MULTI-SCALE EDGE DETECTION AND IMAGE SEGMENTATION

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ABSTRACT

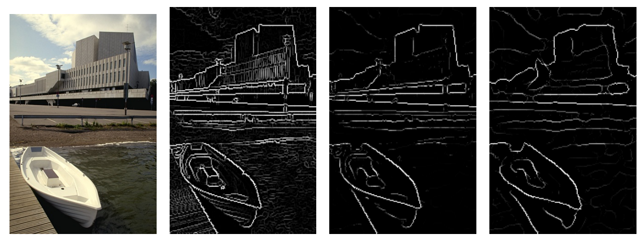
In this paper, we propose a novel multi-scale edge detection and vector field design scheme. We show that using multi-scale techniques edge detection and segmentation quality on natural images can be improved significantly. Our approach eliminates the need for explicit scale selection and edge tracking. Our method favors edges that exist at a wide range of scales and localize these edges at finer scales. This work is then extended to multi-scale image segmentation using our anisotropic diffusion scheme.

1. INTRODUCTION

Most edge detection algorithms specify a spatial scale at which the edges are detected. Typically, edge detectors utilize local operators and the effective area of these local operators define this spatial scale. The spatial scale usually corresponds to the level of smoothing of the image, for example, the variance of the Gaussian smoothing. At small scales corresponding to finer image details, edge detectors find intensity jumps in small neighborhoods. At the small scale, some of these edge responses originate from noise or clutter within the image and these edges are clearly not desirable. More interesting edges are the ones that also exist at larger scales corresponding to coarser image details. When the scale is increased, most noise and clutter is eliminated in the detected edges, but as a side effect the edges at large scales are not as well localized as the edges at smaller scales. For example, it has been shown [1] that smoothing the image with Gaussian filters of increasing variances causes the edges to move from their actual locations. To achieve good localization and good detection of edges, a multi-scale approach is needed. Fig. 1 shows an example of how multi-scale edge detection, using the methods developed in this paper, can precisely localize edges while removing the unwanted noise and clutter. As can be seen, the multi-scale edge detection result in Fig. 1(c) is cleaner than the one in 1(b) and localizes edges better than the result shown in 1(d).

Edge detection and analysis of edges at multiple scales has a rich history since the early days of edge detection [2-4]. Both fine to coarse [3] and coarse to fine [5] approaches for combining edges from a range of scales have been investigated. Most of these works are based on first finding an edge representation at each scale and then combining them using certain heuristics. For fine to coarse methods, usually the smallest scale that results in a good edge detection is selected at each local neighborhood of the image. Along these lines, Canny [4] proposed a fine to coarse method called feature synthesis.

A general trend in many of the multi-scale methods is combining single scale edge detector outputs at multiple



(a) (b) (c) (d)

Figure 1: Localized and clean edges using multiple scales. a) Original image. b) Edge strengths at spatial scale $\sigma = 1$, c) using scales from $\sigma = 1$ to $\sigma = 4$. d) at $\sigma = 4$. Edges are not well localized at $\sigma = 4$.

scales and generating a synthesis of these edges. On the other hand, it is desirable that the multi-scale information is integrated to the edge detection at an earlier stage and the edge detection operation automatically results in multi-scale edges.

More recent multi-scale edge detection techniques are based on estimating optimum scales for local neighborhoods within the image [6-8]. Lindeberg [6] analyzes the scale space representation of edge strengths $\xi(x,y,t)$, where t correspond to a continuous scale, from a differential geometric point of view. The optimum scale at a point is chosen as the scale at which ξ has a maximum in the t direction. A more interesting approach comes from Tabb and Ahuja [8]. This technique is based on designing a vector field for edge detection and image segmentation. The edges are marked as the location where the vectors diverge from each other in opposite directions. The idea of designing a vector field for edge detection is very similar to the Edgeflow technique [9]. Tabb and Ahuja create these vectors by analyzing a neighborhood around each pixel. For a multi-scale representation, the optimum neighborhood size changes from pixel to pixel and needs to be estimated. The technique accepts a parameter that specifies a desired homogeneity level within regions. Using this homogeneity parameter, the neighborhood size and the spatial scale are estimated at each pixel adaptively.

Another approach to multi-scale edge detection and segmentation is Perona-Malik flow [10]. Anisotropic diffusion is based on preventing smoothing around the edge locations. This is equivalent of applying Gaussian smoothing with a spatially adaptive variance. A pixel within an homogenous region is smoothed with a Gaussian of large variance whereas a pixel close to an edge is smoothed at a smaller scale.

An important question still remains. Should the image be analyzed from fine scale to coarse scale or vice versa? In general, this should not matter for a well designed computerized system. Experiments [11] show that neurons in the visual cortex of Old World monkeys[1] are tuned from coarse scales to fine scales. It can be easily argued that at first sight we analyze a scene at a coarse scale and over time we start seeing the finer details. Similarly for a computer vision system, it is desirable that the edges exist at both coarse and fine scales, and the localization of these edges are decided at the finest scale. Note that a boundary at coarse scale might consist of several boundaries at the fine scale when the detail level is increased.

In the next section we will design and propose a multi-scale edge detection method. Our technique is motivated from a geometrical point of view. Unlike previous work in this area, it is not necessary to estimate a scale locally. The objective is to detect edges that exist at both coarse and fine scales, and localize them at the finest scale. In Section 3, we extend our method to multi-scale image segmentation.

2. MULTI-SCALE EDGEFLOW VECTOR FIELD AND EDGE DETECTION

Ma and Manjunath introduced a methodology [9] for creating the Edgeflow vector field at a user defined spatial scale. This vector field is then used for edge detection and image segmentation. Image segmentation is generated in a ad hoc way from the edges by edge linking. We are more interested in the vector field design and edge detection parts of this work. Edgeflow vector field is designed in a way such that the vector flow is towards the boundary at either side of the boundary. For detecting the edges, first a way of vector propagation is applied to the vector field to enhance the edge locations. Edges are then labeled as the locations where vector field reverses its direction. To detect edge locations, x and y components of the vector field are checked for sign changes (along the x and y directions) and the pixel that changes from positive to negative is labeled as the edge pixel. The edge strength equals the absolute difference of the magnitudes at the transition. Our primary purpose in this section is to define a multi-scale vector field that is based on the Edgeflow technique. We will then utilize this multi-scale vector field for multi-scale edge detection. In Section 3, the same vector field will also be used for image segmentation within our anisotropic diffusion framework.

First let us summarize the changes we made to the vector field generation and edge detection procedures that are proposed by the original Edgeflow technique.

- Instead of using the gradient of the smoothed image for computing the vector magnitudes, we utilize relative directional differences.
- We do not apply the vector propagation stage proposed in [9].
- We reduce the Gaussian offset from 4σ to σ. σ is more suitable for gray-scale edge detection, while 4σ is shown to be effective on texture features.

Our main goals in designing the multi-scale edge detector are:

- Localize edges at the finer scales.
- Suppress edges that disappear quickly when scale is increased. These are mostly spurious edges that are detected at the fine scale because of noise and clutter in the image but do not form salient image structures.
- Favor edges or edge neighborhoods[2] that exist at both fine and coarse scales.

In generating our vector field, we will explicitly use a fine to coarse strategy. On the other hand, our multi-scale framework also conducts coarse to fine edge detection implicitly. Take s_1 as the finest (starting) scale and s_2 as the coarsest (ending) scale. We are interested in analyzing an image between scales s_1 and s_2 for finding the edges. The units for scales are in pixels. All images used in this paper are of size 240×160. The interval $[s_1, s_2]$ is sampled with increments of Δs. In [5], Bergholm uses $\Delta s = 0.5$ such that dislocation of edges for successive scales is less than a pixel. Similarly, we will also set Δs to 0.5. The algorithm for generating the multi-scale Edgeflow vector field is given in Algorithm 2.1.

Algorithm 2.1 Algorithm for generating a multi-scale Edgeflow vector field.

Let $I(x,y)$ be the image.
Let C be a positive constant (e.g. 15).
Let A be a positive constant corresponding to an angle (e.g. $\pi/4$).
Let s_1 be the smallest and s_2 be the largest spatial scale at which we are interested in analyzing the image for edges.
Let $\Delta s = 0.5$ pixel be the sampling interval for the scale.
From I, calculate the initial vector field $\vec{S}$ at scale $s = s_1$.
while $s < s_2$ **do**
  Set $s = s + \Delta s$.
  Calculate Edgeflow vector field $\vec{T}$ at scale s.
  $M = Max(\|\vec{S}\|)$
  for all Pixel (x,y) in I **do**
    if $\|\vec{S}(x,y)\| < \frac{M}{C}$ **then**
      $\vec{S}(x,y) = \vec{T}(x,y)$
    else if The angle between $\vec{S}(x,y)$ and $\vec{T}(x,y)$ is less than A **then**
      $\vec{S}(x,y) = \vec{S}(x,y) + \vec{T}(x,y)$
    else
      $\vec{S}(x,y)$ is kept the same.
    end if
  end for
end while
The final $\vec{S}$ gives the multi-scale Edgeflow vector field.

As can be seen, the vector field that is generated at scale s_1 is selectively updated using the vector fields from larger scales. The vector field update procedure can be interpreted as follows: At a small scale, the vector field only exists on a thin line along the edges. Therefore, within the homogenous areas the vectors are of zero length. With increasing scale the reach–coverage area–of the vector field also gets thicker. First of all, we want to preserve the edges detected at the fine scale, which implies that we preserve strong vectors from the fine scale. We also would like to fill the empty areas with vectors from larger scales. The main reason for this is that some edges that do not exist at fine scales, the so called

[1] Old World monkeys are a family of monkeys including baboons and macaques.

[2] For larger scales, edges are displaced from their original locations. For this reason, it makes more sense to discuss edge neighborhoods when larger scales are considered.

shadow, shading or blur edges, will be captured at the larger scales. For these reasons, we check if $\|\vec{S}(x,y)\| < \frac{M}{C}$, and if so, fill this pixel with a vector from a larger scale.

Note also that the proposed method favors edges that exist at multiple scales and suppress edges that only exist at finer scales. The strength of the edges are represented by the strength of the vectors at the edge location where the vector field changes its direction. If the vector directions match at multiple scales, this means that the edges exist at multiple scales. Based on this observation, we check the vector directions from larger and finer scales and if they match, we sum the vectors up to strengthen the edge.

Another possibility is that the edge is shifted from its original location at the larger scale. In that case, the vector at the pixel that is in between the original (small scale) edge and the shifted (large scale) edge will change its direction by 180 degrees. As we discussed before, we favor the edge localization at the finer scale. Therefore the new vector from the larger scale is ignored and the vector from the finer scale is preserved.

Figure 2 shows the results of multi-scale edge detection with $s_1 = 1$, $s_2 = 4$, $\Delta s = 0.5$, $C = 15$, and $A = \pi/4$. Multi-scale edge detection results are compared to edge detection results at $\sigma = 1$ and $\sigma = 4$. These results show that the results corresponding to $\sigma = 1$ localizes edges very well but detect clutter and noise as edges. The results corresponding to $\sigma = 4$ include cleaner results but the edges are not well localized (See Figure 2h). On the other hand, by combining results from scales 1 to 4, we are able achieve edge detection results that both localize edges precisely (as in $\sigma = 1$) and create a cleaner edge detection (as in $\sigma = 4$).

The main advantage of our method is that there is no need to estimate local scales at each pixel. The vector field is designed to contain cues from multiple scales and the scale selection is implicit within the multi-scale vector field. Our approach is able to localize edges with no extra and external effort such as tracking edges or analyzing the displacement of corners, junctions etc., in scale space. Edge detection results show that the edges are localized as desired and salient structures existing at both fine and coarse scales are captured. In the next section we show a multi-scale segmentation method using the vector field designed in this section.

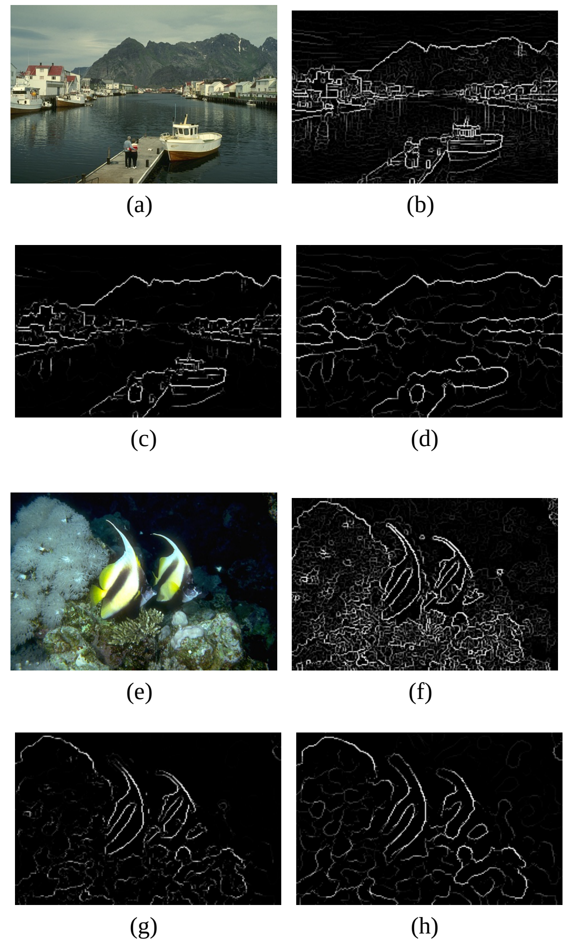


Figure 2: Demonstration of multi-scale edge detection. a and e) Original images. b and f) Edge strengths at spatial scale $\sigma = 1$ pixel. c and g) Multi-scale edge detection using scales from $\sigma = 1$ to $\sigma = 4$. d and h) Edge strengths at scale $\sigma = 4$ pixels.

3. MULTI-SCALE IMAGE SEGMENTATION

In Section 2, we designed a multi-scale Edgeflow vector field and utilized this vector field for multi-scale edge detection. Another interesting application of this vector field is multi-scale image segmentation. In [12, Chapter 3], we introduced a new variational segmentation method that is based on anisotropic diffusion. This anisotropic diffusion scheme utilizes a vector field to find the boundaries. Simply replacing this vector field with the multi-scale Edgeflow vector field, we are able to achieve a multi-scale image segmentation.

The multi-scale segmentation is achieved as follows. From the multi-scale vector field, we first generate an edge stopping function V by solving a poisson equation:

$$\vec{\nabla} \cdot \vec{S} = -\Delta V \tag{1}$$

where $\vec{S}$ is the Edgeflow vector field. Using the vector field and edge stopping function, segmentation is defined as the convergence of the following anisotropic diffusion:

$$I_t = \alpha V \kappa \|\nabla I\| + \beta \vec{S} \cdot \nabla I \tag{2}$$

Fig. 3 demonstrates the behavior of the multi-scale segmentation compared to segmentations at the fine and coarse scales. The results show that using a multi-scale approach we are able to capture salient structures from a range of scales. It is to be noted that region merging using fine scale segmentation will not usually give the similar results as our multi-scale segmentation. For example, in Figures 3 (b-d), there are certain boundaries and structures that emerge as the scale increases and these boundaries are not captured or do not exist at the smaller scales. Figures 3 (e-h) demonstrate the excellent edge localization property of our multi-scale algorithm. Fig. 3 (i-n) show another example of a multi-scale segmentation and shows the better localization of the edges around the head area using multi-scale approach compared to segmentation at scale $\sigma = 6$.

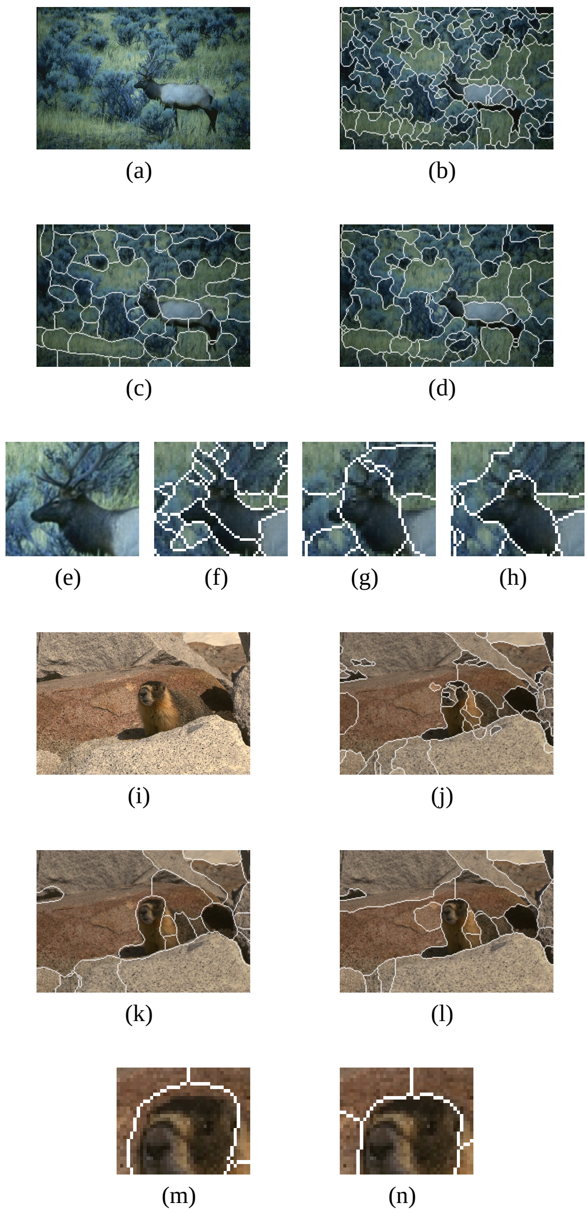


Figure 3: a) Original image. b) Segmentation result at spatial scale $\sigma = 1.5$. c) Segmentation result at $\sigma = 6$. d) Multi-scale segmentations using scales $\sigma = 1.5$ to $\sigma = 6$. e) Detail around the head area. f) Detail for $\sigma = 1.5$ g) Detail for $\sigma = 6$ h) Detail for multi-scale segmentation. i) Original image. j) Segmentation result at $\sigma = 1.5$. k) Segmentation result at $\sigma = 6$. l) Multi-scale segmentations using scales $\sigma = 1.5$ to $\sigma = 6$. m) Detail around head area for $\sigma = 6$. n) Detail for multi-scale segmentation.

4. CONCLUSIONS

In this paper, we have shown that using multi-scale techniques edge detection and segmentation quality on natural images can be improved significantly. We proposed a novel multi-scale edge detection and vector field design scheme. Our approach eliminated the need for scale selection and edge tracking, which has been the main focus of the previous work in this area. Our objective is to find and favor edges that exist at a wide range of scales and localize these edges at finer scales. This work is then extended to multi-scale segmentation using our anisotropic diffusion scheme.

Acknowledgements

This work was supported by the National Science Foundation award NSF ITR-0331697.

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