Monocular depth ordering with occlusion edges extraction and local depth inference

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Abstract: In this paper, a method to infer global depth ordering for monocular images is presented. Firstly a distance metric is defined with color, compactness, entropy and edge features to estimate the difference between pixels and seeds, which can ensure the superpixels to obtain more accurate object contours. To correctly infer local depth relationship, a weighting descriptor is designed that combines edge, T-junction and saliency features to avoid wrong local inference caused by a single feature. Based on the weighting descriptor, a global inference strategy is presented, which not only can promote the performance of global depth ordering, but also can infer the depth relationships correctly between two non-adjacent regions. The simulation results on the BSDS500 dataset, Cornell dataset and NYU 2 dataset demonstrate the effectiveness of the approach.

Keywords: superpixel segmentation, depth ordering inference, weighting descriptor.

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1. Introduction

Depth ordering inference on a monocular image, also known as the 2.1D sketch, was firstly introduced by Nitzberg [1]. It decomposes an image into many non-overlapping regions by occlusion edges and then infer their global depth relationships based on geometric features and foreground-background assignment. Depth ordering inference has many practical applications, such as robot vision [2], visual object tracking [3,4], scene understanding [5,6], object recognition [7,8] and geoscience [9,10]. While it is a natural ability for humans to get depth relationships of different objects from a monocular image, it is still a challenging task for computer vision.

In recent years, some scholars have focused on this promising research direction. It is believed that the essential problems of depth reasoning or the 2.1D sketch are

occlusion edges extraction and depth ordering inference [11 – 15]. For the occlusion edges extraction process, Amer [16] and Yu [2] obtained occlusion edges by setting an over-segmentation scale based on global probability of boundary-oriented watershed transform-ultrametric contour map (gPb-OWT-UCM) [15] and got promising results on depth ordering inference. Hoiem [13] introduced an occlusion recovery strategy, which utilized several low-level and high-level cues to train a conditional random field to extract occlusion edges. In addition to Hoiem, Jia [17] proposed new features based on bag-of-word [8] for occlusion boundary detection. However, their over-segmentation methods only apply color and compactness term to get objects' edges, which are not accurate enough and will lead to wrong objects' contours when extracting occlusion edges. Zhou [18] utilized a Huber Loss to extract occlusion edges and get promising results. As for deep learning methods in recent years [19 – 21], the occlusion edges cannot form a closed shape, which cannot satisfy our purpose.

As for the depth ordering inference, both Amer [16] and Yu [2] employed some geometric cues to calculate the global energy function and utilized the global optimization algorithm to obtain final depth ordering. Chen [6] introduced a training method to obtain the depth relationships of different regions based on the semantic image. Jia [17] employed a scale-invariant feature transform (SIFT) like T-junction feature and the convexity of edge feature to infer local depth relationship, through adding these features into a Markov random field. Jia also obtained global depth ordering effectively. To simplify the inference process, Ming [11] proposed a triple descriptor which combines two T-junction features and an edge feature to infer local depth order and employed the directed graph strategy to acquire final depth ordering. However, the triple descriptor will cause a wrong inference when two T-junction features are inaccurate, and the existing graph-based strategy [11,17] to infer global depth ordering is not well enough when two

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objects are separated. Different from the method of depth estimation [22–26], the depth ordering focus on object-level inference rather than pixel-level inference like depth estimation.

In this paper, we propose a method for depth ordering inference. It mainly consists of three aspects: a distance metric is firstly defined with color, compactness, entropy and edge features to measure the difference between pixels and seeds. In our distance metric, we set an adaptive coefficient to control the relationship between color and compactness, which can make our superpixel segmentation algorithm concentrate more on detecting edges. After the extraction of occlusion edges, a weighting descriptor that combines different weights of T-junction, edge and saliency features is introduced to overcome the limitations of Ming's triple descriptor [11] and get local depth relationship correctly. Then, we propose an inference strategy based on our weighting descriptor which not only enhance the final result of global depth ordering inference, but also correctly infer depth relationships between two separated objects. Simulation results demonstrate that our method

perform well on the BSDS500 dataset, Cornell dataset and NYU 2 dataset.

2. Extraction of occlusion edges

In this section, we define a distance metric with entropy, edge, color and compactness terms to generate superpixels and then extract occlusion edges reliably.

Given a monocular image I , its superpixels are defined as $I = \{S_1, S_2, \dots, S_N\}$, where $S_i \cap S_j = \emptyset$ and $i \neq j$. The method of simple non-iterative clustering (SNIC) [12] only considers color and compactness terms, its distance metric is

$$D(s_n, p_y) = C(s_n, p_y) + \theta \times d(s_n, p_y) \quad (1)$$

where s_n is the seed pixel in superpixels, θ is a constant number, $C(s_n, p_y)$, $d(s_n, p_y)$ are color and compactness terms respectively. However, in monocular images, as Fig. 1(b) and Fig. 1(d) show, the distance between s_n and p_y is much closer than the distance from s_m to p_y , that is,

$$D(s_n, p_y) < D(s_m, p_y). \quad (2)$$

Fig. 1 Illustration of our distance metric and superpixel segmentation maps by different methods on different datasets

This situation will cause a wrong result: pixel p_y belongs to s_n , the edges extracted will be not accurate enough.

The entropy rate can describe the similarity of adjacent pixels efficiently and the edge term can promote the accuracy of the superpixel segmentation [27,28]. Therefore, we employ color and compactness as our main term to generate superpixels and add entropy and edge terms to constraint the distance between pixels and seeds, which can further improve the performance of our algorithm. In addition, we set an adaptive coefficient to control the weights

between color and compactness terms, the proposed algorithm can then concentrate more on object boundaries than SNIC: the weights of compactness terms will increase when two pixels have different colors absolutely (like boundaries), and when two pixels have similar color, the weights of compactness terms will decrease. We define the distance metric as

$$D(s_n, l_n, p_y) = \alpha \times ER(l_n, p_y) - \beta \times E(l_n, p_y) - \gamma \times (C(s_n, p_y) + \delta \times d(s_n, p_y)) \quad (3)$$

where l_n is the labeled pixel in s_n , s_n is the seed pixel in superpixels and p_y is the adjacent pixel with l_n . $ER(l_n, p_y)$ is the entropy term, and $E(l_n, p_y)$ is the edge term obtained by lazy random walks (LRW) [29]. α, β and γ are three positive constant weighting coefficients whose values will be specified in Section 4. Next, we will introduce every term in our distance metric in detail.

2.1 Color and compactness terms

In previous work, the SNIC [12] employed a constant coefficient to control the relationship between color and compactness terms as in (1). It will obtain a wrong segmentation result when the initial seed pixel is very close to the boundary of objects. Like Fig. 1(b) shows, the pixel p_y is much closer to the seed s_n than to the seed s_m , p_y can be easily judged as the same label with s_n . To overcome this drawback, we design an adaptive coefficient ξ to make superpixels detect edges more accurately. We define

$$C(s_n, p_y) = \|LAB_{s_n} - LAB_{p_y}\|_2 \quad (4)$$

$$d(s_n, p_y) = \|s_n - p_y\|_2 \quad (5)$$

$$\delta = \theta e^{-\frac{\xi}{C(s_n, p_y) + \lambda} + 1} \quad (6)$$

where LAB_{p_y} is the corresponding CIELAB color of pixel p_y , $\|s_n - p_y\|_2$ means the Euclidean distance of s_n and p_y . $\xi = \sqrt{\frac{\text{size}(I)}{N}}$ is a balancing coefficient to control the scale of θ , where $\text{size}(I)$ is the number of pixels in I . $\lambda = 10^{-4}$ is a constant number to prevent $C(s_n, p_y) + \lambda = 0$. If the seed s_n and pixel p_y have similar color, the impact of the compactness term will be decreased. If their colors are different obviously, the coefficient δ will be larger than the constant number in SNIC, that is, $D(s_n, p_y)$ will become larger, and the drawback in SNIC can be corrected.

2.2 Entropy term

Because the existing superpixel segmentation methods [12,30] mainly consider the information of the region and the corresponding candidate pixel, the boundary recall is not satisfactory enough (see in Section 4). We employ the static distribution of LRW to build the entropy term of each adjacent pixel in I :

$$P(i, j) = \begin{cases} \frac{w_{ij}}{w_i}, & i \neq j \\ \alpha - \frac{\sum_{j: e_{i,j} \in L} w_{ij}}{w_i}, & i = j \end{cases} \quad (7)$$

$$ER(i, j) = - \sum_{ij} u_i P_{ij} \log_2 P_{ij} \quad (8)$$

where w_{ij} is the Gaussian weighting function as LRW,

$w_i = \sum_{j=1}^4 w_{ij} + w_{ii}$ is the sum of weights of pixel p_i . $u_i = \frac{w_i}{\sum w_i}$ is the stationary distribution in LRW. Following Liu's work [27], the entropy rate can measure the difference of adjacent pixels and describe the similarity between the labeled region and candidate pixels. The self-loops in LRW has the merits of segmenting weak boundaries and complicated texture regions well [29]. Fig. 1(e) and Fig. 1(f) are superpixel segmentation maps generated by our method, which use LRW and RW in entropy terms respectively. It is obvious that our algorithm with LRW can detect weak boundaries well.

2.3 Edge term

To further improve the accuracy of detecting object edges, we employ LRW to calculate the normalized transition probability map TI and the edge term in our distance metric, that is,

$$E(l_n, p_y) = \|\tilde{t}_{l_n} - \tilde{t}_{p_y}\|_2 \quad (9)$$

where $\tilde{T} = 1 - TI$ is the probability of each pixel being an edge. In order to preserve the boundary of objects and reducing the influence of noisy pixel $\tilde{t}_i$ in $\tilde{T}$, when $\tilde{t}_i < 0.25$, we set $\tilde{t}_i = 0$. This simple term can constraint superpixels to detect edges effectively. In Fig. 1(b), l_n is the adjacent pixel with p_y , if l_n is an edge pixel in $\tilde{T}$, $E(l_n, p_y)$ will prevent p_y to be the same label as l_n .

Fig. 1(e) shows superpixels generated by our method and Fig. 1(d), Fig. 1(f) are superpixels generated by SNIC [30]. It is obvious that our method can detect objects contours more precisely.

After the definition of distance metric, the priority queue Q_u [31] is employed to generate the over-segmentation map $\tilde{I}$. Following Ming's work [11], we utilize the adaptive feature subspace learning to extract occlusion edges from $\tilde{I}$. The occlusion edges map is defined as $\Gamma = \{R_1, R_2, \dots, R_Q\}$, where R_q is the region generated by occlusion edges. In the next section, we apply occlusion edges to infer depth ordering of monocular images.

3. Depth ordering inference

In this section, we firstly introduce our weighting descriptor and use it to infer local depth relationships between two adjacent regions. Then, by assigning different weights to our weighing descriptor, the global inference strategy is proposed to obtain the final depth ordering.

3.1 Local depth ordering inference based on the proposed weighting descriptor

Ming [11] introduced a tripe descriptor to infer depth rela-

tionships between adjacent regions. However, for the situation that two T-junctions have wrong local inference as shown in Fig. 2(a), the triple descriptor would cause wrong result: T-junction a and T-junction b with edge e_2 will infer that region E is in front of C.

To solve this problem, we define a weighting descriptor:

$$\gamma_m = (\omega a_1, \omega a_2, \psi e, \zeta \hat{S}) \quad \text{s.t. } \psi > \omega > \zeta \quad (10)$$

where m is the number of weighting descriptors, ψ , ω , ζ are weighting descriptors of different features. Because the T-junction feature may have some wrong local inference, the saliency feature can find the background region, the convexity of edge feature can be the strong feature to infer local relationship, and different values should be set to make weighting descriptors correctly. After evaluating several situations: $\psi = \omega = \zeta$, $\psi > \omega > \zeta$ and $\psi > \zeta > \omega$, we employ $\psi > \omega > \zeta$. Because ψ should be smaller than $\omega + \zeta$ to guarantee the edge feature can be constrained by other two features, and to avoid T-junctions' error, 2ω should be smaller than $\psi + \zeta$. In our experiment, we set $\psi = 0.5, \omega = 0.35, \zeta = 0.3$. We utilize two T-junctions (a_1, a_2), an edge e and saliency features $\hat{S}$ [32] to judge the local foreground-background relationships between adjacent regions (Fig. 2(b)). When the edge and saliency features have the same inference, it can exclude wrong inference by T-junctions. In addition, if the convexity of the edge cannot infer the local relationship (straight lines), we will exclude the wrong edge feature. For example in Fig.

2(a), e_1 is a straight line that cannot correctly infer the local depth ordering, we then decrease the weights of weighting descriptor γ_1 from 1 to 0.9.

Based on our weighting descriptor γ_m and the graph based algorithm in [11], the directed graph Fig. 2(d) of Fig. 2(a) can be obtained. Compared with Ming's triple descriptor [11] (Fig. 2(c)), our descriptor can correctly infer region C is in front of E. Because our weighting descriptor can employ local features better than the triple descriptor. To exclude the contradict inference by different weighting descriptors, different weights can be assigned to each descriptor to build the local depth relationships, if the descriptor has useless feature (like straight line), the weighting of the descriptor will be decreased.

For example, in Fig. 2(a), descriptor γ_1 has one useless feature (its corresponding edge is a straight line). We assign its weight as 0.9. Features in γ_3 are all useful, so we assign its weight as 1. Then, the directed depth order graph G [11] is employed to exclude contradict local inference. Since we have assigned different weights to each γ_m , γ_1 infers that region E is in front of regions B and D, γ_3 infers that region B is in front of region E, and weights $\gamma_1 < \gamma_3$, the directed path E to B can be removed. γ_4 and γ_5 infer that region D is in front of region E, so the directed path E to D in Fig. 2(d) can be removed. Our strategy of removing extra directed paths can avoid the wrong result of global depth ordering inference. The final local depth relationship is shown in Fig. 2(e).

Fig. 2 Illustration of the proposed weighting descriptor and the depth-order map generated by different weighting descriptors

3.2 Global depth ordering inference

If we use the triple descriptor in [11] to obtain the global depth ordering, region C and region A are separated, and there is no feature to infer two separated regions. For example, if node A is regarded as the start node, node C cannot be traversed by finding the longest path. If we regard the other node as the start node, the similar results will ap-

pear either. In this situation, our proposed strategy can be effective. Since the background is at the bottom of the image, we firstly reverse all directed paths in G (Fig. 2(f)), the ground region can then be regarded as the start node. If the node does not have the path to the other node, e.g., node A and node C do not have the path to the other node, it can be regarded as the top node in the graph. Then we

find the longest path between the top node and the start node until all top nodes being calculated. For example, two paths in our example can be searched in Fig. 2(f), $E \rightarrow D \rightarrow B \rightarrow A$ and $E \rightarrow D \rightarrow C$. The final result will be $1 \rightarrow 2 \rightarrow 3 \rightarrow 4$ and $1 \rightarrow 2 \rightarrow 3$, which means region C and region B are on the same layer. Finally, $A \rightarrow B = C \rightarrow D \rightarrow E$ is the correct result of global depth ordering. The following is the algorithm of depth ordering inference:

Algorithm 1 Depth ordering inference

Require Input image I , number of seeds N_c .

Ensure The final result of depth ordering $\hat{D}$.

Step 1 $I \rightarrow$ Distance metric $D(s_n, l_n, p_y)$ priority queue $Q_u \rightarrow$ Over-segmentation map $\tilde{I}$;

Step 2 $\tilde{I} \rightarrow$ Ming's method to extract occlusion edges [11] $\rightarrow$ Occlusion edges map F ;

Step 3 $F \rightarrow$ Weighting descriptors

$\tau_m = (\omega a_1, \omega a_2, \psi e, \zeta \hat{S}) \rightarrow$ The directed graph G ;

Step 4 $G \rightarrow$ Inference strategy $\rightarrow \hat{D}$;

Step 5 Return $\hat{D}$.

4. Experimental results

In this section we firstly validate the boundary recall (BR), under-segmentation error (UE) and running time of the superpixel segmentation method on the BSDS500 dataset [15]. As for depth ordering inference, the accuracy of results is verified on the Cornell depth-order dataset [33] and the NYU 2 dataset [34]. All datasets are performed on an Inter(R) Core(TM) i7-6700 PC 3.40 GHZ with 8 G RAM.

4.1 Superpixel segmentation algorithm evaluation

To provide a fair comparison of superpixel segmentation, we employ the BSDS500 dataset and the method in [35] to evaluate our superpixel segmentation method by comparing with four other algorithms: simple linear iterative clustering (SLIC) [31], SNIC [12], linear spectral clustering (LSC) [36] and entropy rate superpixel (ERS) [37]. In addition, we also provide qualitative results to prove the effectiveness of our approach. The calculation of the entropy term utilizes the transition probability of all images, which makes the value of entropy be very small (about 1×10^{-5}). While for color and compactness terms, the value range is in $[0, 256]$. In order to make all term values be scaled in $[0, 1]$, we set the experimental parameters as $\alpha = 10\ 000$, $\beta = 1$, $\gamma = 0.04$.

4.1.1 Quantitative results

To evaluate the impact of different terms in our algorithm, we supply the comparison with: our method without adaptive coefficient (Ours/no-coefficient), our method with RW

in entropy term (Ours/RW) and our method without edge term (Ours/no-edge) in BR and UE. Fig. 3 shows the quantitative results on boundary recall, under-segmentation error and running time by Stutz [35].

(a) Boundary recall

(b) Under-segmentation error

(c) Running time

— : ERS; — : LSC; — : SLIC; — : SNIC; — : Ours; — : Ours/no-coefficient; — : Ours/RW; — : Ours/no-edge.

Fig. 3 Comparison between our algorithm and other methods

(i) Boundary recall

It is the most commonly used metric to measure the fraction of the ground truth edges overlap within a small disk

shaped $(2r + 1) \times (2r + 1)$ neighborhood of the superpixel boundaries where r is set as 1 in this section. The boundary recall comparison between our method and the other methods is indicated in Fig. 3(a). Benefiting from the high performance on boundary recall, our algorithm can obtain the edge of objects accurately. In addition, because the proposed entropy term focuses on edges detection effectively, the results of boundary recall (BR) will also be improved.

(ii) Under-segmentation error

As mentioned in [35], under-segmentation error is defined as

$$UE(G, S) = \frac{1}{N} \sum_{G_i} \sum_{S_j \cap G_i \neq \emptyset} \min\{|S_j \cap G_i|, |S_j - G_i|\} \quad (11)$$

where G is the ground truth of segmentation. Due to these edge enhancement terms, the comparisons in Fig. 3(b) demonstrate that our algorithm has competitive results with the other state-of-the-art algorithm.

(iii) Running time

In our method, we employ the priority queue to generated superpixels. Therefore, all pixels only need to calculate once, which can save much time. As the comparisons

in Fig. 3(c), our method has a competitive running speed in that high performance.

4.1.2 Qualitative results

Though LSC [36] and ERS [37] perform very well on quantitative results, they cannot generate uniformly superpixels sizes in amounts of images, which would make the occlusion edge extraction hard to carry on. Our superpixel segmentation algorithm can provide competitive performance and regular sizes of superpixels. Fig. 4 shows the qualitative comparison superpixels generated by ERS, LSC, SLIC, SNIC and our method, and the number of pixels generated by five methods is in the same level. To make a fair comparison of the impact of different terms, we also compare with our method without adaptive coefficient (Ours/no-coefficient), edge (Ours/no-edge) and only use RW in the entropy term (Ours/RW) in Fig. 4. The results indicate that if the adaptive coefficient is not utilized, the object with background cannot be segmented correctly. Meanwhile, if not using the edge term in our method, the weights of the entropy term will become large enough and influence the shapes of superpixels (which can lead to irregular shapes).

(a) Our method

(b) ERS

(c) LSC

(d) SLIC

(e) SNIC

Fig. 4 Qualitative comparisons

In addition, the weak boundary of objects will be hard to detect if RW is employed in the entropy term. As we can see, our method can generate regular superpixels and have high qualitative in detecting edges.

4.2 Depth ordering evaluation

To evaluate the results of depth ordering inference, we use Yu's method [2] as our baseline because its satisfactory result and the author also released their source code and evaluation criterion. Then, we compare it with (i) our weighting descriptor to infer local depth relationships with global inference in [2], (ii) local inference in [2] global inference by our method, (iii) Ming's method [11] to extract

occlusion edges, and our method to infer depth ordering, (iv) our method to extract occlusion edges and Ming's method to infer depth ordering, (v) Ming's method. Next, we will introduce the performance of our method on different datasets.

(i) Cornell depth-order dataset

This dataset have 1 087 images with many objects occluding each other in different perspectives. Based on our superpixels, Ming's method [11] is employed to extract occlusion edges. Table 1 shows the accuracy of depth ordering inference. When comparing with the baseline method [2], we have almost 13% improvement.

Fig. 5 Example results

In addition, when compared with the method in [11], our weighting descriptor can improve 0.8%, and our proposed method to extract occlusion edges can enhance about 0.4%. Fig. 5 shows the performance of our method on the Cornell dataset. Benefiting from the accurate superpixels, the boundary of the depth ordering can describe objects' boundary more precisely. In addition, our depth inference can also infer two separated regions, which can improve our final result.

Table 1 Average depth ordering accuracy of different methods on Cornell depth-order dataset (D) and NYU 2 dataset (N)

Dataset	[2]	(i)	(ii)	(iii)	(iv)	(v)	Ours
Cornell	79.1	84.6	84.3	91.8	91.4	91.0	92.1
NYU 2	60.3	70.6	69.5	78.9	78.5	78.0	79.6

(ii) NYU dataset

This dataset contains 1 449 RGBD images. The scenes in this dataset are more complex and challenging. Table 1 demonstrates the results on this challenging dataset. Comparing with the baseline method, we achieve more than 19% improvement in accuracy. And we can also have 1.6% improvement compared with Ming's method [11]. It is mainly because our proposed weighting descriptor can describe local depth relationship better and our superpixel segmentation method can detect objects' contour more accurately. Fig. 5 shows the performance of our method on the NYU2 dataset.

5. Conclusions

In this work, an approach to infer depth ordering from a monocular image is proposed. Our main contributions are: we firstly propose a distance metric for the superpixel segmentation algorithm which combines edge, entropy, compactness and color terms to segment objects' contour more accurately. Secondly, a weighting descriptor is introduced that contains two T-junction features, an edge feature and saliency features to infer local depth relationships between adjacent regions robustly. Finally, an inference strategy is proposed based on our weighting descriptor, which can enhance the performance of final depth ordering inference and get the final depth relationship between two non-adjacent regions. Our approach has been applied on two challenging datasets and the experimental results demonstrate the effectiveness of our method.

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