusion length (PL) and Entanglement

Results from the first experiment confirms that protrusions play a crucial role in causing entanglement in a TP pile. To further examine the relationship between protrusions and entanglement, the next experiment characterises the propensity of a TP to tangle in terms of PL. This experiment tests the following hypothesis.

4.4.1 Hypothesis

$\mathbf{H_2}$ *PL is an informative indicator of entanglement.*

In this experiment, more precise control of the factors with a possible effect on tangling is required, so staples with constant staple width $d = 12\,\text{mm}$ and variable PL l (see Figure 2.5 (a)) are chosen as the TP for this experiment: each staple is identical with

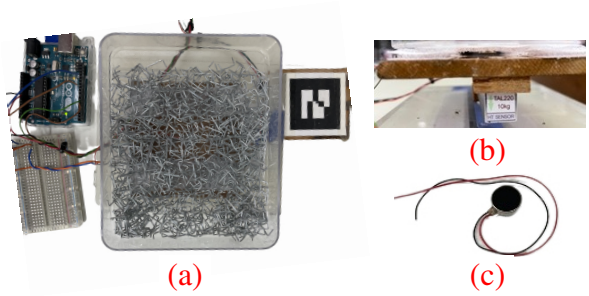

Figure 4.3: Staples are placed in (a) a cuboid container mounted on (b) a weighing device. (c) A micro vibrator is used to vibrate the pile before each pick.

Table 4.1: picked mass (mean±s.d.) of staples (over 60 trials) for protrusion length $l \in \{6, 8, 10, 12\}$mm, staple width $d = 12$mm, gripper aperture $w = 40$mm and pile mass $p = 60$ g.

l (mm)	Picked Mass (g)
6	1.786 ± 1.013
8	2.466 ± 1.370
10	3.184 ± 1.729
12	2.986 ± 1.333

(i) only two protrusions, (ii) fixed protrusion length and (iii) fixed volume, shape and density. The experimental procedure is as follows.

4.4.2 Procedure

A similar procedure to that outlined in section 4.3.2 is followed with two key differences: instead of an open area, picking is performed directly from a cuboid container of dimension 12.8 cm × 10.6 cm × 2 cm mounted on the weighing device, and the TP is vibrated for 10 s using a micro vibrator with rated voltage 3 V and rotating speed 12 000 RPM prior to each pick (see Figure 4.3). This eliminates the manual transfer of material in and out of the container between picks and helps ensure consistent packing of the material across picks. Similar to plastic herbs, the gripper orientation is initialised to $r_\theta = 90°$, target picking location (r_x, r_y) is fixed as the center of the pile and the insertion depth r_z is set such that the tips of the gripper just touch the surface of the cuboid container. The procedure is repeated 60 times for sets of staples with PLs $l \in \{6, 8, 10, 12\}$mm, gripper aperture $w = 40$mm and pile mass $p = 60$ g.

4.4.3 Results

Table 4.1 reports the picked mass as observed for staples with different PLs. The result highlights an informative relationship between PL and the degree of entanglement in a TP pile, confirming **H_2**. It can be seen that the picked mass variance increases initially as PL increases. However, the increasing trend reverses after an intermediate PL $l = 10\,\text{mm}$. A similar trend can also be seen with the average picked mass.

4.5 Discussion

The results in sections 4.3.3 and 4.4.3 demonstrate that protrusions play a clear role in causing tangling, and consequently decreasing picking consistency. Specifically, a significant increase (76 %) in picked mass variance is observed in section 4.3.3 for TPs with protrusions as compared to those without protrusions.

Results from the second experiment with TPs with varied PLs further suggest that PL is an informative feature, especially in a mass-constrained robot picking task involving a variety of TPs with protrusions. In case of no entanglement (see Figure 4.4 (a), (b) and (c)), only the target object is expected to be picked despite the decreasing PL. In case of entanglement (see Figure 4.4 (d), (e) and (f)), contact surface decreases as PL decreases and undesired objects are more likely to fall off—suggesting a monotonic relationship between overall degree of entanglement and PL l. However, surprisingly, in section 4.4.3, a non-monotonic trend is observed. Both picked mass and variance increase initially with the increasing PL. The increase in picked mass variance is attributed to

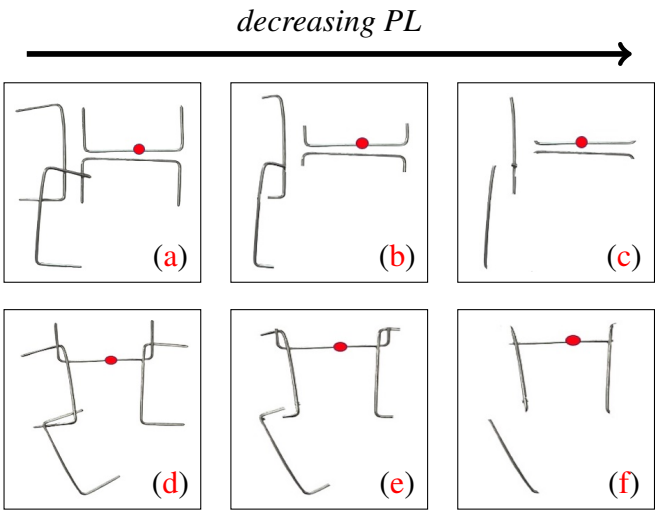

Figure 4.4: Without ((a), (b) and (c)) and with entanglement ((d), (e) and (f)) scenarios. The red dot represents the target object.

increasing entanglement ability with increasing PL. However, picking is observed to be more consistent for PL $l > 10\,\text{mm}$—picked mass variance decreases, suggesting a decrease in the overall entanglement in the pile. As reported in [132], this behaviour is attributed to the interplay between the *ability to pack* and the *ability to entangle* in a TP pile.

4.6 Summary

This chapter has explored the role protrusions play in causing entanglement in a TP pile. Protrusions play an important role in making robotic bin-picking inconsistent. The presence of protrusions on an object improves its *ability to entangle* because of an increase in the contact surface area. This is particularly relevant and problematic when the objects in the bin are presented as a TP because of other relevant factors such as the *ability to pack*. A significant increase (76%) in picking mass variance is observed for plastic herbs with protrusions as compared to those without protrusions. The results suggest that protrusions play a crucial role in causing entanglement in a TP pile, making picking inconsistent.

Furthermore, picking experiments with separate homogeneous bins of staples of varying PLs are conducted. The results demonstrate that PL is an informative feature useful in designing effective picking strategies that can counter entanglement for a wide range of TPs. Interestingly, a non-monotonic relationship is observed between the picked mass variance and PL. This highlights the importance of the *ability to pack* and the *ability to entangle* in developing generalised picking strategies.

The presence of protrusions facilitates entanglement in a TP pile. TPs with protrusions require special measures for overcoming the inherent resistance to separation resulting from this entanglement. The next chapter addresses this issue through a human-inspired non-prehensile (spread) manoeuvre designed to reduce entanglement in a TP pile by separating the grasped bunch from the rest of the pile.

Chapter 5

Robotic Picking of TPs

This chapter presents the proposed method of *entanglement reduction i.e.,* Spread-and-Pick (SnP) in the context of a one-shot mass-constrained bin-picking task. First, the core elements of the SnP method are presented in detail. A picking experiment with staples is presented next to evaluate the usefulness of SnP in reducing the entanglement in a TP pile and making picking consistent. Furthermore, picking experiments involving plastic and real plant materials evaluate the efficacy of SnP through an industrial herb and salad picking task. The experiments specifically compare fixed-point (FP) and collision-free point *i.e.,* GI-based picking strategies with picking following SnP.

This work has been published in [13, 14].

5.1 Introduction

As noted in chapters 2 and 4, TPs such as herbs and salads are generally difficult to separate through traditional methods (*e.g.,* shaking) and require special measures such as *pile interaction* for de-tangling. This section outlines a human-inspired manoeuvre for interacting with a TP pile in a way that reduces the inherent entanglement in the pile.

In general, the robotic picking of a target mass from a TP pile can be decomposed into four main steps: (i) First, the picking point is identified. (ii) Gripper aperture is then set accordingly based on the target mass. (iii) Next, the robot moves to the picking point in the pile and closes the gripper plates. (iv) Finally, it moves above the pile lifting what has been grasped. However, entanglement in the pile causes extra mass to be picked. One approach of avoiding the extra picked mass could be to completely drop what has been picked and then attempt the pick again. When picked the first time, the grasped bunch is separated from the rest of the pile and the second pick after the drop is expected to encounter a lesser degree of entanglement. However, an uncontrolled drop might introduce more uncertainty with objects falling in different unexpected areas of the pile. Additionally,

repeated picks increase the cycle time adversely affecting the packaging efficiency in an industrial environment. Another viable method could be to avoid picking from an entangled point. However, in the real world, entanglement-free scenarios are generally scarce, especially for the bins composed of TPs considered in this thesis.

An alternative would be to leverage non-prehensile actions such as spreading to interact with the pile. As discussed in section 2.3, when in the pile, instead of closing the gripper plates to *grasp*, the gripper plates could be opened first to *spread* such that the target mass in between the gripper plates can be effectively separated from the rest of the pile. Once separated, the gripper plates can then be closed to grasp the entanglement-free target mass. However, picking or spreading randomly is damaging for glsplTP, especially for deformable TPs (*e.g.,* herbs and salads) and is not an effective entanglement reduction strategy. Instead, the approach can be decomposed into two primary steps: (i) collision-free gripper pose and (ii) tangle reduction. In the first step, a collision-free point for the chosen gripper is identified such that it can be inserted into the pile without causing any damage to the TP. In the tangle reduction step, a peak entanglement point is identified around the collision-free point. The gripper is oriented along the line intersecting the collision-free and the entanglement points and finally opened to complete the spreading manoeuvre. Figure 5.1 presents a simple example scenario with three wooden blocks to further discuss the motivation behind the presented method. When the objective is to pick up the middle block, any point on the target block chosen at random can be considered for a given gripper orientation. However, since it is surrounded by other wooden blocks, it is essential to estimate a collision-free point to avoid any collision between the gripper and other wooden blocks. For example, the red dot represents an initial pick point on the target object chosen at random. It can be observed that picking from this point would lead to a collision between the gripper and a block. However, picking from the collision-free point (green dot) will enable the picking of the target object without any collision. In the case of a tangle-prone pile, picking from a collision-free point helps in avoiding damaging the pile and also contributes to entanglement reduction indirectly as individual objects are expected to be away from each other around the collision-free point. In the second step, pile entanglement is countered directly through a spreading manoeuvre. The line of entanglement is estimated and gripper plates are opened to complete the spreading manoeuvre.

Figure 5.2 presents a simple scene providing an overview of the operations done on the acquired depth map. Figure 5.2(a) presents the scene and the system setup consisting of cluttered objects with the middle block as the target object. A depth map of the scene is first acquired using the depth camera. Cross-section A represents the region of the target object that should lie between the gripper plates for a successful grasp. It is acquired by thresholding the depth map using h_t. Specifically, pixel values with a depth value $> h_t$ (*i.e.,* farther from the depth camera) are set to 0 (black) and $=< h_t$ (*i.e.,* closer to the

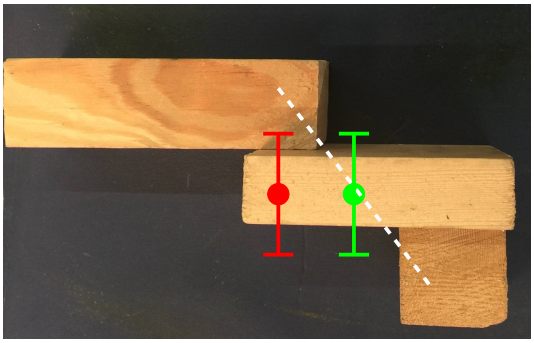

Figure 5.1: Example scenario with wooden blocks. The red and green dots represent the initial pick-up point and collision-free point respectively. The dashed white line represents the line of entanglement.

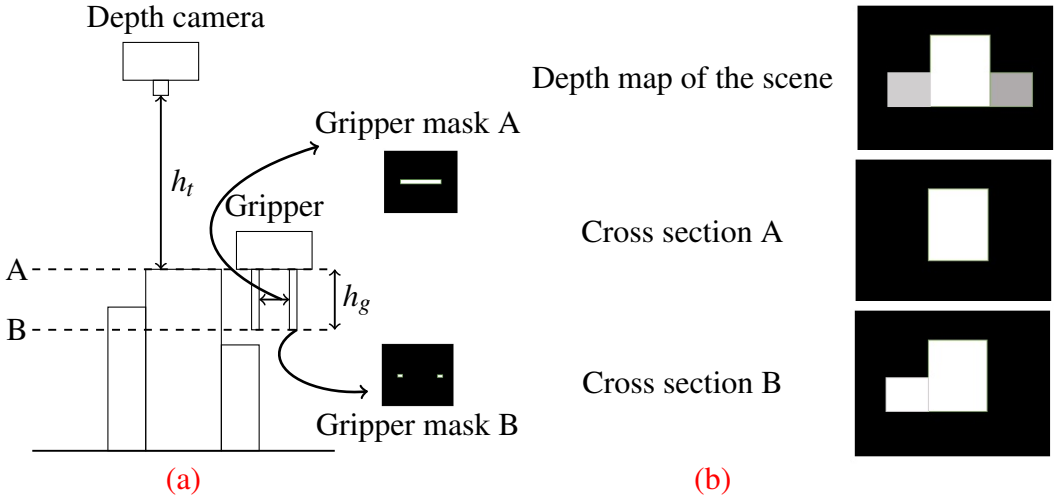

Figure 5.2: Scene modelled by contacts and collision between a gripper and objects. (a) Scene and system setup. Gripper masks A and B are generated using the chosen gripper aperture and the lateral widths of the gripper plates respectively. (b) First a depth map of the scene is acquired. The darker the shade farther the object is from the depth camera. Cross-section A is obtained by thresholding the depth map using the height of the target object h_t. Cross-section B is obtained by thresholding the depth map using the depth h_g to which the gripper advances when grasping.

depth camera) are set to 255 (white). Similarly, cross-section B represents the region in which a collision might occur while the gripper is moving downwards. It is obtained by thresholding the depth map using the insertion depth h_g to which the gripper advances when grasping. Specifically, pixel values with a depth value $> h_t + h_g$ are set to 0 (black) and $=< h_t + h_g$ are set to 255 (white). Gripper masks A and B are not obtained using the depth map and are instead generated using the chosen gripper aperture and the lateral widths of the gripper plates respectively. The next section further describes how these

depth maps and gripper masks are utilised for estimating collision-free and entanglement points.

5.2 Method

5.2.1 Collision-free Gripper Pose: GI

The GI [92] is a vision-based measure for evaluating candidate grasping poses that has proved useful in industrial pick and place settings. It uses a single depth map of the scene to estimate the optimal gripper position and orientation for picking an object. It can be applied for use with different hand mechanisms, including parallel, multi-finger and vacuum grippers. It is particularly suitable for the picking problem considered here since it is unaffected by colour variation (that may occur between different plants) since only a depth map and a 2D gray-scale image are needed to process the scene. It should be noted, however, that its use of depth maps means it is most effective when a perpendicular view of the scene is available.

For an insertion depth r_z, GI estimates a point $\mathbf{r}$ in the bin such that the parallel plates of the gripper could be inserted without colliding with the objects inside. A range of r_θ is evaluated using GI and for the optimal r_θ, the best picking point (r_x, r_y) is estimated.

Figure 5.3 provides an overview of the GI method. First, a depth map of the cluttered scene is acquired using vision (*e.g.,* RGB-D camera). $\mathbf{O_c}$ (see Figure 5.3(b)) represents the region of the target object that should lie between the gripper plates for a successful grasp. It is obtained by thresholding the depth map by the *depth value corresponding to the highest point on the target object* (middle block in Figure 5.3(a)). $\mathbf{O_{c'}}$ represents the region in which a collision might occur while the gripper is moving downwards. It is obtained by thresholding the depth map by the *insertion depth* r_z (see Figure 5.3(c)). $\mathbf{G_c}$ and $\mathbf{G_{c'}}$ (see Figure 5.3(d) and (e), respectively) represent the contact distance between the parallel plates and collision regions (*i.e.,* lateral width of the plates) for the gripper and are obtained through millimetre-to-pixel unit conversion. They are recomputed whenever the opening aperture of the gripper changes. The region where part of the target object lies between the gripper plates (Figure 5.3(f)) is computed through the convolution[1]

$$\mathbf{W_c} = \mathbf{O_c} * \mathbf{G_c}. \tag{5.1}$$

Similarly, the region where the gripper plates could collide with the objects in the pile is obtained as (see Figure 5.3(g))

$$\mathbf{W_{c'}} = \mathbf{O_{c'}} * \mathbf{G_{c'}}. \tag{5.2}$$

[1]Here, and throughout the thesis, $*$ represents the convolution operation.

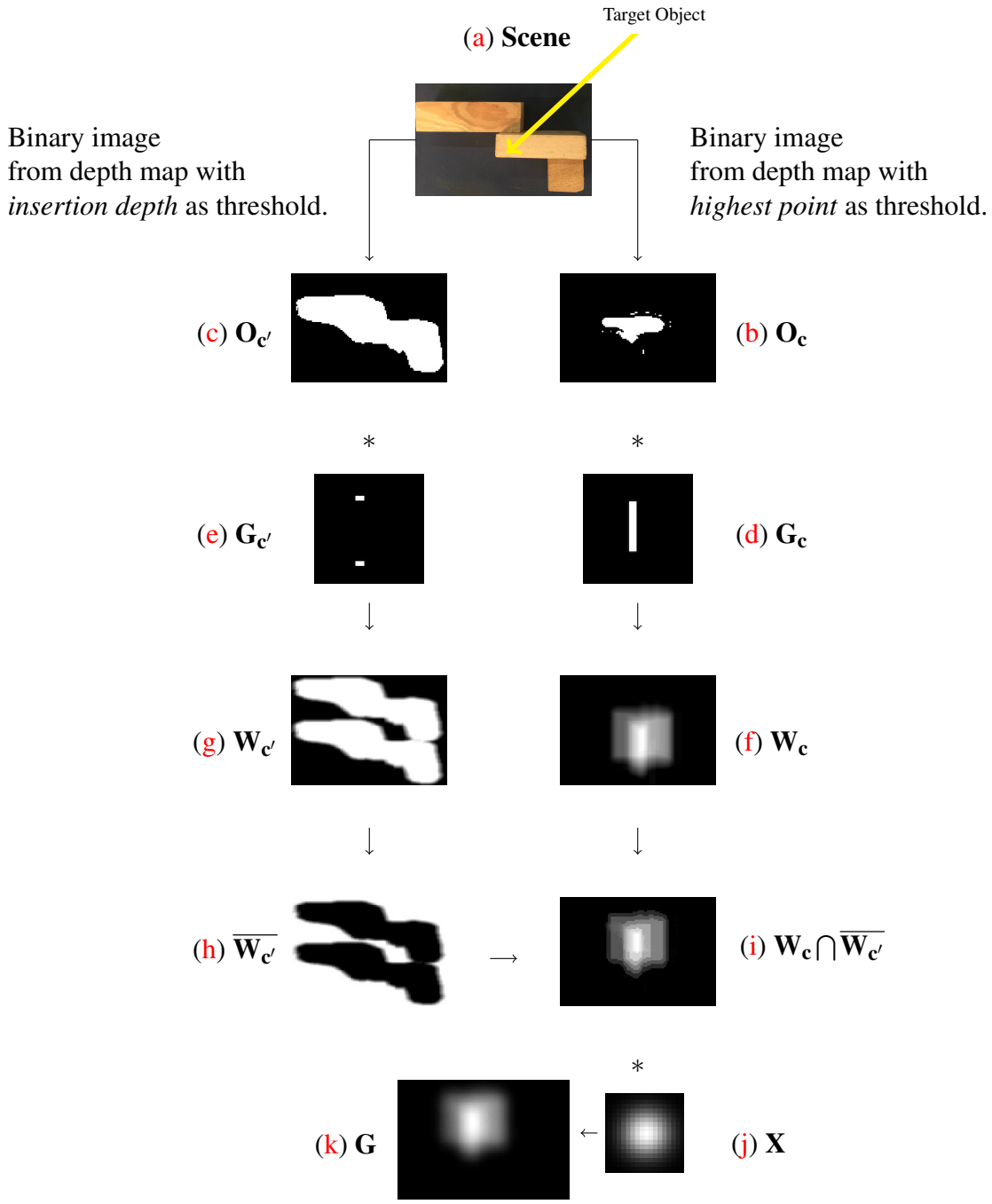

Figure 5.3: Estimating the grasping position (r_x, r_y) using GI for gripper rotation $r_\theta = 90°$. The scene contains three wooden blocks. In this example, the highest object (middle block) is the target object and the insertion depth r_z is set such that the tips of the gripper just touch the surface of the table. The collision-free pick-up point $\mathbf{u}$ is estimated from the peak of the graspability map $\mathbf{G}$.

The region of interest for successful picking is the area where contact between the gripper plates and the target object is detected and there is no collision with other objects

in the bin. Since $\mathbf{W_{c'}}$ represents the region where collisions might occur the latter may be expressed as $(\mathbf{W_c} \cap \overline{\mathbf{W_{c'}}})$, where the notation $\overline{\mathbf{A}}$ represents the *NOT* operation on $\mathbf{A}$ and $\cap$ denotes intersection (see Figure 5.3(i)). Finally, using a Gaussian $\mathbf{X}$ (see Figure 5.3(j)), the graspability map $\mathbf{G}$ is computed as

$$\mathbf{G} = (\mathbf{W_c} \cap \overline{\mathbf{W_{c'}}}) * \mathbf{X}. \tag{5.3}$$

convolution with a Gaussian $\mathbf{X}$ is used to smooth and reduce the noise in the graspability map. The peak of $\mathbf{G}$ is obtained for a range of gripper orientations r_θ to determine the respective pick up point (r_x, r_y) by maximising

$$f(x, y, r_\theta) = \begin{cases} (\mathbf{G})_{xy}, & \text{if } (\mathbf{W_{c'}})_{xy}{=}0 \\ 0, & \text{otherwise.} \end{cases} \tag{5.4}$$

where $(\mathbf{G})_{xy}$ and $(\mathbf{W_{c'}})_{xy}$ represents the value of $\mathbf{G}$ and $\mathbf{W_{c'}}$ at position (x, y) respectively. Gripper orientations for which no peak could be detected are discarded and r_θ is set to the the gripper orientation for which the peak could be determined in $\mathbf{G}$ yielding the picking position

$$\mathbf{u} = (r_x, r_y, r_\theta)^\top = \underset{x,y}{\operatorname{argmax}}\, f(x, y, r_\theta). \tag{5.5}$$

The optimal gripper position and orientation as obtained from the GI identify a reference for the gripper for collision-free picking of the target object. However, this ignores the possibility that parts of the target object could be entangled with other items in the bin such that it may end up picking them along with the target. In case of TPs, experience tells that this frequently occurs resulting in more than the desired mass being picked. In the next section, a strategy is proposed for *reducing tangling during the pick operation* to help alleviate this problem.

5.2.2 Tangle Reduction: SnP

To reduce the level of tangling and thereby achieve more consistent picking, this thesis proposes a SnP approach, inspired by human behaviour. In humans, it is frequently observed that they use their fingers to separate things while picking, especially when they have to work with one hand. The idea here is to mimic this behaviour by adjusting the pick to include a spreading step: specifically, if the target object is between the plates of the gripper, instead of moving them inwards (closing) to grasp the object, they are first moved *outward* to try to disentangle any nearby objects before proceeding with the pick.

The proposed approach extends the GI by identifying regions of high entanglement in the scene and then defining a spreading movement to disentangle them. For a specific r_θ,

$\mathbf{G}_{\mathbf{c}'}$ is used to obtain $\mathbf{W}_{\mathbf{c}'}$, the region that represents gripper-object collision. $\mathbf{W}_{\mathbf{c}'}$ is then used to identify the region of entanglement

$$\mathbf{G}' = \mathbf{W}_{\mathbf{c}'} * \mathbf{X}. \tag{5.6}$$

Using $\mathbf{G}'$, the *peak entanglement position* is computed as

$$\mathbf{v} = (r_x, r_y, r_\theta)^\top = \underset{x,y}{\operatorname{argmax}}\, h(x, y, r_\theta) \tag{5.7}$$

where

$$h(x, y, r_\theta) = \begin{cases} (\mathbf{G}')_{xy}, & \text{if } (\mathbf{W}_{\mathbf{c}'})_{xy}{=}1 \\ 0, & \text{otherwise.} \end{cases} \tag{5.8}$$

The *line of peak entanglement* is then defined as that intersecting $\mathbf{v}$ and $\mathbf{u}$. This line defines the spreading movement in the proposed approach: during the pick operation, the gripper plates are moved outwards along this line to disperse the tangle and improve the consistency of picking. PL, being an informative feature in the design of the picking strategies, can also be used in the future to adjust the proposed outward movement considering the tangling propensity of different TPs. Figure 5.4 illustrates the working of the robot while following the SnP approach.

5.2.3 Mass-constrained Picking

In the industrial setting, the picking task is typically specified in terms of a target mass so it is necessary to find a way to translate the training data into the required pick parameter δ. The purpose of SnP is to reduce the pile entanglement to a reasonable threshold such that the remaining element of δ (*i.e.,* gripper aperture w) can be estimated efficiently for any target mass m_t. The training set $\mathscr{D}$ to learn the skill as expressed in (2.2) is collected by running $\mathscr{N}$ picking trials for different pick parameter δ and consists of a matrix of pick parameters $(\delta_1, ..., \delta_p) \in \mathbb{R}^{4\times\mathscr{P}}$ and the corresponding matrix of observed picked masses $\begin{pmatrix} m_1^{\delta_1} & \dots & m_1^{\delta_p} \\ \vdots & \ddots & \vdots \\ m_n^{\delta_1} & \dots & m_n^{\delta_p} \end{pmatrix} \in \mathbb{R}^{\mathscr{N}\times\mathscr{P}}$. This data $\mathscr{D}$ is used to fit a predictive model through supervised learning. Specifically, a simple least-squares regression is computed as

$$m = N(w) \tag{5.9}$$

to determine a relationship between the gripper aperture width w and picked-up weight m. Using (5.9) for a target weight m_t, gripper width is estimated as

$$w = N^{-1}(m_t) \tag{5.10}$$

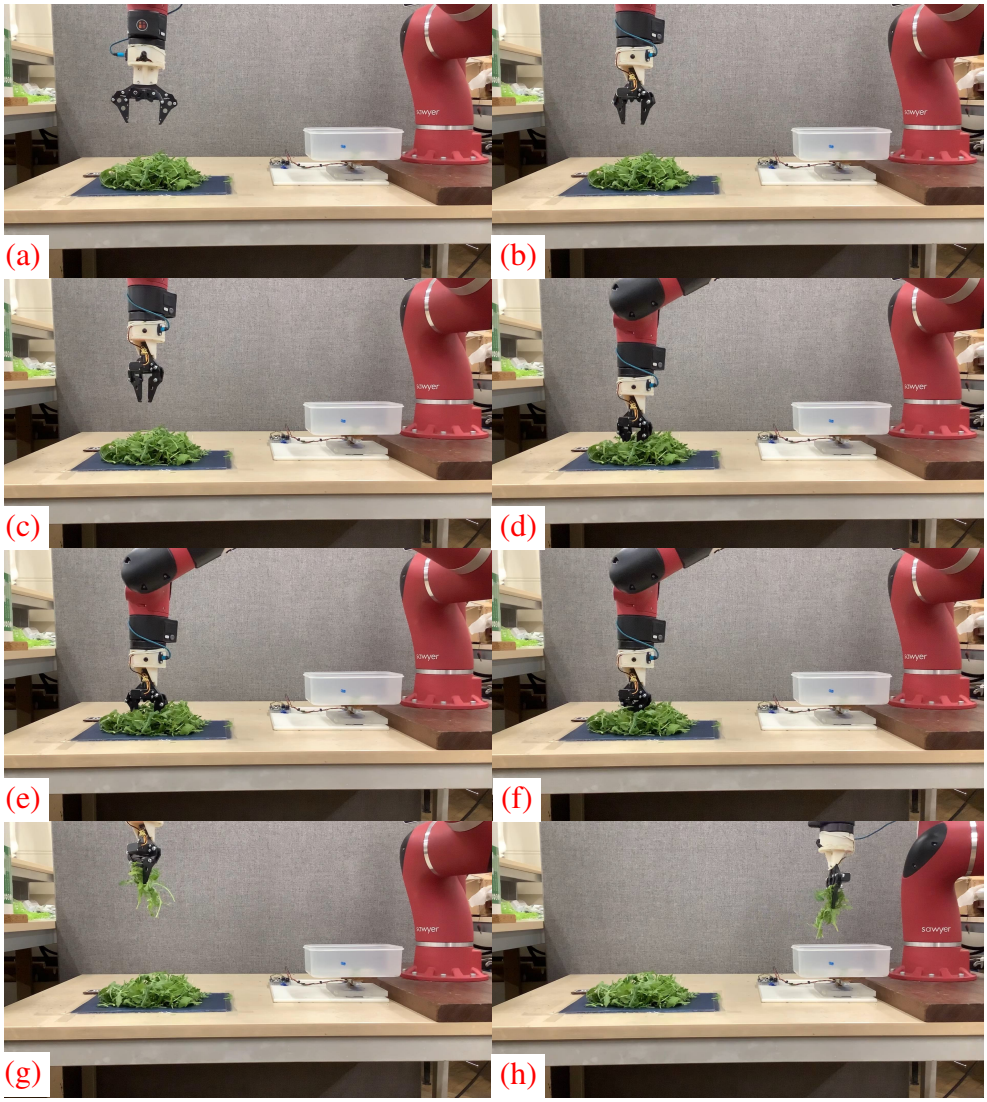

Figure 5.4: Time lapse illustrating SnP approach. (a) Robot reaches a fixed point above the pile. (b) Gripper orientation adjusted to align with *line of peak entanglement.* (c) Gripper aperture set to chosen width. (d) Gripper moved into herb pile to pick from the optimal collision-free point according to GI. (e) Gripper plates moved outwards to maximum aperture width. (f) Gripper closed. (g) Gripper raised with items picked. (h) Picked items dropped onto scale to record mass.

The inverse of the model is then used to achieve the desired skill (2.2). It should be noted, however, that the chosen model should be monotonic to be inverted.

Table 5.1: picked mass (mean±s.d.) of staples (over 60 trials) for PL $l \in \{6, 8, 10, 12\}$mm, staple width $d = 12$mm, gripper aperture $w = 40$mm and pile mass $p = 60$ g.

l (mm)	FP (g)	SnP (g)
6	1.786±1.013	1.439±0.753
8	2.466±1.370	2.437±1.141
10	3.184±1.729	3.632±1.640
12	2.986±1.333	2.621±1.156

5.3 Evaluation

5.3.1 Fixed-Point Picking & Spread-and-Pick: Staples

The first experiment considers a simple picking task to compare the picking mass variance following FP and SnP-based approaches. Staples with varied PLs are chosen as the TP. To evaluate the effectiveness of the SnP approach as compared to FP picking, this experiment tests the following hypothesis.

Hypothesis

H_3 Picking following SnP results in a significant increase in picking consistency as compared to FP-based picking.

Staples with constant staple width $d = 12$ mm and variable PL l (see Figure 2.5 (a)) are chosen as the TP for this experiment: each staple is identical with (i) only two protrusions, (ii) fixed protrusion length and (iii) fixed volume, shape and density. The experimental procedure is as follows.

Procedure

A similar procedure to that outlined in section 4.4.2 is followed. For SnP, after lowering its end-effector into the pile, the robot performs the spreading manoeuvre, closes the gripper plates, moves its end-effector vertically upwards to a fixed position, records the picked mass and then drops what has been picked back into the container. The procedure is repeated 60 times for sets of staples with PLs $l \in \{6, 8, 10, 12\}$mm, gripper aperture $w = 40$mm and pile mass $p = 60$ g. The same procedure is then repeated for FP picking. Note that, in the latter, (i) no spreading movement is performed and (ii) the target picking location is fixed as the centre of the pile.

Result

Table 5.1 reports the picked mass (mean±s.d.) for the FP and SnP methods. It is observed that the standard deviation of the picked mass is the least for SnP among all cases. This demonstrates that SnP reduces entanglement in the pile without having to precisely define and measure the overall *degree of entanglement*, making picking more consistent and hence confirming H_3.

5.3.2 Random & Collision-free Picking: Plastic Herbs with Protrusions

The second experiment considers a simple picking task to compare picking using collision-free positions with random positions (neither using peak entanglement position). Plastic herb with many protrusions are chosen as the GM. This experiment tests the following hypothesis

Hypothesis

H_4 *Picking from the collision-free point results in a greater picking accuracy as compared to random picking*.

Procedure

During the experiment, a fixed mass of plastic herbs are placed in a pile in an open picking area of dimension $30\,\text{cm} \times 25\,\text{cm}$. Each picking operation consists of the robot reaching into the pile as per the pick parameter δ, closing its gripper, and lifting what is grasped free of the surface. In detail, in each pick, the gripper orientation is initialised to $r_\theta = 90°$, target picking location (r_x, r_y) is chosen randomly and the insertion depth r_z is set such that the tips of the gripper just touch the surface of the picking area. The robot moves its end-effector to a fixed position above the picking area, sets the gripper aperture w to the chosen width and lowers it into the pile. There, it closes the gripper plates, moves its end-effector vertically upwards to a fixed position, and drops what has been picked into the weighing device to record the picked mass. To ensure a similar physical arrangement of the plant material between trials, any material picked is returned, the entire quantity is manually transferred to a $18.5\,\text{cm} \times 13.5\,\text{cm} \times 4.5\,\text{cm}$ cuboid container and then replaced onto the picking area for the next pick. Picking is conducted 30 times for gripper aperture $w = 40\,\text{mm}$ and pile mass $p = 30\,\text{g}$. For the random picking scenario, collision-free point is not estimated and picking is performed from the chosen random point. Same procedure is followed for the collision-free scenario, except picking is performed from the estimated collision-free point instead of the random point.

Table 5.2: picked mass in picking plastic herbs with protrusions (mean±s.d. over 30 trials).

Method	Picked mass (g)
Random Picking	4.963 ± 4.712
Collision-free Picking	4.549 ± 3.735

Table 5.3: picked mass in picking plastic herbs with protrusions (mean±s.d. over 30 trials).

Method	Picked mass (g)
Random Spread	5.854 ± 2.987
SnP	4.281 ± 1.942

Result

Table 5.2 reports the picked mass (mean±s.d.) for the random and collision-free picking methods. It is observed that the standard deviation of the picked mass is less for the collision-free case as compared to the random picking method. This demonstrates that picking from collision-free point contributes in making picking more consistent and hence confirms H_4.

5.3.3 Random Spread & Spread-and-Pick: Plastic Herbs with Protrusions

The third experiment considers a simple picking task to compare the proposed SnP with random SnP. Specifically, collision-free point is utilised in both cases, except pile is spread randomly for the latter. Plastic herb with many protrusions are chosen as the GM. This experiment tests the following hypothesis

Hypothesis

H_5 Spreading as per the estimated line of entanglement results in a greater picking accuracy as compared to random spreading.

Procedure

During the experiment, a fixed mass of plastic herbs are placed in a pile in an open picking area of dimension $30\,\text{cm} \times 25\,\text{cm}$. Each picking operation consists of the robot reaching into the pile as per the pick parameter δ, closing its gripper, and lifting what is grasped free of the surface. In detail, in each pick, the gripper orientation is initialised to $r_\theta = 90°$, the target picking location (r_x, r_y) is chosen randomly and the insertion depth r_z is set such that the tips of the gripper just touch the surface of the picking area. The robot moves

its end-effector to a fixed position above the picking area, sets the gripper aperture w to the chosen width and lowers it into the pile. There, it closes the gripper plates, moves its end-effector vertically upwards to a fixed position, and drops what has been picked into the weighing device to record the picked mass. To ensure a similar physical arrangement of the plant material between trials, any material picked is returned, the entire quantity is manually transferred to a $18.5\,\text{cm} \times 13.5\,\text{cm} \times 4.5\,\text{cm}$ cuboid container and then replaced onto the picking area for the next pick. For SnP, after lowering its end-effector into the pile, the robot performs the spreading manoeuvre as per the estimated line of entanglement, closes the gripper plates, moves its end-effector vertically upwards to a fixed position, records the picked mass and then drops what has been picked back into the container. The procedure is repeated 30 times for gripper aperture $w = 40\text{mm}$ and pile mass $p = 30\,\text{g}$. The same procedure is then repeated for the random SnP picking. In both cases, a collision-free point is estimated, however, in the latter, spreading movement is performed randomly instead of spreading along the line of entanglement.

Result

Table 5.3 reports the picked mass (mean$\pm$s.d.) for the random and proposed SnP methods. It is observed that the standard deviation of the picked mass is less for the proposed SnP as compared to the random spreading. This demonstrates that spreading as per the estimated line of entanglement contributes to making picking more consistent and hence confirms H_5.

5.3.4 Industrial Herb and Salad Picking Task

In this section, the proposed SnP method is evaluated with respect to its efficacy in improving consistency in an industrial picking task, namely, picking a target mass of fresh herbs and salads (flat-leaf parsley and wild rocket, see Figure 2.7). Picking experiments involving bins composed of plastic herbs with protrusions (see Figure 2.6(a)) are also reported. Plastic herbs are a reasonable mock-up of real herbs and their use enable some degree of control against natural variations in the real plant material (*e.g.,* due to plant material drying out, or becoming damaged over successive picks). Specifically, the next experiment test the hypothesis:

Hypothesis

H_6 *Picking following SnP results in a greater picking accuracy as compared to GI-based picking.*

Table 5.4: PE in picking plastic herbs (mean±s.d. over 20 trials) with standard error of the linear model as 0.140.

m_t (g)	Method	Picked Mass (g)	PE (g)
8	GI	4.832 ± 5.013	5.191 ± 2.709
	SnP	8.318 ± 4.681	3.772 ± 2.655
10	GI	8.791 ± 9.176	6.516 ± 6.408
	SnP	7.228 ± 3.514	3.820 ± 2.253
12	GI	12.621 ± 9.307	6.995 ± 5.959
	SnP	10.523 ± 5.907	5.090 ± 3.149

Table 5.5: PE in picking wild rocket (mean±s.d. over 10 trials) with standard error of the linear model as 0.113.

m_t (g)	Method	Picked Mass (g)	PE (g)
15	GI	9.434 ± 3.937	6.008 ± 3.133
	SnP	10.033 ± 2.793	5.091 ± 2.533
20	GI	14.137 ± 6.274	6.529 ± 5.495
	SnP	15.799 ± 4.819	5.297 ± 3.414

Procedure

Data is collected using the mock picking station rig shown in Figure 4.1 and used to fit a predictive model of the required pick parameter δ given a target masses for each TP considered. Specifically, picking is performed 20 times for gripper aperture $w \in \{20, 30, 40, 50, 60\}$mm for plastic herbs and 10 times for $w \in \{20, 30, 40\}$mm for real herbs, using the procedure outlined in section 4.3.2. As discussed in section 5.2.3, this data is used to estimate a linear model, that is inverted to derive the skill as presented in (2.2) for computing required gripper aperture for target mass m_t. The remaining elements of δ (*i.e.,* picking location and orientation $\mathbf{r}$) are computed according to the procedure described in sections 5.2.1 and 5.2.2 respectively. To evaluate the accuracy and consistency of picking, this method is applied to pick a series of target masses: $m_t \in \{8, 10, 12\}$g for plastic herbs ($m_t \in \{15, 20\}$g for real herbs) and the picking error (PE) (*i.e.,* absolute difference from actual mass picked) is recorded. This is repeated for 20 trials for plastic herbs (10 trials for real herbs). For comparison, the experiment is also repeated using standard GI-based picking (*i.e.,* picking at the collision-free point, and omitting the spreading movement). To further test the robustness, the experiment is also repeated with the variation that the picking model for wild rocket is applied to picking material from a different plant, namely, flat-leaf parsley.

Result

Tables 5.4 and 5.5 report the PE for picking plastic herbs and wild rocket, respectively. It is observed that the PE with SnP is lower among all cases, and is up to 41% lower for

Table 5.6: PE in picking flat-leaf parsley (mean±s.d. over 10 trials). Gripper aperture w are estimated using the wild rocket model.

m_t (g)	Method	Picked Mass (g)	PE (g)
15	GI	14.250 ± 8.944	7.444 ± 4.365
	SnP	12.228 ± 7.064	6.464 ± 3.466
20	GI	15.921 ± 8.886	7.535 ± 5.863
	SnP	17.893 ± 3.951	3.729 ± 2.257

picking $m_t = 10\,\text{g}$ of plastic herbs and up to 19% for picking $m_t = 20\,\text{g}$ of wild rocket. A significant decrease in the PE variance is also observed with SnP for all cases. Finally, Table 5.6 provides the PE for picking flat-leaf parsley using the model derived for wild rocket. As observed, the PE is lower for SnP compared to the GI-based approach for all target masses considered with up to 51% for picking $m_t = 20\,\text{g}$. These results show that the proposed SnP approach effectively reduces PE and improves picking consistency for a variety of herbs and salads, confirming H_4.

5.4 Discussion

The results from the study in section 5.3.1 and the industrial herb and salad picking task (section 5.3.4) demonstrate the power of the proposed SnP approach in reducing error and improving picking consistency by tackling tangling in TPs. In the former, controlled staple-picking experiment, SnP results in a lower standard deviation of the picked mass in all cases, demonstrating the important effect that reducing tangling can have. Moreover, in the herb/salad picking task the PE is shown to be lower when using SnP in all cases. Interestingly, comparing the PE for plastic and real herbs, the reduction in PE is lower for the former. This difference is attributed to factors such as moisture variation and a generally higher degree of entanglement in the real herbs. It is worth noting that, the real herb material occasionally prevented the gripper plates from fully opening due to their tendency to tangle around the gripper itself. The presence of moisture in real plant material also tends to cause adhesion between herb strands in addition to the mechanical entanglement, potentially exacerbating the effect. Surprisingly, the maximum decrease in PE is observed for target mass $m_t = 20\text{g}$ for flat-leaf parsley (see Table 5.6), even though gripper aperture was estimated using the wild rocket picking model. The interplay between the *ability to pack* and the *ability to entangle* is considered responsible for such an observation.

Overall, it can be seen that the proposed SnP method proves effective in directly countering tangling in a variety of TPs. It is not practical to train a separate model for all individual TPs and the insights regarding protrusions as presented in this work, provide a

useful way of generalising a picking model, especially considering the physical properties of the TPs.

5.5 Summary

In summary, this chapter presents an *entanglement reduction* strategy that effectively reduces the entanglement in a TP pile compared to the traditional approach of picking from a collision-free point. Compared to prior work, the proposed method explicitly counters the issue of entanglement in a TP pile. Overall, it can be seen that the proposed SnP method proves effective in directly countering tangling in a variety of GMs.

Countering the issue of object entanglement is important for the successful deployment of robotic bin-picking systems, especially when the bin is composed of TPs such as herbs and salads. Using the proposed method of entanglement reduction, the one-shot mass-constrained picking can be made more predictable without directly estimating the overall degree of entanglement in the pile. As such, the presented method makes a valuable contribution toward robotic bin-picking systems for TPs and achieving effective entanglement reduction for a variety of challenging GMs.

The principal idea, the presented method revolves around is that the picking performance for a one-shot mass-constrained picking task is closely linked to the entanglement in the pile. Here, it is acknowledged that entanglement is unavoidable for TPs considered in this thesis. The aim instead is to reduce entanglement to a level where the picked mass is predictable. Specifically, the proposed method aims to reduce the picked mass variance resulting from the entanglement in a TP pile, such that the uncertainty in the training data required for learning the picking skill presented in (2.2) can be reduced.

Chapter 6

Conclusions

This thesis has been dedicated to the issue of *picking excess mass due to entanglement* such as occurs in bins composed of *tangle-prone* materials, especially in the context of a one-shot mass-constrained robotic bin-picking task. Specifically, it proposes a human-inspired entanglement reduction method for making the picking of TPs more predictable. A video demonstration of the robot performing the proposed SnP manoeuvre is provided as supplementary material [1].

RAS have transformed many aspects of human lives and possess the potential of greatly revolutionising large-scale industries. Specifically, in agriculture, a reduction in available labour and arable land, with an increasing population, is threatening global food security [28, 30, 31] and the need for efficient RAS is more relevant than ever before. Apart from alleviating long-standing issues in the sector, RAS are expected to contribute more than $50 billion to global gross domestic product [32], helping in attracting a skilled workforce to an otherwise traditional field such as agriculture. As noted by Rose et al. [133], RAS offer many economic, social and cultural benefits to the agri-food sector. It is strongly believed that RAS capable of manipulating challenging TPs such as herbs and salads have many benefits for the agricultural workforce, which is what motivated the research presented in this thesis. Such systems can improve production efficiency, reduce human errors and free up the labour tied with mundane manual tasks. This additionally, provides an opportunity for upskilling, consequently improving the well-being and lifestyle of the agri-food workforce.

The main contributions of the thesis can be summarised as follows:

1. Intriguing insights from humans picking from a tangled TP bin are presented in chapter 2. These insights were obtained from a recordings of human pickers packaging herbs and salads in an industrial environment at a large supplier of fresh produce,

[1] The demonstration video can be found at youtu.be/QDrriGcwN-Y

specialising in watercress, herbs and salads. Using these insights, a human-inspired non-prehensile motion (spread) was identified for effectively reducing entanglement in a variety of TP bins. Overall, this work, being one of the first to study the largely unexplored task—robotic manipulation of tangle-prone TPs, plays an important role in bringing it to the attention of the robotics research community. Furthermore, challenges, considerations and assumptions generally necessary for working with TPs are highlighted such that future work can benefit from it in building robust RAS capable of efficiently manipulating a diverse range of TPs.

2. Chapter 3 provides an in-depth review of prior work. A review of the current state-of-the-art RAS in the agriculture sector highlights the gap in addressing all vital components of the ASC. It is observed that the majority of current RAS in the sector cater to the production activities (*e.g.,* land preparation, sowing and planting, harvesting) and other equally critical components such as packaging still do not tap into the full potential of such systems. Similar to insights from human pickers presented in chapter 2, a review of prior work dealing with robotic manipulation in clutter further highlights the advantages of human-like non-prehensile motions (*e.g.,* push, pull, spread) for effective manipulation of objects in highly stochastic scenarios.

3. Insights from natural sciences and robotic manipulation of non-tangling TPs presented in chapter 3 underline the importance of understanding the mechanics of TPs for efficient manipulation. To that end, experimental studies are presented in chapter 4 which demonstrate that protrusions play an important role in causing mechanical entanglement in a TP pile. It is also noted that the *ability to pack* and the *ability to entangle* are two indispensable factors to be considered while manipulating TPs. Results from the experiments involving TPs with varied PLs further demonstrate the usefulness of PL in developing generalised picking strategies for effectively countering entanglement.

4. Based on the insights from chapters 2 to 4, SnP, a novel entanglement reduction method applicable to a variety of TPs is proposed in chapter 5. Specifically, assisted by vision-based methods, it leverages human-inspired non-prehensile motion (spread) for *entanglement reduction* through *pile interaction*. Here, it is acknowledged that entanglement is unavoidable for TPs considered in this thesis. The aim instead is to reduce entanglement to a level where the picked mass is predictable. Robotic picking experiments with TPs (plastic herbs and staples) demonstrate the effectiveness of SnP in reducing the picked mass variance resulting from the en-

tanglement in a TP pile. Real herbs and salads are used in the final evaluation to assess the usability of SnP in a practical industrial application in Chapter 6. An industrial herb and salad picking task demonstrate the power of the proposed SnP approach in reducing error and improving picking consistency by tackling tangling in challenging TPs.

Overall, this thesis has studied the mechanics of a variety of TPs improving the understanding of the phenomenon of entanglement as observed in TP bins. Furthermore, based on intriguing insights from human pickers, a novel entanglement reduction method *i.e.,* SnP is proposed that effectively reduces the entanglement in a variety of TP bins. The primary approach has been to directly counter entanglement with an aim of reducing it to a level where the picked mass is predictable, instead of avoiding entanglement by picking from collision or entanglement-free points or regions. This is so because in the real world collision or entanglement-free scenarios are generally scarce. The proposed approach does not require estimating the degree of entanglement in the pile, is applicable for use with a variety of different hand mechanisms, including parallel, multi-finger and vacuum grippers and is unaffected by colour variation (that may occur between different plants).

6.1 Future Work

This thesis is one of the first few works that address the issue of object entanglement in TP bins in the context of robotic bin-picking. A number of potential improvements and future research directions are possible. Some of the feasible future extensions of this thesis are as follows:

– **Protrusions and PL:**
This work is one of the first few that explores robotic picking of tangle-prone piles in terms of protrusions and PL. Naturally, protrusions exist in a variety of ways and proposing a truly general geometric definition encompassing all natural and man-made objects with protrusions is non-trivial. However, it is acknowledged that a more general definition of terms such as protrusions and PL will bring further value to this research. Specifically, further analysis of objects with protrusions from a geometrical perspective could help in developing better picking strategies. Fractal geometry is a branch of mathematics that provides a general framework for the study of irregular sets or functions that cannot be described effectively using classical calculus. Roughly over a period of hundred years, the theory of fractal geometry has seen several advances and still continues to be a developing field. Today, fractal geometry has found applications in several areas of science and engineering,

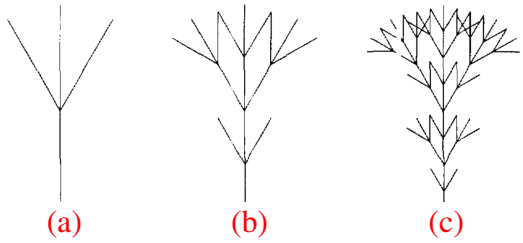

Figure 6.1: Modelling trees and plants using fractals. (a) 2nd, (b) 3rd and (c) 4th iterations [135].

including physics, digital imaging, computer graphics, computational geometry, geology and biology. Along with man-made objects such as networks, computer graphics and antennas, it also has been utilised to model complex natural phenomena such as plant growth, pattern formation, diffusion, lightning and turbulence. Fractal geometry has been shown of great use for modelling irregular and fragmented objects such as natural plants [134–137]. Figure 6.1 demonstrate the use of a certain type of fractal called L-systems for modelling trees and plants. Glenny et al. [138] studied the fractal geometry of bronchial trees in four different strains of laboratory mice to demonstrate that airway branching patterns are encoded within the DNA. Smith et al. [139] explore how neurons exploit fractal geometry to optimize their network connectivity. Husain et al. [140] leverage the concept of fractal geometry to measure the degree of geometric irregularity present in a coastline. Specifically, fractal geometry has proven to be useful when dealing with the class of geometrical objects called fractals where classical Euclidean Geometry is not enough to describe their complex nature. However, since its inception, the field of fractal geometry has gone through several iterations and a purely mathematical definition of fractals is still at the centre of research in this area [141, 142]. Future work may consider fractal geometry to simulate tangle-prone materials such as herbs, facilitating a more robust mathematical representation, specifically in the context of a one-shot mass-constrained robotic bin-picking task.

– **Learning to drop:** SnP enables the robot to reduce the entanglement and in turn improves the picking consistency by directly interacting with the herb pile. However, it is acknowledged that entanglement is unavoidable for the plant material considered in this study and some extra mass is still expected to be picked. A more efficient approach could be employing a hybrid method where SnP is used along with a dropping strategy. Specifically, in the first step SnP can be utilised to reduce pile entanglement. This assists in separating the target bunch from the rest of the pile. In the second step, a dropping strategy is used to drop any extra mass. Figure 6.2(a)

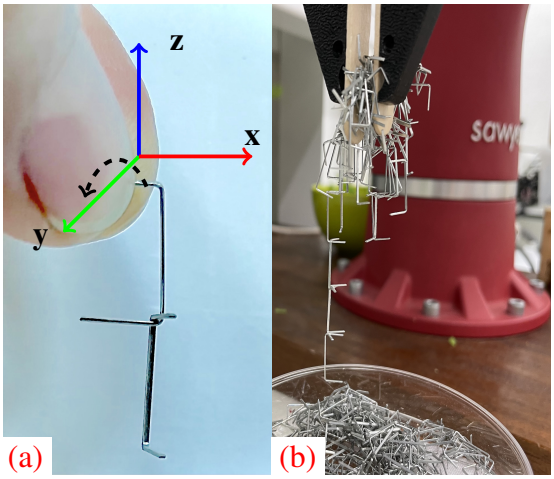

Figure 6.2: Entanglement leads to extra mass being picked for bins composed of TPs such as staples.(a) When the objective is to pick one staple, an anti-clockwise rotation (dashed black line) along the y-axis can drop the extra staple. (b) However, identifying a dropping strategy to be able to drop more than one staple in a controlled manner is non-trivial.

demonstrates a simple dropping strategy for two tangled staples. As can be seen, an anti-clockwise rotation along the y-axis could help in dropping the extra undesired staple. Methods that extend this behaviour to multiple staples (see Figure 6.2(b)) can help in dropping the undesired extra mass picked because of the inherent pile entanglement. Specifically, a taxonomy of primitive dropping movements can be identified. These movements can then be used in combination to drop any undesired extra mass. Additionally, future work may consider other relevant in-hand strategies to drop the extra mass without repeating the pick or using non-standard hand mechanisms.

– **Ability to pack and entangle:** Picking experiments involving TPs with varied PLs highlight the significance of the ability of a TP to pack and entangle, especially considering a one-shot mass-constrained robotic bin-picking task. Considering the ability to entangle independently from the ability to pack, it is intuitive to expect the overall degree of entanglement in the pile to increase as the contact surface area increases *i.e.,* PL increases. However, the results from the experiments reported in section 4.4 demonstrate the picked mass variance decreases for PL $l > 10\,\text{mm}$, suggesting a decrease in pile entanglement. This suggests that the ability to pack, a property unique to the TPs, plays a salient role in offsetting the effect of increasing PL (see Figure 6.3). Specifically, the interplay between packing and entanglement in a TP gives rise to observed non-monotonic behaviour. A concrete representation of the ability to pack and the ability to entangle could aid in developing a better

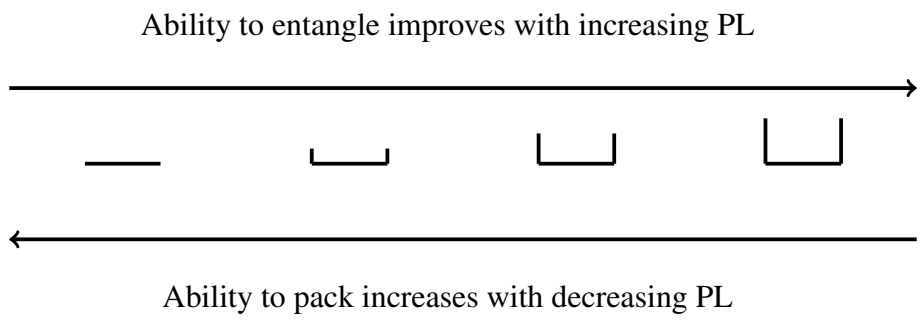

Figure 6.3: Interplay between the ability to pack and the ability to entangle in a TP (staple) pile.

understanding of the relationship between them, providing further insights into the phenomenon of entanglement in a TP pile.

- **Picking skill representations:** In the industrial setting, the picking task is typically specified in terms of a target mass so it is necessary to find a way to translate the training data into the required gripper aperture. It should be noted, however, that the chosen model should be monotonic for to be inverted. For simplicity, the training data collected from the picking experiments conducted in this thesis is used to fit a simple linear relationship between the gripper aperture and the target mass. However, other representations (*e.g.,* non-linear) remain to be explored. Future work could explore other relevant picking skill representations, especially considering notable factors such as the ability to pack and the ability to entangle.

- **PL and SnP:** This research demonstrate the significance of protrusions and PL in the context of a one-shot mass-constrained robotic bin-picking task. The effect of PL on the overall degree of entanglement in a TP pile offers a variety of useful insights for developing RAS that can counter object entanglement in a pile. However, one of the main limitations of this work is that it does not incorporate PLs in the proposed entanglement reduction method *i.e.,* SnP. Instead of spreading fully for all TPs, PL information could be employed to spread efficiently, improving performance and cycle time. Future work could explore the effect of spreading on TPs with different PLs to further improve the efficacy and cycle time of the proposed method.

- **Hardware limitations:** The experimental set up is a mock-up of the packaging workstation of a large fresh herbs and salads producer equipped with a robotic manipulator. As the robotic platform, a 7-degree of freedom (DoF) Rethink Robotics Sawyer is used, with a maximum reach of ± 1260 mm and precision of 0.1 mm. A two arm system could be considered in the future as a comparison with a one arm

system utilised in this research. The robot is equipped with a parallel gripper from Actobotics (product code: 637092) as its end-effector. The latter has maximum opening aperture of $w = 71.12\,\text{mm}$ and is controlled using a Hitec HS-422 Servo Motor with operating voltage range 4.8 V-6.0 V. Other efficient design of grippers such as multi-finger grippers could potentially improve the performance, usability and accuracy of the presented system. As the vision module, the platform uses an Intel realsense d435i depth camera recording depth data at a frequency of 15 Hz. Although robust, realsense d435i is a research-grade camera and is affected by lighting conditions. Use of industrial grade depth cameras can further increase the performance of the proposed method.

– **Picking without replacement:** In this thesis, experiments involving repeated robotic picking from bins composed of TP are conducted. After each pick, the picked mass is dropped or replaced back in the pile. However, in the real world, picking from a bin without replacement—picking until the bin is empty, is frequently encountered. It would be beneficial to move a little closer to the real-world scenario of picking *without replacement*.

– **Neuromuscular control and skill learning:** As discussed, in chapter 2, the ability of human hands and fingers to work in synergy makes humans capable of achieving non-trivial objectives with relative ease and high precision. Neuro-motor control such as reaching and pointing movement with arms has been the focus of several studies from the computational neuroscience community [143]. In recent years, computational neuroscience has become a crucial constituent in neurobiological research. The computational neurobiology of *untangling* is also an interesting avenue to study various techniques used by humans, especially when manipulating a tangle-prone media such as a pile of herbs or salads using just one hand. Future work could look into developing a better understanding of how humans learn untangling skills, forming new theories of neuromuscular control and skill learning.

Appendix A

List of Publications

Conferences

1. Ray, P., Howard, M. J., (2020). Robotic Untangling of Herbs with Parallel Grippers. UKRAS20 Conference: “Robots into the real world” Proceedings, 137-139. doi: 10.31256/Wd8Aj7K.

2. P. Ray and M. J. Howard, "Robotic Untangling of Herbs and Salads with Parallel Grippers," 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2020, pp. 2624-2629, doi: 10.1109/IROS45743.2020.9342536.

Appendix B

Data and Software

Data

1. The data supporting this research are openly available from the King's College London research data repository, KORDS, at https://doi.org/10.18742/19977779.

Software

1. The software supporting this research are openly available from the King's College London Robot Learning Lab, RLL, at https://github.kcl.ac.uk/RLL/Spread-and-Pick.

Further information about the data and conditions of access can be found by emailing research.data@kcl.ac.uk

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