Robotic Untangling of Herbs and Salads with Parallel Grippers

Prabhakar Ray[1*] & Matthew J. Howard

***Abstract*— Robotic packaging of fresh leafy produce such as herbs and salads generally involves picking out a target mass from a pile or crate of plant material. Typically, for low-complexity parallel grippers, the weight picked can be controlled by varying the opening aperture. However, often individual strands of plant material get entangled with each other, causing more to be picked out than desired. This paper presents a simple *spread-and-pick* approach that significantly reduces the degree of entanglement in a herb pile when picking. Compared to the traditional approach of picking from an entanglement-free point in the pile, the proposed approach results in a decrease of up to 29.06% of the variance in for separate homogeneous piles of fresh herbs. Moreover, it shows good generalisation with up to 55.53% decrease in picked weight variance for herbs previously unseen by the system.**

I. Introduction

Industries manufacturing machinery, transportation equipment and various everyday retail products on a large scale have benefited immensely from intelligent and collaborative assembly-line robots. However, to date, the application of such technologies to the processing of fresh horticultural produce remains mostly dependent on manual labour. The suppliers of fresh herbs and salads, for instance, grow stock under glass or in fields and then must transport them to packaging stations and pack them as per the weight requirements of retailers. The manual packaging process involved is not only costly in terms of labour, but also suffers from human errors and low production efficiency.

A more scalable approach could be automation through adaptive robotic systems, 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 Fig. 1(a)), making it difficult for a robotic system to extract a uniform quantity suitable for supply to the consumer. 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, that adversely affects both shelf-life and appearance).

In the past, the entanglement between objects in a pile or a bin has been addressed through physical interaction [1], [2]. However, existing methods do not consider the case of singulating and picking multiple objects under external constraints such as weight. Moreover, often picking approaches rely on detailed models (*e.g.,* from CAD) of the objects in the bin. Acquiring such models when the objects in question are leafy herbs and salads is highly challenging. Vision-based methods have also been explored [3], however, their iterative nature adds to the cycle time, which is not favourable in an industrial setting.

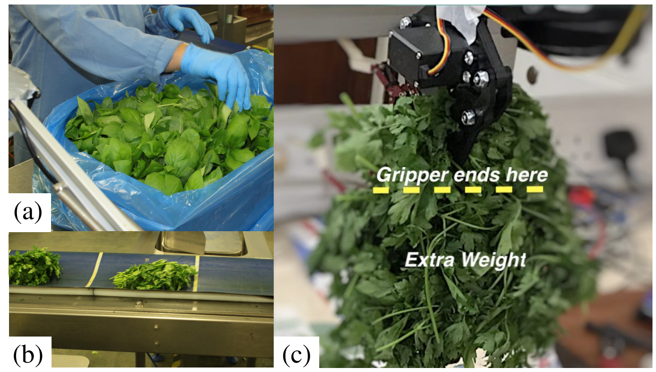

Fig. 1: Handling fresh salads and herbs. (a) Plant material enters the packaging centre as a tangled mass in crates or boxes. (b) Smaller, fixed-mass portions must be extracted and fed via conveyor belt for packaging. (c) Tangling makes the mass lifted in a simple pick operation difficult to predict.

As an alternative, this paper proposes a *spread-and-pick* method, which reduces entanglement in the herb pile, and in turn makes the pick operation more predictable in terms of the picked-up weight. The proposed method has the benefit that it does not require any large scale data collection and does not depend on the prior availability of any geometrical information. Experiments are reported in which a 7-degree of freedom (DoF) robot equipped with a parallel gripper is used for picking herbs and a significant reduction in the variance of weight picked among the trials is seen. Moreover, picking trials on herbs previously unseen by the system show good generalisation. Overall, the results suggest that the proposed method could be an effective solution for manipulating a variety of these challenging materials in food production.

II. Related Work

The picking of (individual, rigid) objects from containers is frequently termed as the *bin-picking problem* and has a long history in the robotic automation literature. Traditionally, researchers have studied bin-picking in the context of two main challenges: (i) *gripper-object collision* and (ii) *object entanglement*. The issue of gripper-object collision

[1]Prabhakar Ray and Matthew J. Howard are with the Centre for Robotics Research, Department of Engineering, King's College London, London, UK. prabhakar.ray@kcl.ac.uk

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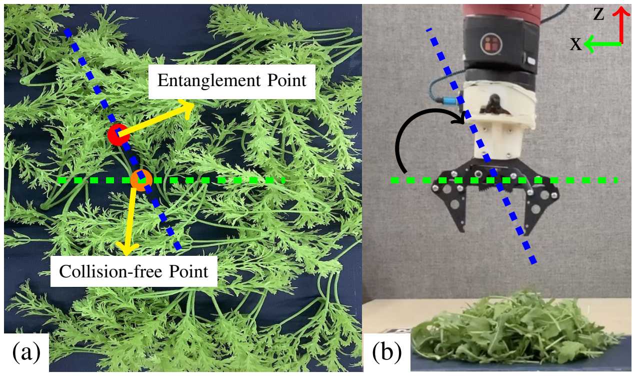

Fig. 2: Overview of the proposed *spread-and-pick* approach. (a) Top view of the pile. (b) Front view showing the gripper. The dashed green line represents the initial orientation of the x-axis of the gripper. The dashed blue line represents the *line of entanglement*. The black curved arrow represents the direction of rotation. Once the collision-free and entanglement points are identified, the gripper is rotated around the z-axis such that it aligns with the line of entanglement.

has received much more attention than object entanglement. In regard to (i), most methods rely either on geometrical information of the objects or a vision-based module. The advent of efficient cameras has resulted in increased popularity of vision-based methods.

Taylor *et al.* [4] propose using simple geometric primitives such as planes, spheres, cylinders and cones for object recognition in the bin. Changes in surface types and depth discontinuities are then used to segment the cluttered scene. A vision-based algorithm is proposed in [5], to resolve gripper-object collision by identifying and picking the topmost object in a pile. Schwarz *et al.* [6] propose a deep learning-based approach for picking individual objects from a cluttered bin. These methods prove effective for avoiding gripper-object collision. However, they do not address the issue of potential entanglement of objects.

Kaipa *et al.* [7] use CAD models for planning singulation of individual objects from a heterogeneous pile. A human-robot collaboration approach is proposed in [8] for dealing with grasping errors due to issues such as object occlusion and random object posture in a bin, including object entanglement. Although the latter considers the issue of entanglement directly, the objective is the singulation of a single rigid individual object, rather than extracting a uniform quantity of material, as considered in this paper.

Recently, Schenck *et al.* [9] explore the manipulation of a granular media, specifically pinto beans, with the aim of extracting a small quantity from a bigger pile and dropping it into a container. However, as pinto beans do not tangle, the issue of picking excess mass due to entanglement—as considered here—was not encountered.

In terms of objective, perhaps the closest work to the present study is that of Kuriyama *et al.* [10] in which the design of a soft pneumatic gripper is presented for packaging chopped food materials such as green onion. The authors report that although the amount (weight) of material picked using the gripper can be controlled by varying the insertion depth, the variation among trials is significant—likely due to the effect of tangling.

Finally, Matsumura *et al.* [11] 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 weight is predictable.

III. Method

Severe entanglement in the herb pile causes the picked weight to be highly variable for any given grasping strategy. Although some level of tangling is unavoidable in the plant material considered, the primary aim of the present work is to reduce the variability of picking through a *spread-and-pick* strategy. Fig. 2 illustrates how the proposed approach works. In the first step, the location of a *collision-free point* is estimated from an image of the grasping scene as a picking location. 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 weight 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 weight is separated from the rest of the pile.

A. Collision-free Gripper Pose: Graspability Index

The graspability index (GI) [12] is 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. 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 grayscale image are needed to process the scene. It should be noted, however, that this 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 $\mathbf{r} = (r_x, r_y, r_\theta)^\top$ in the bin such that the parallel plates of the gripper could be inserted without colliding with the objects inside (where r_θ denotes the orientation of the gripper around its z-axis). 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.

Fig. 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 Fig. 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

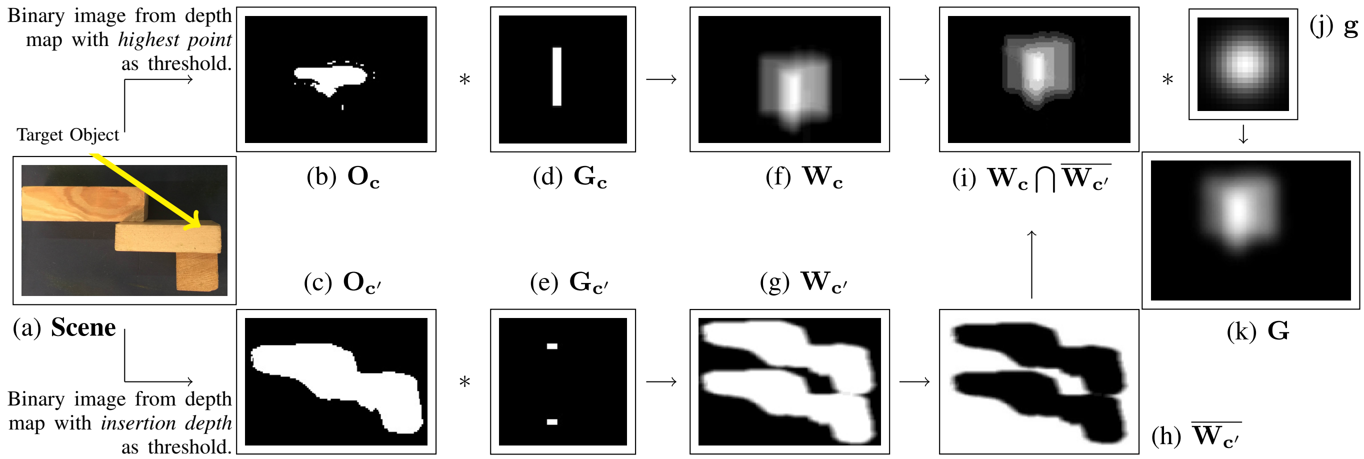

Fig. 3: Estimating the grasping position (r_x, r_y) using graspability index for gripper rotation $r_\theta = 90°$. The scene contains three wooden blocks. In this example, the highest object (middle block) is the target object and the insertion depth r_z is set such that the tips of the gripper just touch the surface of the table. The collision-free pick-up point (r_x^*, r_y^*) is estimated from the peak of the graspability map $\mathbf{G}$.

the depth map by the *height of the target object* (middle block in Fig. 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 Fig. 3(c)). $\mathbf{G_c}$ and $\mathbf{G_{c'}}$ (see Fig. 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 (Fig. 3(f)) is computed through the convolution[1]

$$\mathbf{W_c} = \mathbf{O_c} * \mathbf{G_c}. \tag{1}$$

Similarly, the region where the gripper plates could collide with the objects in the pile is obtained as (see Fig. 3(g))

$$\mathbf{W_{c'}} = \mathbf{O_{c'}} * \mathbf{G_{c'}}. \tag{2}$$

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 Fig. 3(i)). Finally, using a Gaussian $\mathbf{g}$ (see Fig. 3(j)), the graspability map $\mathbf{G}$ is computed as

$$\mathbf{G} = (\mathbf{W_c} \cap \overline{\mathbf{W_{c'}}}) * \mathbf{g}. \tag{3}$$

Convolution with a Gaussian $\mathbf{g}$ 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

$$f(x, y, r_\theta) = \begin{cases} (\mathbf{G})_{xy}, & \text{if } (\mathbf{W_{c'}})_{xy}{=}0 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

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

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 $r_\theta{}^*$ is set to the the gripper orientation for which the peak could be determined in $\mathbf{G}$ yielding the picking position

$$\mathbf{r}^* = (r_x^*, r_y^*)^\top = \underset{x,y}{\operatorname{argmax}}\, f(x, y, r_\theta{}^*). \tag{5}$$

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 herbs, experience tells that this frequently occurs resulting in more than the desired weight being picked (see Fig. 1(c)). In the next section, a strategy is proposed for *reducing tangling during the pick operation* to help alleviate this problem.

B. Tangle Reduction

To reduce the level of tangling and thereby achieve more consistent picking, this paper proposes a *spread-and-pick* 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, $\mathbf{G_{c'}}$ is used to obtain $\mathbf{W_{c'}}$, the region that represents gripper-object collision. $\mathbf{W_{c'}}$ is then used to identify the region of entanglement

$$\mathbf{G'} = \mathbf{W_{c'}} * \mathbf{g}. \tag{6}$$

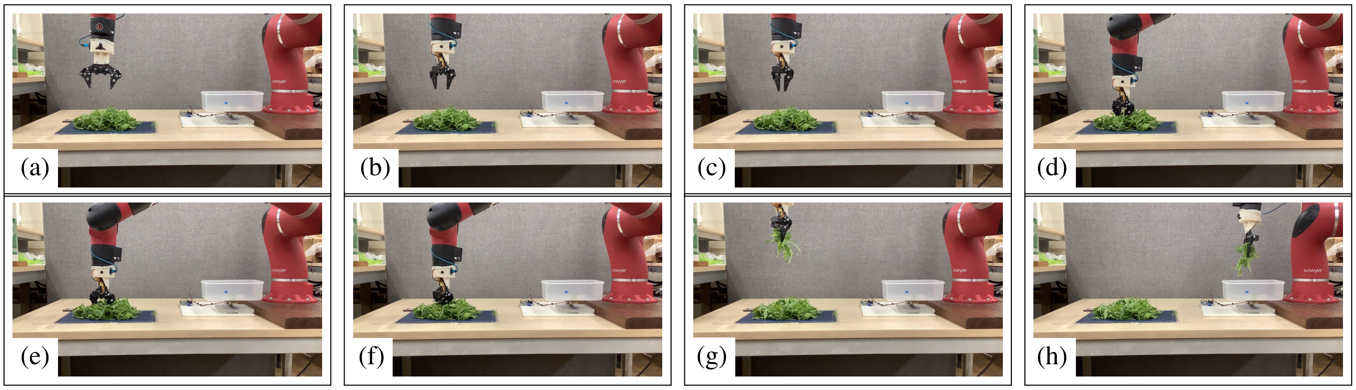

Fig. 4: Time lapse illustrating *spread-and-pick* approach. (a) Robot reaches a fixed point above the pile. (b) Gripper orientation adjusted to align with *line of peak entanglement*. (c) Gripper aperture set to chosen width. (d) Gripper moved into herb pile to pick from the optimal collision-free point 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 weight.

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

$$\mathbf{r}' = ({r_x}', {r_y}')^\top = \underset{x,y}{\operatorname{argmax}}\, h(x, y) \tag{7}$$

where

$$h(x, y) = \begin{cases} (\mathbf{G}')_{xy}, & \text{if } (\mathbf{W}_{\mathbf{c}'})_{xy}{=}1 \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

The *line of peak entanglement* is then defined as that intersecting $\mathbf{r}'$ and $\mathbf{r}^*$. 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. Fig. 4 illustrates the working of the robot while following the *spread-and-pick* approach. Please refer to the supplementary video to see the robot in operation.

IV. Experiments

In this section, the proposed *spread-and-pick* method is evaluated with respect to its efficacy in improving picking accuracy and consistency in an industrial herb and salad picking task. The experimental procedure is as follows [2].

A. Procedure

The experimental set up is a mock-up of the herb-packing workstation of a large fresh herbs and salads producer equipped with a robotic manipulator (see Fig. 5). As the robotic platform, a 7-DoF Rethink Robotics Sawyer is used, with a maximum reach of $\pm 1260\,\mathrm{mm}$ and precision of $0.1\,\mathrm{mm}$. The robot is equipped with a parallel gripper from Actobotics as its end-effector. The latter has maximum opening aperture of $w = 71.12\,\mathrm{mm}$ and is controlled using a Hitec HS-422 Servo Motor with operating voltage range $4.8\,\mathrm{V}$-$6.0\,\mathrm{V}$. 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's position is chosen such that its field of view exactly covers the picking area and it records depth data at a frequency of $15\,\mathrm{Hz}$. During the experiment, the main herb pile is located in the picking area of dimension $(30\,\mathrm{cm}$ x $25\,\mathrm{cm})$. The weight picked is recorded using a parallel beam type load cell with a combined error of $\pm 0.05\%$ and maximum weighing capacity of $10\,\mathrm{kg}$. A HX711 amplifier combined with an Arduino microcontroller is used for data acquisition from the load cell.

Using this set up, a series of robotic picking operations are conducted. Each picking operation consists of the robot reaching into a pile of tangled plant material (herbs or salad leaves) of fixed mass, closing its gripper, and lifting what is grasped free of the surface. More specifically, in each pick, the gripper orientation is initialised to $\theta_z = 90^\circ$ 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 weight. For simplicity and lower cycle-time, only 3-DoF of the robot are used for picking movements and the highest point in the pile is chosen as the target picking location. 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 $18\,\mathrm{cm} \times 13.5\,\mathrm{cm} \times 7\,\mathrm{cm}$ container before being returned to the picking area for the next pick. The results reported below include experiments on batches of (i) plastic and (ii) real herbs and salads (wild rocket and parsley)(see Fig. 6). The use of plastic herbs enables the effectiveness of the proposed approach to be assessed without spurious effects arising from natural variations in the herbs, or changes in their physical properties (*e.g.,* due to plant material drying out, or becoming damaged over successive picks). When using real plant material, for each method and each w, a fresh batch of

[2]The data supporting this research are openly available from King's College London at `https://doi.org/10.6084/m9.figshare.12685883.v1`. Further information about the data and conditions of access can be found by emailing `research.data@kcl.ac.uk`

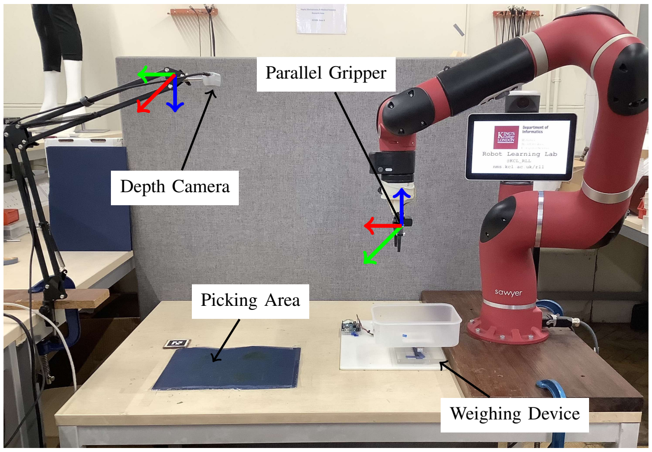

Fig. 5: Overview of the experimental set up. Red, green and blue arrows represent x-, y- and z-axes, respectively. The coordinate frame attached to the robot is used as the frame of reference.

herbs or salad leaves is used to try to minimise such effects.

In the industrial setting, the picking task is typically specified in terms of a target weight m_t so it is necessary to find a way to translate this into the gripper aperture required. In the experiments reported here, a simple calibration procedure is used. Specifically, for each type of plant material used, and each picking approach considered, picking is conducted 20 times for $w \in \{20, 30, 40, 50, 60\}\text{mm}$ for plastic herbs and 10 times for $w \in \{20, 30, 40\}\text{mm}$ for real herbs. The resultant data is used to fit a simple linear relationship

$$m = N(w) \tag{9}$$

between the gripper aperture width w and weight picked m that is then inverted to provide an estimate of the required gripper width for target weight m_t

$$w = N^{-1}(m_t). \tag{10}$$

To evaluate performance, the accuracy and consistency of picking when using the proposed *spread-and-pick* approach is measured for a series of target weights. In particular, 20 trials of picking are conducted for $m_t \in \{8, 10, 12\}$ for plastic herbs and 10 trials of picking for $m_t \in \{15, 20\}$ for real herbs, and the mean and standard deviation of the weight picked is recorded. For comparison, the experiment is also repeated using standard GI-based picking, where the experimental procedure is identical with the exception that the spreading movement is not performed during the picking operation.

B. Results & Discussion

Table I reports the weight picked for plastic herbs for the GI and *spread-and-pick* approaches. It is observed that for the proposed method, the standard deviation of the picked-up weight is smaller for the proposed approach. The maximum percentage decrease in standard deviation is 61.71% in the case of plastic herbs.

TABLE I: Picked weight of plastic herbs (mean±s.d. over 20 trials) for different target weights.

Target Weight(g)	Method	Picked Weight(g)
8	Graspability Index	4.832±5.013
	Spread and Pick	8.318±4.681
10	Graspability Index	8.791±9.176
	Spread and Pick	7.228±3.514
12	Graspability Index	12.621±9.307
	Spread and Pick	10.523±5.907

Table II shows the result of picking for a pile of wild rocket. Similar to plastic herbs, a decrease in the standard deviation of the picked-up weight is observed for the proposed *spread-and-pick* approach up to a maximum 29.06% decrease. This suggests that the proposed approach is successful in reducing tangling in both real and plastic plant material.

To test the robustness of this result, a further experiment was conducted in which the picking model for wild rocket is applied for picking material from a different plant, namely, flat-leaf parsley. Table III provides the mean and standard deviation of the picked weight for parsley using the model derived for wild rocket. As can be seen, the standard deviation of the picked weight is again lower for the proposed approach compared to the GI-based approach for all target weights considered, with a maximum decrease of 55.53% observed.

A decrease in the standard deviation of the picked weight suggests that the proposed *spread-and-pick* approach effectively improves the consistency and predictability of picking for a variety of herbs and salads. In comparison with the plastic herbs, the observed percentage decrease for real herbs and salads is lower. 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 in case of real herbs and salads, occasionally the gripper plates could not open completely due to this tangling. 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. In terms of mean picked weight, surprisingly, the wild rocket least squares model performs better on parsley for both GI and *spread-and-pick* methods despite being fit on picking data from a different plant (see Table II and III). This behaviour is attributed to variability in the physical properties of wild rocket and parsley. The presence of transverse ends leads to mechanical entanglement in a pile and longer the length of these transverse ends, the higher is the degree of entanglement [13]. The leaves extending out from the stem of a herb strand could be considered equivalent to these transverse ends (see Fig. 7), and in the case of parsley, as the leaves extend out to a greater length, a higher degree of entanglement is expected and hence a greater amount is picked up than that which can fit between the plates of the gripper causing the mean picked weight to be closer to the target weight.

TABLE II: Picked weight of wild rocket (mean±s.d. over 10 trials) for different target weights.

Target Weight(g)	Method	Picked Weight(g)
15	Graspability Index	9.434±3.937
	Spread and Pick	10.033±2.793
20	Graspability Index	14.137±6.274
	Spread and Pick	15.799±4.819

TABLE III: Picked weight of flat-leaf parsley (mean±s.d. over 10 trials) for different target weights. Gripper widths w are estimated using the wild rocket least squares model.

Target Weight(g)	Method	Picked Weight(g)
15	Graspability Index	14.250±8.944
	Spread and Pick	12.228±7.064
20	Graspability Index	15.921±8.886
	Spread and Pick	17.893±3.951

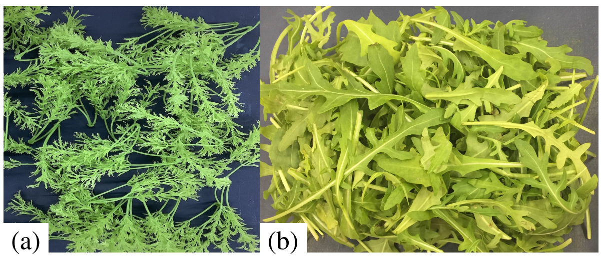

Fig. 6: Separate homogeneous piles used in experiments, composed of (a) plastic and (b) real herbs.

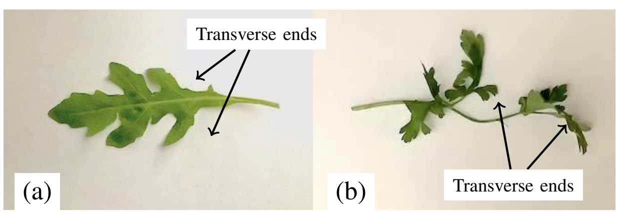

Fig. 7: Sample strands of (a) wild rocket and (b) parsley showing the difference in the transverse ends.

V. Conclusion

In this paper, a method for countering the unpredictable nature of picking tangle-prone materials such as fresh herbs and salads is described. The proposed method augments the normal picking operation with a spreading manoeuvre, specifically aimed at reducing the entanglement and thereby enhancing the consistency of picking a desired weight of material. The method does not require any large scale data collection and is effectual in the absence of 3D object models.

The effectiveness of the approach has been demonstrated through picking operations involving a physical robot and homogeneous tangle-prone piles composed of real herbs including (i) wild rocket and (ii) flat-leaf parsley.

Future work will further explore ways of reducing entanglement and quantifying the performance of *spread-and-pick* in an industrial setting. Estimating the line of entanglement for a range of initial gripper orientations could improve the performance of *spread-and-pick* approach. It would also be beneficial to move a little closer to the real-world scenario of picking *without replacement*. Moreover, 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.

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