Robust Image Contour Detection by Watershed Transformation

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ABSTRACT

Two approaches of multistage gradient robustification for image contour detection are presented in this paper: two stages of Difference of Estimates and Difference of Estimate followed by an optimal filtering. Watershed transformation is then applied to these robustified gradient images to effectively detect image contours which are guaranteed to be in closed form. Multistage gradient robustification provides the flexibility of using different image processing techniques and produces good detection results for the images highly corrupted with noise.

1. INTRODUCTION

Contour detection is a key step in computer vision systems. It converts a gray-scale image into a binary one which preserves a great deal of useful information in the original image. The rest of the vision process can deal with the simple form, instead of dealing with the gray-scale image directly. The contours of an image are usually considered to be lines where the gray tone is varying quickly compared to the neighbourhood.

The contour can be emphasized by taking the gradient of the image. If this gradient image is regarded as a relief, the searched contours correspond to some crest lines of the gradient function. Not all crest lines are interesting in segmenting the image, however. Only the closed contours should be extracted. The gray scale skeleton of the gradient image has parasitic dendrites, i.e. lines that are not closed. In order to remove these useless lines we resort to watershed transformation.

Watershed transformation [3, 4] starts with a gradient image as input, the contours of an image are defined as the watersheds of its gradient, the morphological gradient is thus the basis of the morphological approach to contour detection.

The standard morphological gradient suffers from the problem of excessive noise sensitivity and inevitably leads to erroneous contours. Multistage gradient robustification method is proposed in this paper as an extension of Difference of Estimates(DoE) approach to robustify gradient operators in noise environments.

2. MORPHOLOGICAL GRADIENT AND DIFFERENCE OF ESTIMATES

Morphological gradient operators enhance variations of pixel intensity in images. It's defined as the difference between the dilated version and the eroded version of the original image X:

$$G(X) = (X \oplus B) - (X \ominus B) \tag{1}$$

In case the structuring element B is flat, the morphological operations of dilation $\oplus$ and erosion $\ominus$ are then equivalent to the computation the local maximum and minimum. Therefore, the gradient at any point $(m, n) \in X$ is the maximum variation of the gray level intensities in the given window:

$$G_x(m,n) = max\{W_x(m,n)\} - min\{W_x(m,n)\} \tag{2}$$

Fig. 1.b,e and Fig. 2.b,e show the output of the above-defined gradient operator acting

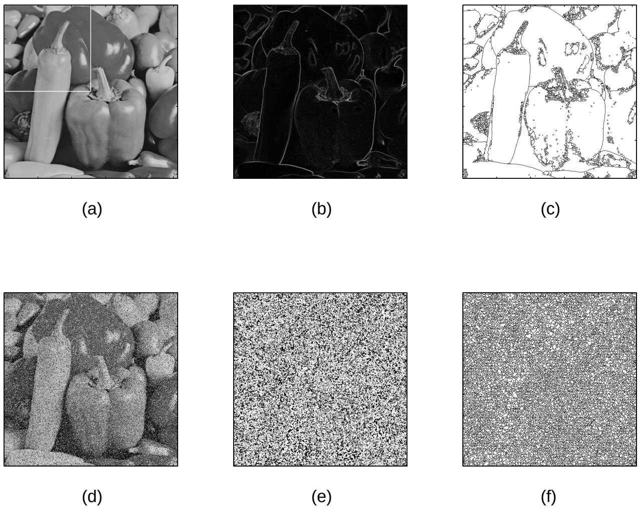

Figure 1: a)Original image *Peppers* (512×512), the marked square is the training set; b)Morphological gradient of a); c)Detected contours of b); d)Image *Peppers* corrupted with salt(10%) and pepper(10%) noise; e)Morphological gradient of d); f)Detected contours of e).

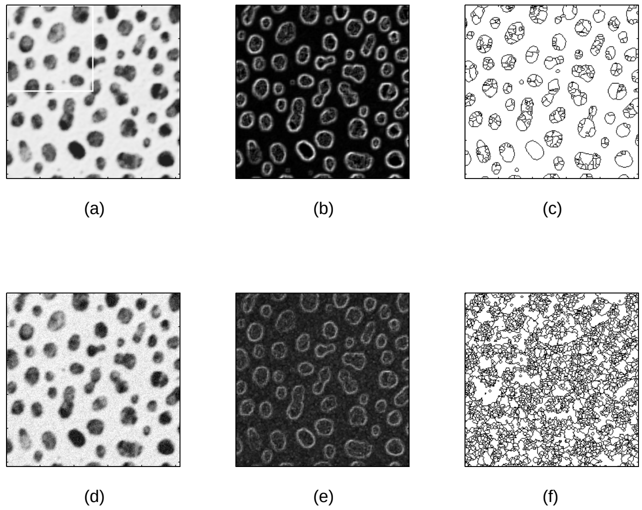

Figure 2: a)Original image *Cermet* (256×256), the marked square is the training set; b)Morphological gradient of a); c)Detected contours of b); d)Image *Cermet* corrupted with Gaussian noise(mean=0,variance=200); e)Morphological gradient of d); f)Detected contours of e).

on the test images, Fig. 1.c,f and Fig. 2.c,f are their corresponding contours detected using watershed transformation. It is obvious to see that the standard gradient operator is not resistant against noise. The Difference of Estimates (DoE) approach [6] is therefore proposed to robustify the gradient operator. Let $\tilde{X}$ be the corrupted version of desired image X, DoE is formulated as

$$DoE_{\tilde{x}}(m,n) = \mathcal{N}_{max}(W_{\tilde{x}}(m,n)) - \mathcal{N}_{min}(W_{\tilde{x}}(m,n)) \quad (3)$$

The rationale is that we choose two nonlinear filters $\mathcal{N}_{max}$ and $\mathcal{N}_{min}$ to replace the $max\{\cdot\}$ and $min\{\cdot\}$ filters such that the difference of estimates, $DoE_{\tilde{x}}(m,n)$ is a good approximation to the difference of the local maximum and minimum of the noiseless image. The optimal nonlinear filters $\mathcal{N}_{max}$ and $\mathcal{N}_{min}$ are designed under MAE criterion.

Figure 5.a,b, Figure 6.a,b show the significant improvement of threshold Boolean filter(TBF) [7] based gradient operator and order statistic(OS) based gradient operator acting on the impulse and Gaussian noise corrupted images. TBF gradient [4] drops the stacking constraint and requires less computation than stack filter gradient which was proposed in [6, 8]. OS gradient [4] drops the symmetry restriction existing in quasi-ranges [9], thereby relaxing the limits to the available tuning.

For effective noise suppression in highly corrupted image, gradient operator usually requires a large window and consequently suffers from very high computational complexity. This situation may be remedied by multistage gradient robustification which will be discussed in detail next.

3. TWO-STAGE OF GRADIENT ROBUSTIFICATION

Two approaches were studied to accomplish two-stage gradient robustification. The first way is to apply nonlinear filters sequentially to estimate the dilation and erosion of uncorrupted image X from noise corrupted observation $\tilde{X}$:

$$G_2(\tilde{X}) = \mathcal{N}_{max2}\{\mathcal{N}_{max1}(\tilde{X})\} - \mathcal{N}_{min2}\{\mathcal{N}_{min1}(\tilde{X})\} \quad (4)$$

Another way is a mixture of the DoE and adaptive filtering schemes: one stage of Difference of Estimates followed by an optimal filtering to further enhance the performance:

$$G_2'(\tilde{X}) = \mathcal{F}_{opt}\{\mathcal{N}_{max1}(\tilde{X}) - \mathcal{N}_{min1}(\tilde{X})\} \quad (5)$$

The flow charts for these two methods are depicted in Fig. 3, and Fig. 4. The algorithms

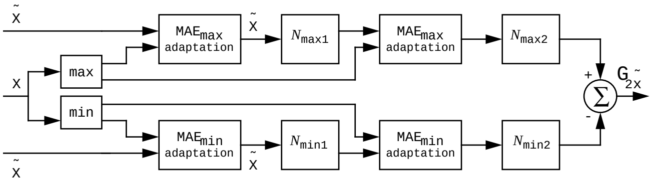

Figure 3: Two-stage of Difference of Estimates

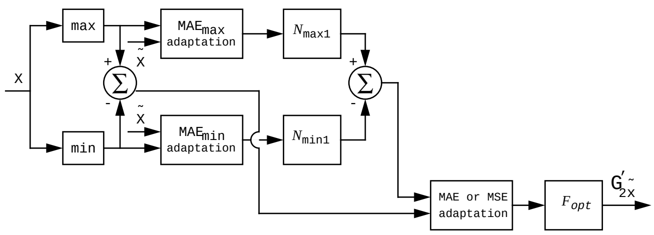

Figure 4: Difference of Estimates followed by an optimal filtering

proceed as follows:

1)First, nonlinear filter $\mathcal{N}_{max1}$ ($\mathcal{N}_{min1}$) is designed through adaptation algorithm minimizing the mean absolute error between $max(X)$ ($min(X)$) and $\mathcal{N}_{max1}(\tilde{X})$ ($\mathcal{N}_{min1}(\tilde{X})$).

2)Noise corrupted image $\tilde{X}$ is then filtered by $\mathcal{N}_{max1}$ ($\mathcal{N}_{min1}$), producing an output $\mathcal{N}_{max1}(\tilde{X})$ ($\mathcal{N}_{min1}(\tilde{X})$). A one-stage gradient operator is formed by

$$G_1(\tilde{X}) = \mathcal{N}_{max1}(\tilde{X}) - \mathcal{N}_{min1}(\tilde{X}) \qquad (6)$$

3.1)For two-stage DoE(MaxMax–MinMin), step 1 is repeated to obtain the filter $\mathcal{N}_{max2}$ ($\mathcal{N}_{min2}$), here MAE adaptation is carried out between $max(X)$ ($min(X)$) and $\mathcal{N}_{max2}(\mathcal{N}_{max1}(\tilde{X}))$ ($\mathcal{N}_{min2}(\mathcal{N}_{min1}(\tilde{X}))$).

3.2)For DoE+$\mathcal{F}_{opt}$ approach, the optimal filter $\mathcal{F}_{opt}$ is designed by adaptation algorithm minimizing MAE e.g. [10, 11, 12] or MSE [13] between the output of standard morphological gradient operator acting on the original uncorrupted image X and the output of the filter $\mathcal{F}_{opt}$ operating on the previous one-stage gradient $G_1(\tilde{X})$.

4)Two-stage gradient operators expressed by Eq. 4,5 are then used in processing other images to obtain accurate approximations of noiseless morphological gradient.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

There are a wide variety of possible combinations of DoE and adaptive filtering algorithms to construct a two-stage gradient operator. Based on the good performance of TBF, OS and LMS linear filter [4] for impulse and Gaussian noise removal, they are chosen to present here to form two-stage gradient operators.

For impulse corrupted *Peppers* image (Fig. 1.d), we consider a cascade of two TBF filters to more robustly estimate the noise-free dilation and erosion, and it is presented below:
$G_2(\underline{X}(n)) =$

$$F_{TBF3}\{F_{TBF1}(\underline{X}(n))\} - F_{TBF4}\{F_{TBF2}(\underline{X}(n))\} \qquad (7)$$

$\underline{X}(n)$ is the observed noisy image window process containing $N_1 + N_2 + 1 = N$ samples:

$$\underline{X}(n) = [x(n-N_1), x(n-N_1+1), \ldots, x(n+N_2)]^T \qquad (8)$$

For Gaussian noise corrupted image *Cermet* (Fig. 2.d), the OS gradient is followed by an optimal FIR filtering to form a two-stage gradient operator:

$$G_2'(\underline{X}(n)) = F_{FIR}\{F_{os\_(r1)}(\underline{X}(n)) - F_{os\_(r2)}(\underline{X}(n))\} \qquad (9)$$

$r1$ and $r2$ do not necessarily have to be symmetric like $N+1-r$ and r in the quasi-ranges. We call

$$G_{mq}(\underline{X}(n)) = F_{os\_(r1)}(\underline{X}(n)) - F_{os\_(r2)}(\underline{X}(n)) \qquad (10)$$

modified quasi-ranges.

The linear FIR filter is expected to effectively attenuate Gaussian noise.

The simulation results for these two methods are shown in Fig 5.c,d, Fig 6.c,d. They are superior to any one-stage gradient robustification in terms of noise cancellation.

The number of regions in the detected contour image was used as a quantitative measurement to evaluate the performance of proposed gradient operators. Table 1 lists the results obtained.

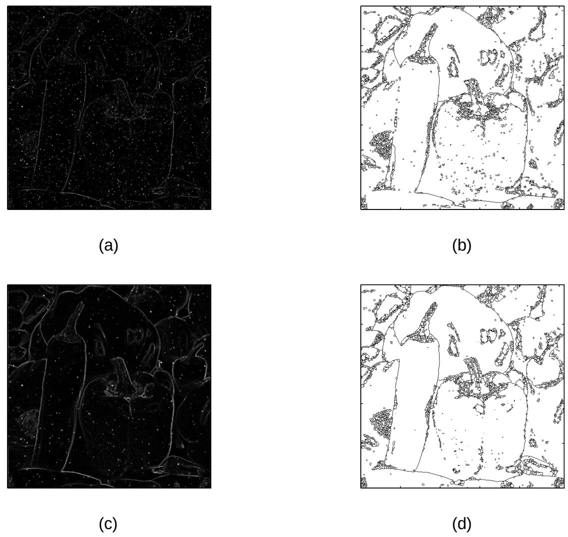

Figure 5: a)One-stage TBF gradient of noisy *Peppers*; b)Detected contours of a); c)Two-stage TBF gradient of noisy *Peppers*; d)Detected contours of c).

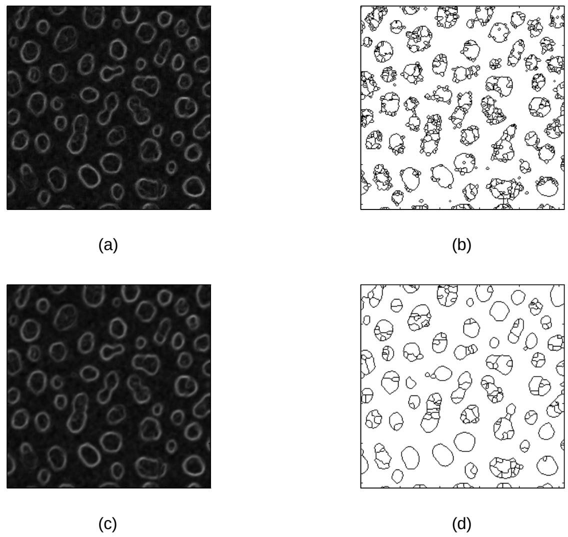

Figure 6: a)One-stage gradient of noisy *Cermet*; b)Detected contours of a); c)Two-stage gradient of noisy *Cermet*; d)Detected contours of c).

Table 1: Comparisions of different algorithms[1]:

Method	Number of regions in contour detected image	
	Impulsive Peppers	Gaussian Cermet
Standard grad.	15417	3170
One-stage DoE	4074(TBF)	1089(OS)
Two-stage DoE	3336(TBF)	232(OS+FIR)

5. CONCLUSIONS

Based on the DoE approach to gradient robustification and adaptive filtering for noise removal, we derived two multistage gradient algorithms to achieve good contour detection for noisy images. The first approach is a cascades of two DoE operators. The second one is one-stage DoE followed by an adaptive filtering to further improve the performance, proper incorporation of linear method in this approach is very effective for Gaussian noise attenuation. Results obtained by applying these new schemes to both impulse and Gaussian noise corrupted images indicate that they are more noise resistant than their one-stage counterparts for highly corrupted images at the cost of higher computational complexity. On the other hand, they are more cost efficient compared with one-stage DoE with large window size.

[1] Algorithms are specified in ( ), window size is 3×3

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