POPs: Pluck Out the Petals

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***Abstract*—In this work, we present a method for precisely segmenting individual petals within flower images. Petal segmentation is challenging due to its intricate structures and substantial variations among petals across diverse flower species. Moreover, frequent occlusions and the uniformity in appearance and shape of petals within a single flower add complexity to the segmentation process, making it error-prone. We introduce a generalized approach to segment petal instances for any flower species. We first detect contours for the outermost set of petals and segment them out from the Corolla. We iteratively repeat this process until we reach the floral centre. To this end, we developed a robust contour detection technique and employed a prompt-based segmentation model for petal segmentation. Our results demonstrate the effectiveness of prompts generated by our approach in facilitating efficient petal segmentation. Additionally, we have developed a manual supervision tool, FloraSeg, tailored for segmenting petals in cases where flowers exhibit many petals with complex geometries. Our experiments demonstrate that the fully automatic segmentation method achieves results comparable to those obtained through manual human annotation. Additionally, incorporating a few manual cues from the FloraSeg tool into our approach consistently yields precise petal segmentation, aligning closely with manually annotated outcomes. We present results from a wide range of flower species to emphasize the effectiveness of the proposed approach in the petal segmentation task. This work has significant applications in developmental biology, particularly in advancing our understanding of flower development and conducting structural phenotyping of flowers.**

I. Introduction

Modelling flowers is a challenging task in the field of computer vision and graphics due to their complex geometry and diverse appearance. The primary challenge in flower modelling arises from the frequent occlusion among petals. The closely packed arrangement of visually similar flower petals poses a challenge in segmenting them individually. Petal segmentation is essential as it offers valuable insights into their geometries, significantly aiding in modelling the overall geometry and appearance of the entire flower. In this work, we present a method for precisely segmenting individual petals given an image containing a flower. We also estimate other important geometrical attributes associated with flower structure.

In the fields of computer vision and graphics related to flowers, we observe that the predominant emphasis has been on the detection and segmentation of entire flowers. Petal segmentation, on the other hand, has received considerably less attention. The absence of annotated datasets for petal segmentation poses a barrier to supervised learning. Our approach seeks to address this gap in research by focusing on the challenge of petal segmentation, leveraging both geometric and visual aspects of individual petals in flowers. To this end, we automate the existing interactive class-agnostic segmentation model through the implementation of our proposed **PoPs Algorithm**, which stands for Pluck out the Petals. Our systematic approach involves the iterative extraction of individual flower petals, initiating from the outermost blossomed layer and progressing towards the floral centre. Depending on various factors discussed later, the proposed fully automated approach may result in noisy outputs. As a solution, we have developed a tool called **FloraSeg** designed to facilitate manual intervention, ultimately leading to precise petal segmentation.

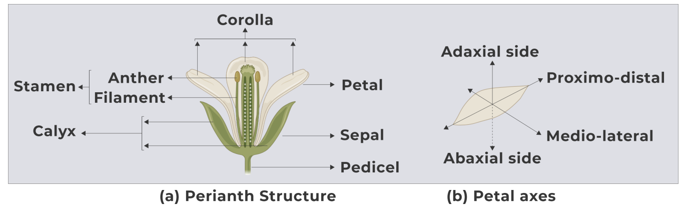

Fig. 1. Essential biological terminology relevant to flower anatomy. In (a), major components contributing to flower structure are depicted, and in (b), geometric aspects related to individual petals or sepals are illustrated.

To the author's knowledge, this paper is the first to introduce a generalized approach for petal segmentation across diverse flower species. The key contributions of our work are:

- We present **POPs**, an iterative method to segment individual flower petals, starting from the outermost blossomed layer towards the inner-most.
- We introduce an interactive tool named **FloraSeg**, which facilitates manual supervision in conjunction with **POPs**, thereby enhancing the petal segmentation process.

II. Related Work

Interactive Segmentation. Object segmentation is a well-studied and highly-researched area in computer vision. Numerous studies have explored different aspects of segmentation, including interactive segmentation [15], [9], [21], Edge detection [1], Semantic Segmentation [16], [3], [25], Panoptic Segmentation [8], [24], [4], etc. Most current approaches typically employ cross-entropy loss or its variants in training deep neural networks, which constrains the model to a predefined number of classes. Several class-agnostic methods, such as [10], [22], have been introduced to overcome these limitations. However, the effectiveness of these approaches is closely tied to the training data they rely on.

Flower Detection and Segmentation. Numerous studies have explored the segmentation and detection of complete flowers within a given image. For flower detection, [5], [11] utilize fine-tuning of existing object detection baselines such as [7], [19]. In the case of bi-level co-segmentation, as introduced

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in [2], foreground extraction relies on using the conventional GrabCut technique [15]. In more recent works, such as [17], [18], the focus has shifted to the detection and segmentation of specific flower species, namely, Apples, Grapes, and Roses, respectively. These methods leverage deep neural architectures for their tasks.

Petal Detection and Segmentation. While there has been prior research on segmenting entire flowers in the given image, relatively limited attention has been devoted to segmenting individual petals. It's important to note that the petal detection method proposed in [13] encounters challenges when dealing with flowers containing many petals or occlusions. As petal segmentation yields significant geometric and textural information essential for 3D flower modelling, [23] takes a manual approach by specifying the central positions of each petal as initialization to guide the segmentation process. However, their data-driven petal modelling approach utilizes 3D information and leverages known depth information to enhance petal segmentation.

III. Methodology

A. Background

Vividly coloured flowers have evolved to attract animal pollinators, primarily insects and birds, as outlined in [20]. A flower is primarily composed of multiple petals and sepals. Petals of flowers exhibit a diverse range of colours, shapes, and sizes, usually forming a circular or whorled pattern around the flower's reproductive centre. In contrast, sepals are primarily found when the flower is in bud form and has not yet fully opened. As the flower fully blooms, sepals often retract away from the centre, revealing the petals and the reproductive structures within. This is depicted in Figure 1(a). These components collectively contribute to the flower's structure and function. The collection of all petals is called Corolla, and the collection of all sepals is called Calyx. In some cases, petals and sepals exhibit similar appearances, leading to the term tepal used to describe these indistinguishable floral parts. The orientation of a petal, extending from the base (proximal) to the tip (distal), is referred to as the Proximal-distal axis. Likewise, the axis from the centre (medial) to the side (lateral) is termed the Mediolateral axis of the petal. The terms Adaxial and Abaxial denote the upper and lower surfaces of the petal, respectively. Figure 1(b) illustrates these axes.

B. Approach

Our approach consists of two key modules: Iterative Petal Segmentation using the POPs Algorithm and Manual Supervision utilizing the FloraSeg tool.

1) Pluck Out Petals (POPs) Algorithm: We propose a fully automatic approach to segment petals given a flower image. The POPs algorithm employs an iterative strategy to segment the outermost layer of petals, progressively moving towards the floral centre, as illustrated in Figure 3.

Foreground Extraction. Given that our primary goal is petal segmentation, we assume that flower detection and segmentation have already been performed on the provided image. Assuming that the input image contains a well-focused flower, we streamline the entire flower segmentation using depth thresholding on a depth map obtained by a pre-trained MiDas network [14]. Depending on the specific input image, appropriately applying depth thresholding with $\mathcal{D}_\tau$ yields the necessary foreground mask, where the foreground corresponds to the flower for petal segmentation. For challenging images, our tool **FloraSeg**, integrated with Segment Anything [9], provides the necessary mask through manual prompts provided via mouse input. This manual intervention ensures the accurate segmentation required for the task. Figure 3 illustrates the foreground extraction process.

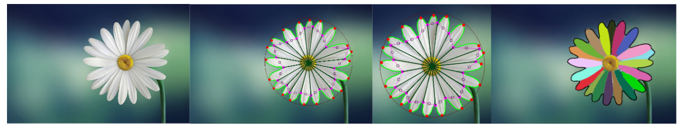

Fig. 2. For an input flower image (a), our approach generates curated prompts (b) for precise petal segmentation (c). The POPs algorithm accurately places a point on each petal, specifically at the centre along the line connecting the valley points. This identified point acts as a prompt, guiding the segmentation of the respective petals. In conjunction with Figure 3, we show the output of our algorithm on a Bellis perennis flower (Common Daisy).

Contour Detection and Refinement. Given an image $\mathcal{I}$ and a mask $\mathcal{M}$ that defines the flower region (where $\mathcal{M}$ equals 1 for the flower region and 0 for the background), we first identify all the pixels that collectively constitute the largest possible contour, denoted as $\mathcal{X}$, on the mask. We then perform curve-fitting on the pixel set $\mathcal{X}$ yielding a closed curve equation denoted as $\mathcal{C}$ employing [6]. Subsequently, we calculate a set of N equidistant points along the curve $\mathcal{C}$ such that the spacing between any two consecutive points $n \in N$ is uniform. To enhance the smoothness of the curve $\mathcal{C}$, we apply a smoothing operation using Gaussian weighting. This operation considers $2n$ neighbours of the i-th point, as detailed in Equation 1.

$$C_{\mathrm{s}}(i) = \frac{\sum_{j=i-n}^{i+n} w(j) \cdot C(j)}{\sum_{j=i-n}^{i+n} w(j)} \tag{1}$$

Here, $w(j) = e^{-\frac{(j-i)^2}{2r^2}}$, and parameter r, governs extent of smoothing. The identified curve corresponds to the outermost-blossomed layer of the flower, as illustrated by a light green outline in Figure 2(b). The local extremes along this curve represent a petal's tip or valley.

Automatic Prompt Generation. Given the curve C_s composed of N points, we identify all possible local extrema $\mathcal{E} = \mathcal{T} \cup \mathcal{V}$, which is a collection of all maxima points $\mathcal{T}$ and minima $\mathcal{V}$ on the curve C_s. We first estimate curvature $\mathcal{K}$ for the closed curve C_s, such that $\kappa_i \in \mathcal{K}$ is the curvature of i-th point on curve C_s. The set of all local maxima constitutes the tip (distal) points of the petals and is represented as $\mathcal{T} = \{(x_i, y_i) \mid \kappa_i > \kappa_{i-1} \text{ and } \kappa_i > \kappa_{i+1}\}$. Similarly, we calculate all the local minima points constituting the valleys of the petals, $\mathcal{V} = \{(x_i, y_i) \mid \kappa_i < \kappa_{i-1} \text{ and } \kappa_i < \kappa_{i+1}\}$. We then filter the obtained extrema with a curvature prominence

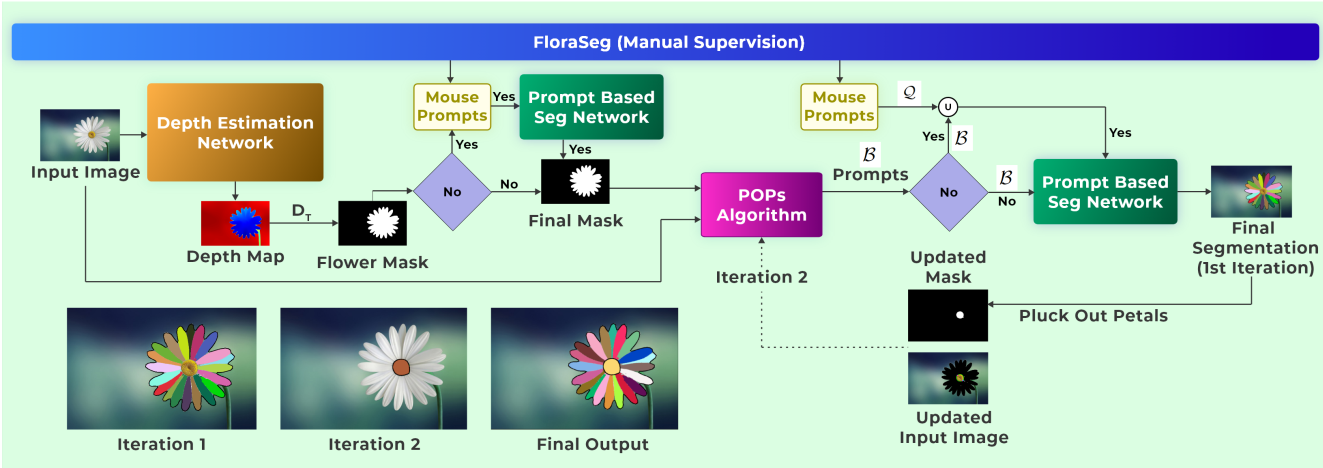

Fig. 3. Overview of the proposed approach: Initially, we achieve binary segmentation by applying depth-map thresholding to the input image, with the foreground representing the flower region. We estimate monocular depth using a pre-trained MiDas [14] network. The POPs Algorithm is then employed iteratively to segment petals from the outermost-blossomed layer. At each iteration, the identified petals are masked, and the next outermost-blossomed layer becomes the focus for the subsequent iteration. This iterative process continues until the entire flower region has been successfully segmented into individual petals. The automated prompts generated by POPs can be utilized by any prompt-based segmentation technique to achieve the segmentation. We employ the Segment-Anything model [9] in this paper for illustration. The depth-based flower segmentation and the POPs Algorithm are designed to accommodate manual intervention through the **FloraSeg** tool, enabling improved performance and accurate segmentation. The results depicted in this figure demonstrate a fully automated approach with **No** manual supervision.

of value (κ_τ) representing the minimum curvature required for the detected extrema to be considered as maxima or minima. Beginning from a randomly chosen initial point $p_0 \in \mathcal{V}$, we arrange all points $p \in \mathcal{E}$ in order of the arc length traversed along curve C_s, between points p_0 and p. Following the intuitive understanding that consecutive tips or valleys cannot occur on a curve, we enhance the refinement of points in $\mathcal{T}$ and $\mathcal{V}$ by eliminating such consecutive points and retaining only the one with the maximum prominent curvature. Now, all possible triplets in $\mathcal{E}$ denoted as $\mathcal{P} = \{(p_{i-1}, p_i, p_{i+1}) \mid p_{i-1}, p_{i+1} \in \mathcal{V}, \quad p_i \in \mathcal{T}\}$ signify a petal of the flower in outermost-blossomed layer represented by curve C_s. In Figure 2(b), the detected petals are depicted, where red points represent the distal points $(\mathcal{T})$ of the petal, and pink points represent the valley points $(\mathcal{V})$ of the petal. For each petal $p \in \mathcal{P}$, we determine a point that lies inside it by calculating the bisecting point of the line connecting its two valleys, depicted as a black outlined circle in Figure 2(b). This midpoint point serves as our prompt for segmentation. Let $\mathcal{B}$ denote the set of all these points inside the petal, such that $b_i \in B$ is a point inside the petal $p_i \in P$. Due to the similar appearances of all petals in a flower in terms of colour and shape, segmenting petal $p_i \in \mathcal{P}$ using only one prompt $b_i \in \mathcal{B}$ can lead to errors. To enhance our prompts, we consider the 1-neighbourhood of each petal, where petal $p_i \in P$ is labelled as 1 (foreground), and neighbouring petals $p_{i-1}, p_{i+1} \in P$ are labelled as 0 (background). Consequently, for petal $p_i \in \mathcal{P}$, our extended prompt is $B_{p_i} = \{b_{i-1}, b_i, b_{i+1}\} \in \mathcal{B}$ with corresponding labels $L_{p_i} = \{0, 1, 0\}$.

Prompt based Petal Segmentation. Utilizing a set of prompts $\mathcal{B}$ and corresponding labels $\mathcal{L}$ for all petals in $\mathcal{P}$, we employ prompt-based segmentation using the Segment Anything model as described in [9]. For more details about this prompt-based segmentation model, we direct readers to refer to [9]. Note that $\mathcal{B}$ and $\mathcal{L}$ are generated automatically by our POPs algorithm, which ensures a fully automated process. However, this fully automated process may occasionally lead to inaccurate petal segmentation for more complex flower structures. To address this issue, we expand the set of prompts used in the segmentation model [9] by incorporating manual prompts $\mathcal{Q}$ and labels $\mathcal{A}$. We update B_{p_i} as $B_{p_i} = B_{p_i} \cup Q_{p_i}$ and L_{p_i} as $L_{p_i} = L_{p_i} \cup A_{p_i}$, where $Q_{p_i} \in \mathcal{Q}$ and $A_{p_i} \in \mathcal{A}$ denote manual prompts and labels, respectively, for the i-th petal $p_i \in \mathcal{P}$.

Iterative Plucking out the Petals. Given a set of prompts $\mathcal{B}$ and labels $\mathcal{L}$ for all detected petals $\mathcal{P}$, we obtain the segmentation mask for the outermost blossomed layer of the flower. In subsequent iterations, we update the binary mask $\mathcal{M}$ using the petal segmentation mask obtained for the outermost-blossomed layer. This exposes the next layer of petals as the new outermost layer, allowing us to repeat the segmentation process iteratively until the entire foreground in $\mathcal{M}$ is segmented out, as illustrated in Figure 4.

2) *FloraSeg Tool:* The **FloraSeg** tool streamlines manual supervision in two crucial steps employed by PoPs to achieve accurate petal segmentation: foreground extraction and the input of manual prompts for incorrectly segmented petals. In cases where the binary mask $\mathcal{M}$ generation using depth thresholding is unsatisfactory, FloraSeg provides interactive segmentation capabilities, enabling users to extract the foreground region representing the flower accurately. Furthermore, in the case of unsatisfactory segmentation for petal $p_i \in \mathcal{P}$, the automated prompts B_{p_i} and labels L_{p_i} generated by the POPs Algorithm are expanded. This extension involves the incorporation of manual prompts Q_{pi} and labels A_{p_i}, as discussed previously, achieved through a mouse.

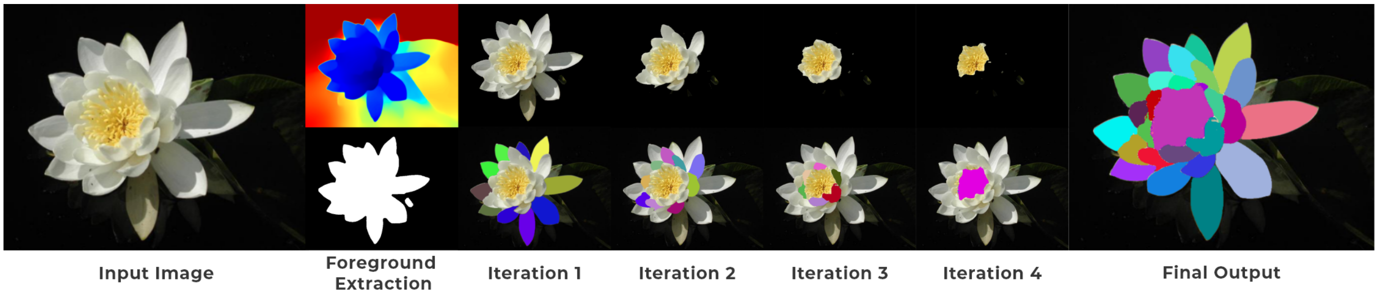

Fig. 4. For a given flower image, we find the binary mask $\mathcal{M}$ representing the flower region as foreground. Subsequently, we iteratively segment the petals starting from the outermost blossomed layer and gradually move inwards until the entire foreground $\mathcal{M}$ is segmented.

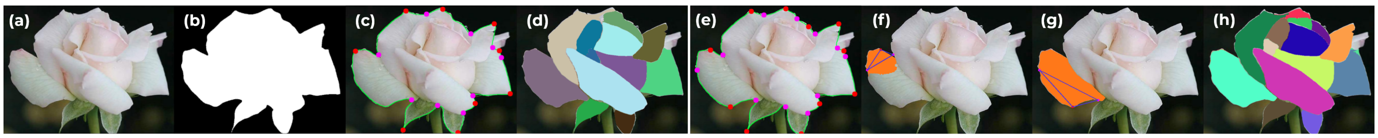

Fig. 5. For a provided flower image (a) and its corresponding foreground mask (b), the influence of the curvature threshold κ_τ on the identification of petal tip (distal) points $\mathcal{T}$ and valleys $\mathcal{V}$ is demonstrated. In (c) and (e), tips and valleys are highlighted with red and pink points, respectively. When multiple extrema are detected on a single petal, resulting in the generation of multiple segments as depicted in (f) and (g), we merge the segmented masks if the overlapping between them surpasses a predefined threshold value. The final segmented outputs are presented in (d) and (h) for both cases.

IV. Results and Discussions

We assess the proposed methodology using a diverse range of flowers categorized in the Oxford 102 category flower dataset [12]. This dataset includes flowers with varying degrees of simplicity and complexity in appearance and structure. Figure 6 displays qualitative results obtained through the fully automated POPs algorithm and refinements after manual interventions facilitated by the FloraSeg tool. Table I provides a comparison between the total number of petals ($|\mathcal{P}|$) segmented by the POPs algorithm and the count performed manually. The table presents quantitative data for the flowers depicted in Figure 6, maintaining the same row order. The set $\mathcal{Q}$ comprises all prompts manually provided by the FloraSeg tool, contributing to the segmentation refinement. D_τ denotes the depth threshold utilized to extract the foreground for the corresponding flowers.

Effect of Curvature Threshold. Ideally, we aim for one tip point and two valleys per petal, but achieving this consistently is challenging due to diverse petal shapes. In Figure 5(c) and 5(e), extrema points are shown for curvature thresholds of $\kappa_\tau = 0.02$ and $\kappa_\tau = 0.05$. A lower threshold, like $\kappa_\tau = 0.02$, results in more extrema points on a single petal. When multiple extrema points appear on a single petal, our prompt labelling scheme assigns both foreground and background labels to the same petal, resulting in the generation of multiple masks for that petal, as illustrated in Figure 5(f) and 5(g). This phenomenon is especially pronounced in flowers characterized by highly irregular petal boundaries, which do not exhibit a distinct triangular structure. We implement a mask-merging process to enhance the robustness of petal segmentation and address this ambiguity. Segmentation masks are merged if their intersection with others exceeds a specified threshold μ_τ. The merging of masks enhances the robustness of the POPs approach, making it more resilient in scenarios where prompt generation is ambiguous. Figure 5 illustrates the merging of multiple petal masks from Figure 5(f) and 5(h) into a unified mask displayed in Figure 5(h). It is noteworthy that the final outputs in Figure 5(d) and 5(e) are nearly identical, even though Figure 5(d) was generated with more accurate prompts.

TABLE I
Quantitative comparison between the total number of petals by proposed approach with the count performed manually

Flower Image	POPs			FloraSeg		Human Ann.
	D_τ	#Petals $\lvert\mathcal{P}\rvert$	#Iters	$\lvert\mathcal{Q}\rvert$	#Petals	#Petals
Nelumbo N.	0.62	23	4	3	28	27
Rosa R.	0.7	16	3	4	19	19
Bulbasaur H	0.78	8	2	1	8	5
Nelumbo N.	0.78	15	2	3	17	16
Dahlia P.	0.78	117	8	6	112	>110
Gerbera J.	0.78	34	2	3	37	37
Nigella D.	0.62	11	2	2	9	8
Cyclamen G.	0.78	7	1	1	7	5
Dimorphotheca E.	0.7	33 (18+15)	4	1	34 (18+16)	(32) 17+15

In our experimental evaluations, we determined empirically that a curvature threshold of $\kappa_\tau = 0.05$ and a merging threshold of $\mu_\tau = 80\%$ yield satisfactory performance across diverse flower structures.

V. Conclusion

The proposed method, known as POPs (Pluck Out the Petals), introduces an iterative approach to segmenting individual flower petals, starting from the outermost blossomed layer towards the innermost. This technique relies on detecting extrema, namely the distal (tip) and valley points of the petals, which act as prompts for segmentation. Additionally, the FloraSeg tool has been developed to facilitate manual supervision, enhancing the precision of petal segmentation in intricate flower structures. The effectiveness of the segmentation is validated by demonstrating its accuracy compared to human-performed annotations. This research holds significant implications for developmental biology, offering valuable insights

Fig. 6. The second column shows the foreground mask obtained through depth thresholding for a flower image. The third column depicts the iterative segmentation of flower petals using the POPs Algorithm. In the fourth column, refined results are presented with the aid of manual prompts from the FloraSeg tool. Changes made after and before manual prompts are marked with the symbol ▲ (Zooming in is recommended for better visibility).

into flower development and enabling structural phenotyping of flowers. Furthermore, The work contributes to a deeper geometric understanding of petal arrangement in flowers, showcasing the considerable potential for applications in 2D and 3D modelling tasks within the realm of computer graphics.

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