Hierarchical Image Peeling: A Flexible Scale-space Filtering Framework

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Abstract

The importance of hierarchical image organization has been witnessed by a wide spectrum of applications in computer vision and graphics. Different from image segmentation with the spatial whole-part consideration, this work designs a modern framework for disassembling an image into a family of derived signals from a scale-space perspective. Specifically, we first offer a formal definition of image disassembly. Then, by concerning desired properties, such as peeling hierarchy and structure preservation, we convert the original complex problem into a series of two-component separation sub-problems, significantly reducing the complexity. The proposed framework is flexible to both supervised and unsupervised settings. A compact recurrent network, namely hierarchical image peeling net, is customized to efficiently and effectively fulfill the task, which is about 3.5Mb in size, and can handle 1080p images in more than 60 fps per recurrence on a GTX 2080Ti GPU, making it attractive for practical use. Both theoretical findings and experimental results are provided to demonstrate the efficacy of the proposed framework, reveal its superiority over other state-of-the-art alternatives, and show its potential to various applicable scenarios. Our code is available at [https://github.com/ForawardStar/HIPe](https://github.com/ForawardStar/HIPe).

1. Introduction

Within the past decades, increasing attention to hierarchically organizing images has been drawn from the communities of computer vision and multimedia, by concerning the principle of perceptual systems. For example, an image can be spatially segmented into a set of object instances or super-pixels [14, 26, 35, 53, 52, 8, 13], which serve as primitives for further processing. Different from the spatial whole-part perspective, this paper concentrates on another organization manner from a scale-space/information eliciting perspective. We call this task image disassembly for distinguishing it from image segmentation, the formal definition of which is given as follows:

**Definition 1 (Image Disassembly).** Given an image \( I \), a family of constituent components \( \mathcal{C} := \{C_1, C_2, ..., C_n\} \) of \( I \) such that \( I = \sum_{i=1}^{n} C_i \) is called an image disassembly.

The above definition comprises all possible image disassembly strategies. The problem is highly ill-posed since the number of unknowns to recover is \( n \) times as many as given measurements. Therefore, we need to impose additional priors or constraints on the desired solution for \( C_i \)'s. Since a long time ago, the significance of multi-scale representations of images has been verified, which derives the idea of scale-space filtering. According to human-vision mechanism and scale-space theory, one typically acquires different information at various scales. Simply speaking, a

![Figure 1: A peeling example by referring a manually-edited edge guidance with a gradually-changed scale in spatial. (d) corresponds to the row indicated by the yellow arrow in (a).](image-url)
larger scale provides more about structural message of a certain scene, while a smaller one more about textural information. In the literature, a variety of image filtering approaches attempt to separate images into structure and texture components. However, given different images and tasks, hardly a sound way exists for determining which scales are correct or best ones. Furthermore, one may desire a result containing spatially different scales in one case. Please see Figure 1 and 2 as examples. Rather than eliminating the ambiguity in scale and seeking an optimal image separation, assembling images in a hierarchical, flexible, and compact fashion is more desired. It should be a very useful feature for practical use in various multimedia, computer vision and graphics applications, such as image restoration [44, 48], image stylization [16, 5], stereo matching [37, 63, 23], optical flow [57, 46] and semantic flow [68, 21], where users expect to adjust and select the most satisfactory results.

For ease of explanation, we respectively denote \( I^t := \sum_{i=t-1}^{n} C_i \) and \( I^{t+1} := \sum_{i=t}^{n} C_i \), such that \( I = I^t + I^{t+1} \). Taking the case shown in Fig. 2 as an example, the information left after subtracting \( t \) of \( n \) \( C_i \)'s from the input \( I \), say \( I^t \), is regarded as the filtering/peeling result. To achieve the above mentioned versatile utility, we advocate the following properties:

- **Peeling Hierarchy.** For \( \forall \ t \in \{1, 2, ..., n - 1\} \), \( I^t \) should not generate any spurious details passing from \( I^{t-1} \) to keep the fidelity of peeling, while more information of \( I \) should be contained by \( P^t \) than \( P^{t-1} \).

- **Structure Preservation.** \( I^t \) should provide a concise yet dominant structure of \( I^{t-1} \), and thus of \( I \). The edges maintained in \( I^t \) should be sharp while the rest regions keep as flatten as possible.

- **Flexibility.** In comparison with tuning numerical parameters, to instruct/constrain the peeling procedure, a more intuitive and flexible way, e.g. adopting perceptually meaningful cues, might be preferred by users.

- **Model Efficiency.** More and more tasks are expected to be executed in a timely fashion. As a core module of processing, aside from the effectiveness, the efficiency of model is critical.

### 1.1. Related Work

The earliest attempt on scale-space filtering may trace back to [55], which obtains a group of derived images by convolving the original image with different Gaussian kernels. Despite the simplicity, its isotropic nature causes the content blind side. In order to mitigate the isotropic issue, Perona and Malik [43] proposed an anisotropic diffusion method, which tries to keep boundaries sharp and coincided with the semantically meaningful boundaries at each scale.
fied results in most cases, they typically require multiple iterations to converge in optimization, each of which involves computationally expensive operators, e.g. the inverse of large matrices, limiting their applicability to real-time tasks.

In comparison, with the emergence of deep neural networks, the processing in the testing phase could be largely accelerated because only feed-forward operations are needed \[17, 59, 31, 10, 6, 38\]. The pioneering work in this category goes to \[59\], which trains a network to speed up the procedure. Similarly, the work of \[31\] achieves the acceleration via proposing a hybrid neural network. Both of these two models can merely output one result closest to the (either gradient or image) reference generated by a target filter with one specific parameter configuration, among multiple candidates with distinct scales. There exists an unsupervised fashion proposed by \[11\], which however is unable to produce multiple results of an image with different filtering levels. More recently, several approaches still unable to produce multiple results of an image with unsupervised fashion proposed by \[11\], which however is multiple candidates with distinct scales.

2. Methodology

2.1. Problem Analysis

The main goal of this paper can be expressed by Definition \[1\] with peeling hierarchy and structure preservation satisfied (specified feasibility). We employ the first-order derivative of a component, namely \(\nabla C_t\), to reflect its detail/structure information. Directly solving such a problem is way too hard due to the complex relationship among multiple components. To make the problem easier to deal with, we simplify it as a series of two-component decomposition sub-problems, based on the following theorem.

**Theorem 1 (Sequential Peeling).** Suppose, for any \(t\), \([C_t, I^t]\) is a feasible solution to separating \(I^{t-1}\) into two components. The sequential separation results are also feasible to the original hierarchical image peeling problem.

**Proof.** According to the peeling hierarchy property, the set of non-zero elements in \(\nabla I^t\) should be a subset of that in \(\nabla I^{t-1}\). Together with the structure preservation, the uncorrelation between \(\nabla C_t\) and \(\nabla I^t\) should be guaranteed, denoted by \(\nabla C_t \perp \nabla I^t\). Having \(I^t = I^{t+1} + C_{t+1}\) and \(\nabla C_{t+1} \perp \nabla I^{t+1}\) yields \(\nabla C_t \perp \nabla I^{t+1} + \nabla C_{t+1}\) and \(\nabla C_t \perp \nabla C_{t+1} \perp \nabla I^{t+1}\). In the sequel, both \(\nabla C_1 \perp \ldots \perp \nabla C_{t+1} \perp \nabla I^{t+1}\) and \(\nabla P_{t+1} \perp \nabla I^{t+1}\) hold, which establish the claim. \(\Box\)

The above finding boils down the original image disassembly problem to a sequential processing, naturally motivating us to design a recurrent strategy. Each recurrent unit performs structure preserving image peeling to a controllable extent. Let us here concentrate on the unit function, which can be written usually in the following shape:

\[
\arg\min_{C_t, I^t} \Phi(C_t) + \alpha \Psi(I^t) \quad \text{s.t.} \quad I^{t-1} = I^t + C_t, \tag{1}
\]

where \(\Phi(\cdot)\) and \(\Psi(\cdot)\) are the regularizers on \(C_t\) and \(I^t\) respectively, which can be \(\ell_1\) or \(\ell_2\) depending on different
the input-output viewpoint, say \[ n \] techniques, one can alternatively train a neural network to detect edges for guiding the generation of the output. Equipped with deep learning techniques, the model can be trained to mimic related operators and the whole procedure. Once the network is trained, the inference could be accomplished at cheap expenses. On the other hand, the peeler part in Figure 3 for more details. Please see the peeler part in Figure 3 for more details.

HITe-Peeler \( P \). Generally, our framework can not only learn the behavior of any existing filter, like muGIF \[ 18 \], RTV \[ 60 \], and L0 \[ 58 \], but also be trained in an unsupervised manner (no edge and expected filtered image pair). At each recurrent step, the core mission of the peeler is to produce a result from the input, which should strictly adhere to the guidance, no matter what the guidance looks like only if reasonable. At the moment, the guidance \( G^t \) is assumed being already at hand. We will see how to form the guidance shortly. Due to the hard constraint \( G^{t-1} = G^t + C_t \), the peeler could map the input \( I^{t-1} \) only to one component, \( C_t \) or \( G^t \). Then, the other component can be consequently obtained by subtracting the mapped result from the input. For better considering contextual features, the peeler network ought to catch relatively large receptive fields. To this end, we follow \[ 11 \] \[ 64 \] by utilizing dilated convolutions to progressively enlarge the receptive field with the dilation rate exponentially increasing, instead of resorting to a deeper network, to cut model size. Please see the peeler part in Figure 3 for more details.

HITe-Guider \( G \). For the input \( I^{t-1} \), the expected filtering result can be obtained by setting the parameters of a filter to \( \alpha^t \) (for different scales, \( \alpha^t \) may vary), i.e. \( I_{\alpha^t} \leftarrow G(I^{t-1}) \). Putting the aforementioned concerns together yields a strategy that recurrently solves \( \{C_t, I_t^t\} \leftarrow G(I^{t-1}) \). Putting the aforementioned concerns together yields a strategy that recurrently solves \( \{C_t, I_t^t\} \leftarrow G(I^{t-1}) \). Please notice that our strategy also allows edge maps constructed by users, and can be generalized to other possible types of guidance. We emphasize that none of existing works can produce a filtering result adhering to the edge guidance like the case in Fig. 1.

2.2. Hierarchical Image Peeling Network

Figure 3 shows the architecture of our hierarchical image peeling network (HITe-Net for short), which performs in a recurrent fashion and consists of two logical modules. One module \( G \) responds to the guidance prediction, while the other \( P \) takes care of the peeling functionality conditioned on the given/predicted guidance. By this logical partition, the two modules can be greatly decoupled, thus further simplifying the problem. In addition, both the model reduction and training procedure can benefit from the partition, because the original space is considerably restricted.
like AlexNet \[28\] or VGG16 \[50\], to obtain multi-scale representations (different params. for different scales). As shown in Figure 3, such an issue can be mitigated in our framework, since we reusing the network parameters, and recurrently take the previous output features \(F^{t-1}\) as the input again to get the features \(F^t\) with larger receptive fields (shared params. for different scales). Experiments will reveal that our solution can reach promising performance.

2.3. Network Training

For different scales, \(I^t\) are the processed results by setting different \(\alpha^t\)'s. The \(\alpha^t\) corresponding to \(G^t\) gradually increases through setting \(\alpha^{t+1} \leftarrow \eta \times \alpha^t\) \((t \in \{1, 2, ..., T\}, \eta \geq 0)\). Please notice that the HIPe-Net can recur as many iterations as required, not limited to \(T\). Besides, the interval of filtering controlled by \(\alpha^t\) in the training phase can also be adjusted according to particular demands.

The objective consists of guider consistency, peeler reconstruction, peeler preservation, and peeler consistency, the formulation of which is uniform for both supervised and unsupervised manners. The only difference is whether the ground truth \(I^t\) is available. For the supervised peeling, \(I^t\) and \(\nabla I^t\) are procurable where \(I^t\) is allowed to be generated by any existing filter. For the unsupervised peeling, the ground truth \(I^t\) is unavailable, thus we have \(I^t := I^0 = I\) and \(\nabla I^t \approx \nabla I^t := (1-\alpha^t)\nabla I^t := 1 + \alpha^t \nabla I^t - 1 \circ G^t\), with \(\nabla I^t := (1-\alpha^t)\nabla I + G^t\), where \(\circ\) denotes the Hadamard product, \(\alpha^t \leq 1\) and \(G^t\) aims to enhance important edges and is manually annotated. For ease of explanation, we uniformly use \(\nabla I^t\) to represent \(\nabla I^t\) in the following.

Guider consistency is to enforce the predicted guidance map \(G^t\) to be consistent with \(I^t\) in the gradient domain. The guider consistency loss is as follows:

\[
L^\varphi_{con} := \sum_{t=1}^{T} \| G^t \circ \nabla I^t \|_1 + \beta_g \| G^t \circ \nabla I^t \|_1, \tag{2}
\]

where \(\nabla I^t := \mathbf{1} - \nabla I^t\), \(G^t := 1 - G^t\), \(1\) means the \(\ell_1\) norm, and \(\mathbf{1}\) denotes the all-one matrix with a compatible size. Further, \(\beta_g\) is a constant parameter for balancing the two terms. This loss determines if a location of \(G^t\) is an edge element or not by comparing the magnitudes of \(\nabla I^t\) and \(\beta_g \nabla I^t\).

Peeler reconstruction desires the output \(I^t\) and \(I^t\) to be as close as possible. A reconstruction loss is adopted:

\[
L^\varphi_{rec} := \sum_{t=1}^{T} \| I^t - I^t \|_2^2, \tag{3}
\]

where \(\| \cdot \|_2\) designates the \(\ell_2\) norm.

Peeler preservation aims to maintain the structural pixels in \(I^t\), corresponding to the pixels with values close to 1 in \(G^t\). The gradient responses naturally reflect structure information of an image, thus the peeler preservation loss is defined as the distance between the gradient responses of \(I^t\) and \(I^t\) as below:

\[
L^\varphi_{pre} := \sum_{t=1}^{T} \| G^t \circ \nabla I^t - G^t \circ \nabla I^t \|_2^2. \tag{4}
\]

Peeler consistency strictly constrains the peeling process to be in line with the edge map \(G^t\). Inspired by \[18\], the peeler consistency loss suppresses the gradient magnitude of each pixel in \(I^t\) with different strengths. It gives a small penalty on the structural pixels indicated by \(G^t\) while a large one on the textural pixels, which is expressed as:

\[
L^\varphi_{con} := \sum_{t=1}^{T} \| \nabla I^t \circ G^t + \epsilon \|_2^2, \tag{5}
\]

where \(\epsilon = 0.005\) is used to avoid division by zero. To make the training procedure more stable and accelerate the convergence speed, the HIPe-Peeler and HIPe-Guider are trained independently. Since the peeler needs to be trained with \(G^t\) given, we first learn the guider part by using \(\lambda^\varphi_{con} L^\varphi_{con}\) only, then freeze the guider and train the peeler using \(L^\varphi_{pre} + \lambda^\varphi_{pre} L^\varphi_{pre} + \lambda^\varphi_{con} L^\varphi_{con}\).

3. Experimental Validation

Our model is implemented in PyTorch. All the experiments are carried out on a machine with a GeForce RTX 2080Ti GPU and an Intel Core i7-8700 3.20 GHZ CPU. The optimizer exerts the RMSprop algorithm whose learning rate is set to 0.001 at the beginning and linearly decreases with the increase of epochs. The images are all resized to 256 \(\times\) 256 at the training stage and can be any size at the testing. We denote by Ours-S and Ours the supervised \((I^t)_{\text{generated by muGIF}} \text{~}[18]\) and unsupervised settings in this section, respectively. The weights are set to \(\lambda^\varphi_{con} = 1.5, \lambda^\varphi_{pre} = 0.4, \text{~and~} \lambda^\varphi_{con} = 4\). The training data for HIPe-Guider are from the BSDS300 dataset \[39\], and those for HIPe-Peeler are the natural images from the RTV \[60\] and ADE20K datasets \[67\] (3,120 images in total).

3.1. Peeler Evaluation

This part is to test the abilities of different methods in terms of edge preserving filtering. Traditional methods including L0 \[58\], RTV \[60\], RGF \[65\], SD \[20\], L1 \[3\], muGIF \[18\], realLS \[34\], and enBF \[33\], as well as deep learning approaches including DEAF \[59\], FIP \[6\], and PIO \[9\] are involved in comparisons. The codes of competitors we use are all provided by the authors. To measure the image quality, the gradient correlation coefficient, \(i.e.\)
GCC($P, I) := \text{mean}(|\nabla P \circ \nabla I|_1)$, is adopted, indicating the uncorrelation in the gradient domain and theoretically supported by [19]. The evaluation for GCC is performed on the 200 images from the test set of BSDS500 [1]. In addition, the running time is considered to reflect the efficiency.

We tweak the hyper-parameters of the competitors to reach a similar smoothing degree for fairness. Table[1] reports the numerical results in GCC, and Figure[4] depicts a visual comparison among the competitors. As can be seen from the numbers, our HIPe takes the first place in terms of GCC, indicating that $\nabla I$ and $\nabla P$ considerably satisfy the orthogonality. As for the visual effect, we observe that the visual quality of the results by L0, RGF and PIO is relatively poor when the smoothing degree increases, and PIO suffers...
Table 1: Quantitative comparison in GCC. The smoothing degrees are controlled around a similar level for aligning different methods. The best results are highlighted in bold. Lower GCC values indicate better performance.

| Method | L0 | RGF | SD | RTV | realLS | muGIF |
|--------|----|-----|----|-----|--------|--------|
| GCC ($\times 10^{-2}$) | 0.49 | 0.49 | 0.61 | 0.48 | 0.49 | 0.48 |

Table 2: Runtime comparison on processing a 1080p image ($1627 \times 1080$) in seconds. The CPU times are unmarked and GPU times are marked by †, respectively.

| Method | L0 | RGF | SD | RTV | L1 | realLS |
|--------|----|-----|----|-----|----|--------|
| Time   | 6.36 | 3.16 | 53.27 | 9.31 | 913.17 | 1.75 |

| Method | muGIF | enBF | DEAF | FIP | PIO | Ours-S |
|--------|--------|------|------|-----|-----|--------|
| Time   | 11.12 | 1.21 | 5.13 | 0.034 | 0.008 | 0.41 |

Figure 6: Edge detection comparison in terms of precision-recall curve on the BSDS500 dataset.

Figure 7: An example of our edge confidence map.

Figure 8: Effectiveness analysis on different strategies.

Moreover, both the traditional and deep models, except for our HIPe, can hardly process images with spatially-variant scales and/or user provided/edited guidance maps, as shown in Fig. 5, which would remarkably broaden the applicability of filtering/peeling. By simultaneously considering the peeling quality, efficiency and flexibility, our method is among the most attractive choices for practical use.

3.2. Guider Evaluation

This section evaluates the ability of guidance prediction. Due to the scale-space nature, our HIPe-Guider can easily construct an edge confidence map for an image through combining the edge maps obtained from different recurrent steps. Specifically, we train the HIPe-Guider using annotated edges in the BSDS500 dataset as $G^{gr}$ and recursively run it for 24 rounds. The maps are simply averaged, which are all processed by non maximum suppression. An example is shown in Figure 7. We compare the results of edge detection on the BSDS500 dataset using precision-recall curve and F-score. The competing candidates are non-deep methods, including Canny [4], Pb [41], gPb-UCM [1], ISCRA [45], and SE [7], and deep methods, including DeepContour [47], HED [56] and RCF [36]. As shown in Figure 6, our method obtains the ODS-F (optimal dataset scale F-score) of 0.748, being obviously superior to Canny and Pb, competitive with DeepContour and even slightly better than ISCRA, gPb-USM and SE. Compared with the deep supervised HED and RCF, there indeed exists a margin. This is reasonable because we do not introduce any pre-trained classification network as backbone. Our HIPe-Guider (998KB) is significantly smaller than DeepContour (27.5Mb), HED (56.1Mb) and RCF (56.5Mb).

3.3. Other Issues

Ablation analysis. The edge predictor in HIPe-Guider only involves the guider consistency loss $\mathcal{L}^G_{con}$. Thus, we omit the ablation analysis from the loss perspective. As for the peeling manner, the peeler has two possible ways to map the input $I^{t-1}$ to one component. In this work, we incline to the mapping of $C_t \leftarrow \mathcal{P}(I^{t-1}, G^t)$. The reason from noticeable color shift issue. Though performing remarkably better, RTV and muGIF fail to completely smooth or preserve some regions, like the right corner of first case, and the border of flowers. In comparison, our approach can achieve visually pleasing filtering results in terms of region flattening and edge preserving, thanks to the ability of our peeler to strictly adhere to the unambiguous edge guidance.

Additionally, the time costs of different methods at inference stage are displayed in Table 2. Clearly, our method is much more efficient than the traditional methods even on a CPU. The HIPe-Peeler and PIO can reach super real-time speeds to handle 1080p images on a 2080Ti GPU.

Moreover, both the traditional and deep models, except for our HIPe, can hardly process images with spatially-variant scales and/or user provided/edited guidance maps, as shown in Fig. 5, which would remarkably broaden the applicability of filtering/peeling. By simultaneously considering the peeling quality, efficiency and flexibility, our method is among the most attractive choices for practical use.
Table 3: Quantitative comparison in MAE. The lower the MAE, the better. \textit{Name + Ours} refers to predict from the saliency maps generated by \textit{Name}.

| Method          | ECSSD   | PASCAL-S | HKU-IS | SOD    | DUTS-TE |
|-----------------|---------|----------|--------|--------|---------|
| HS [61]         | 0.228   | 0.260    | 0.213  | 0.280  | 0.244   |
| HS [61] + Ours  | 0.128   | 0.197    | 0.121  | 0.209  | 0.159   |
| PoolNet [24]    | 0.039   | 0.074    | 0.132  | 0.100  | 0.039   |
| PoolNet [24] + Ours | 0.034   | 0.071    | 0.026  | 0.096  | 0.036   |
| CSF [15]        | 0.033   | 0.068    | 0.030  | 0.098  | 0.037   |
| CSF [15] + Ours | 0.028   | 0.065    | 0.025  | 0.094  | 0.034   |
| EGNet [66]      | 0.040   | 0.074    | 0.131  | 0.097  | 0.039   |
| EGNet [66] + Ours | 0.033   | 0.071    | 0.026  | 0.097  | 0.036   |

Figure 9: Visual comparison between HS and HS + Ours.

Figure 10: The three rows correspond to the applications of low-light enhancement, image abstraction, and depth-guided RGB image filtering, respectively, proving that our framework is effective for the salient object detection since some useful features may be prominent at different scales. Single scale smoothing may not produce better results, e.g. some salient structures might be over-smoothed in large-scales. Note that for all saliency detection methods, the input is identical and no extra information is used. The proposed image disassembly/peeling produces several levels for capturing different cues.

4. Concluding Remarks

This paper has proposed a modern framework for hierarchically organizing images. A flexible and compact recurrent network, namely hierarchical image peeling net, has been developed based on theoretical analysis to efficiently and effectively fulfill the task, which jointly takes into account the peeling hierarchy, structure preservation, flexibil-
ity, and model efficiency, making it attractive for practical use. The network can be trained in both supervised and unsupervised manners. Experimental results have been provided to demonstrate the advantages of our design. Our framework also has much potential to derive new applications and inspire new technical lines to solving existing problems, such as object detection and image segmentation.

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