

Adaptive wavelet based edge detection in noisy images

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Abstract— Edge detection is used widely from consumer applications to military and medical image analysis. One of the challenges in edge detection is getting the best trade-off between reliable detection and noise robustness. Because of that it is important to develop reliable edge detection algorithm which can adapt to different noise levels keeping false detections at minimum. In this paper we propose edge detection algorithm based on stationary wavelet transform which can automatically adapt to different noise levels. Robustness of this algorithm was tested for several noise levels and was compared to Canny algorithm which parameters were adjusted manually for introduced noise level.

Keywords-component; edge detection; wavelet transform; multi-resolution analysis; image processing.

I. INTRODUCTION

Edges are one of the most important image features. Hence edge detection is usually one of the first steps for image segmentation, enhancement, scene analysis, diagnostics, and other computer vision applications. Edge detectors are used in a wide range of applications from consumers and military applications to medical image analysis. Edges are abrupt change in intensity of neighboring pixels which can occur for variety of reasons such as illumination change, object contours, depth of field discontinuity, occlusions, shadows, etc. In fact any small change in intensity between neighboring pixels can be considered as a potential edge. This is the reason why performance of the best edge detection algorithms with good detectability properties decreases significantly in presence of noise. Due to the sensitivity of edge-based applications it is important to have reliable and robust algorithm whose performance is good even in noisy environments. Good algorithm should be able to maximize real detections while keeping false ones as low as possible automatically without need for manual parameters adjustments.

Canny described this tradeoff in his paper [1] stating that robustness to noise comes at the cost of worse localization and detection. In order to achieve desired behavior, noise resistance versus good localization, parameters of edge detection algorithm such as smoothing filter and the threshold of detection must be chosen carefully since they depend on the amount of noise present in input image.

Several researchers have introduced the concept of multi-scale edge detection [2]-[9]. Tradeoff between localization and

noise robustness was transferred to problem of selection of appropriate scale.

In our algorithm we automatize the process of edge detector optimization by using noise estimator, and adjusting smoothing and threshold values accordingly. We have incorporated this into multi-resolution framework based on stationary discrete wavelets transform which enables us to get higher levels of robustness.

In section II we give a brief overview of current edge detection techniques. In section III we are focusing on multi-resolution analysis and its value for edge detection application. We present detailed algorithm description in section IV. Experimental results as well as comparisons with Canny's algorithm for different noise levels are located in section V. We conclude in section VI with future work suggestions.

II. EDGE DETECTION APPROACHES

Since edge represents an abrupt change in pixels values it will be represented as a peak in the gradient domain. One of the earliest researches of edge detection is summarized in [10], where authors proposed the usage of convolution with the second derivative of a Gaussian. Edges were identified by detection of zero-crossings in filtered image. This method is prone to false detections and does not provide good localization. Also the usage of zero-crossings itself does not provide enough information about the direction of edges since it is difficult to distinguish the type of zero-crossing.

Edge detection operators based on the gradient magnitude detection are widely used and are a part of some well known edge detection algorithms. Edge detection operators are discrete kernels which are usually applied horizontally and vertically on input image to extract gradient values for each direction and from this information find gradient magnitude and edge direction. Most popular gradient based edge detection operators are Prewitt, Roberts and Sobel.

John Canny in [1] presented a complete algorithm which is still considered to be state-of-the-art edge detector. Canny in his algorithm defines series of steps in which the first was image smoothing using Gaussian low pass filter, then DoG (difference of Gaussian) operator was used which he showed to be the well approximation of the ideal edge filter. After finding the intensity gradient magnitude, he proposed the step of non-maxima suppression making all detected edges only 1 pixel

thick. To keep detected edges connected double thresholding scheme is applied in which weak edges were preserved only if they were connected with strong ones. To further improve quality of detected edges and avoid discontinuity final step of morphological linking was used.

Canny edge detection algorithm has superior results when it is tuned for certain image. However since detection is done using only one scale it is difficult to obtain good detection of small sharp edges and smooth large edges at the same time. To overcome this issue multi-resolution approach to edge detection was introduced. In multi-resolution approach image is smoothed with different size filters extracting edge information at different scales. Combining results from different scales enables better detection and noise resistance.

There are many papers proposing improvements of the original Canny algorithm [12]-[15]. Some of them address adaptability and automatic parameter selection [14], [15]. We have incorporated adaptability into multi-resolution framework using simplified version of Canny algorithm and obtain results comparable with original algorithm performance tuned for introduced noise level.

III. MULTI RESOLUTIONAL ANALYSIS

Multi-resolution image decomposition is usually consisted of progressive smoothing and high-pass filtering for details extraction. Larger smoothing leaves only large scale details discarding high frequency details as well as noise. Because of that, higher levels of multi-resolution decomposition contain significantly less noise than lower ones. On the other hand if we look at the edges at higher levels their energy is distributed on more neighboring pixels compared with lower levels making localization more difficult.

One of the oldest and well known multi-resolution decomposition is Gauss and Laplace pyramids. They are generated by progressive smoothing of input image with Gaussian low pass filter. Laplace pyramid is generated as difference between adjacent levels, holding details for each scale and enabling original image reconstruction. However Laplace pyramid holds only information about details (edges) magnitude, but there is no information about direction which is needed for the later steps in algorithm. This information can be obtained by applying some edge detector, Sobel, Perwitt, Roberts on different levels of Gaussian pyramid.

Because of its ability of multi-scale singularity detection wavelet transform quickly become one of the interesting tools for edge detection. Stephene Mallat and Siften Zhong in their paper [3] have shown that a multi-scale Canny edge detection is equivalent to finding the local maxima of a wavelet transform. They also explained how to characterize different types of edges from the evolution of the modulus maxima across scales of wavelet. To fully exploit power of multi-resolution approach information from different levels should be combined to achieve optimal edge detection. A lot of papers focused on this combination between levels for best exploitation of different edge properties across the scales [4]-[9]. Multiplication of adjacent scales was proposed in [7] while [8] proposes usage of fusion rules for scale combination. In our algorithm we are using scale multiplication.

IV. PROPOSED ALGORITHM

A. Adaptive smoothing

Since we are using high pass filtering for edge detection, image smoothing is important for initial noise suppression and connection of broken edges. Parameters of smoothing filter should be chosen carefully. Aggressive filter will destroy objects shape while weak filter will leave more noise making false detection higher.

We have used diagonal details, which are result of high-pass filtering through both dimensions, from the first level of wavelet decomposition to estimate noise strength and accordingly set strength of smoothing filter. Following work of Johnstone and Donoho [11] we estimate noise standard deviation using robust metric such as median of absolute deviation. If we assume that noise has Gaussian distribution then standard deviation could be estimated as:

$$\sigma_1 = 1.4826 \cdot \text{median}|W_d^1 - \text{median}(W_d^1)| \quad (1)$$

For smoothing filter we were using 5x5 Gaussian filter whose standard deviation was set to be a multiple of the estimated noise strength $\sigma_{sf} = k \cdot \sigma_1$. In our experiments on different images with different noise levels we found that best results are obtained when parameter k is set to 22.

B. Wavelet decomposition and scale multiplication

Image is decomposed into multiple resolution levels using the stationary wavelet transform, where analysis filters are up-sampled through levels instead of down-sampling the resulted planes. Constant size of detail planes on different levels enabled easier level combination in later steps. In our work we have using Haar wavelet because it is similar to standard edge detection operators and enables efficient extraction of gradient information in each direction. At each level 3 types of details are available horizontal, vertical and diagonal. Horizontal and vertical details provide information about gradient strength in each direction which is the similar to the results obtained from Sobel filtering. Main advantage of wavelet decomposition is that details are distributed through the levels enabling easier manipulation and more accurate edge detection. As mentioned in section II the energy of edges will be spread to more pixels as we go to higher levels making accurate localization difficult. On the other hand noise will exist only in the first few levels and will be filtered out in higher levels. Details form two different levels are presented in Figure 1 which depicts these tradeoffs.

To combine edges at different scales we use multiplication of adjacent levels in wavelet transform.

$$\begin{aligned} W_h^{mi} &= W_h^i \cdot W_h^{i-1} \\ W_v^{mi} &= W_v^i \cdot W_v^{i-1} \\ W_d^{mi} &= W_d^i \cdot W_d^{i-1} \end{aligned} \quad (2)$$

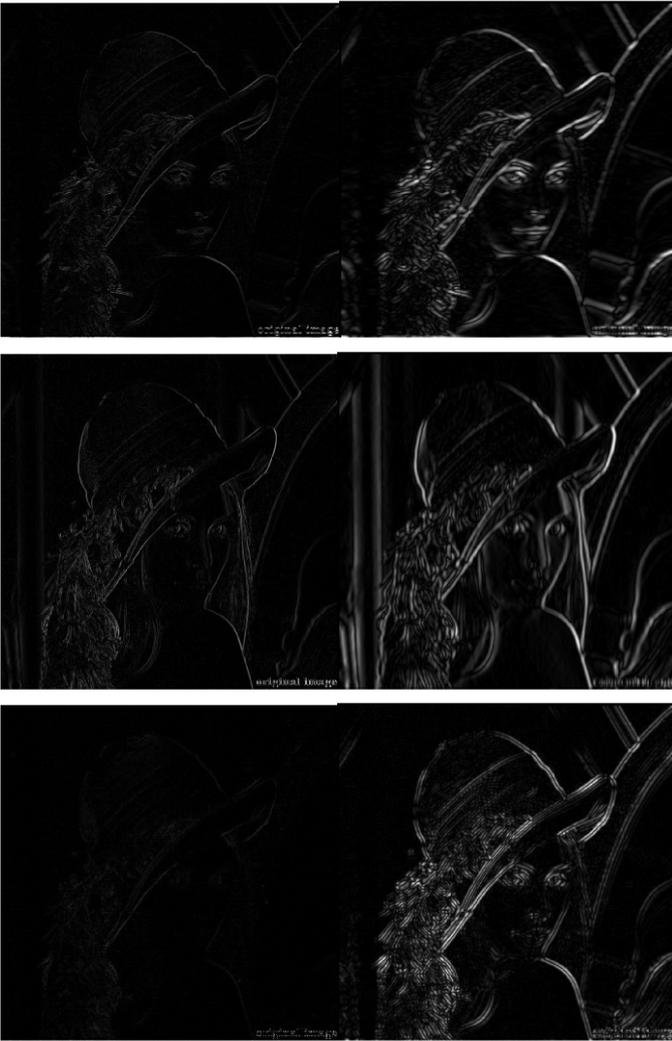


Figure 1. Horizontal (top), vertical (middle) and diagonal (bottom) details of stationary wavelet transform for the first (left) and third (right) level of decomposition.

By multiplication small values in smooth regions from higher level will attenuate noise in product's smooth regions and sharper edges in lower level will thin thick edges from higher level. Details of two adjacent levels as well as the result of multiplication are shown in Figure 2. Sometimes multiplication can be too aggressive and can destroy some fine edges which exist only in the lower levels of the wavelet transform.

Since different size filters in stationary wavelet transform introduce different phase delays each level plane should be shifted to compensate the phase differences before multiplication through levels.

As we go to the higher levels edges are starting to lose their shape making detection of fine details impossible. In our experiments best trade-off between noise (false edges) and edge shape was at the second level of wavelet decomposition. The best results were obtained from multiplication of the second and third levels of wavelet decomposition.

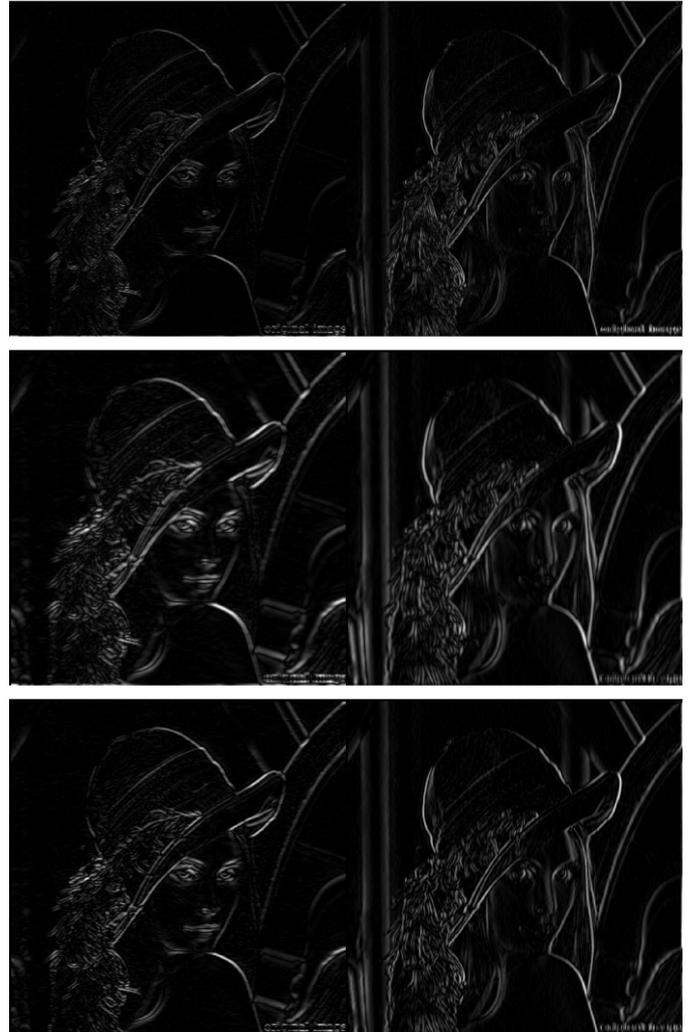


Figure 2. Horizontal (left) and vertical (right) details of the second (top) and third (middle) level of wavelet decomposition as well as multiplication result of these two levels (bottom).

C. Gradient magnitude

Since we already have information about gradient at each direction we can easily construct gradient magnitude map. Although gradient magnitude by definition is calculated only from horizontal and vertical gradient projections (horizontal and vertical wavelet details) we added also diagonal details to strengthen response to diagonal edge which results in weaker horizontal and vertical gradients. Gradient magnitude is extracted from detail planes using the following expression:

$$G_m^i = \text{sqrt}((W_h^{mi})^2 + (W_v^{mi})^2 + (W_d^{mi})^2) \quad (3)$$

Gradient magnitudes from the second and the third level of wavelet transform with and without multiplication with previous level are shown in Figure 3.



Figure 3. Gradient magnitude extracted at the second (top) and third (bottom) level of stationary wavelet decomposition without (left) and with (right) multiplication with previous level.



Figure 5. Input (left) and output (right) of non-maximum suppression.

D. Local non-maxima suppression

Edges are centered in the local maximums of the gradient magnitude map. Method for local non-maximum developed by Canny contains two steps. First one is to determine gradient direction at each pixel. In the second step only pixels which represents local maximum between two neighbors located orthogonally to the gradient direction are left in the map and all others are discarded (set to 0).

In our suppression we have quantized direction angles to 45 degrees as depicted on Figure 4. To obtain direction information we have used horizontal and vertical details which represent local maximum between two neighbors located orthogonally to the gradient direction and not details after multiplication since they have smoother gradients. Figure 4 shows also the masks used for each suppression direction. Result before and after local non-maximum suppression is shown in Figure 5.

Since edge pixels have large gradient value and since most of the noise is concentrated around zero we label all pixels which gradient magnitude is larger from 2.8σ as edge pixel. Result of edge labeling is shown on Figure 6.

E. Edge labeling

Unlike Canny which employs double thresholding scheme to deal with tradeoff between false edges and good detection we employ single threshold for simplicity. Threshold used for labeling edge points is estimated for each level and depends on strength of the noise present in input image. With this scheme automatic threshold adaptation is achieved for different noise levels without need for parameter adjustments. Noise strength is estimated in each level using the following relation:

$$\sigma_i = 1.4826 \cdot \text{median}|W_d^i - \text{median}(W_d^i)| \quad (4)$$

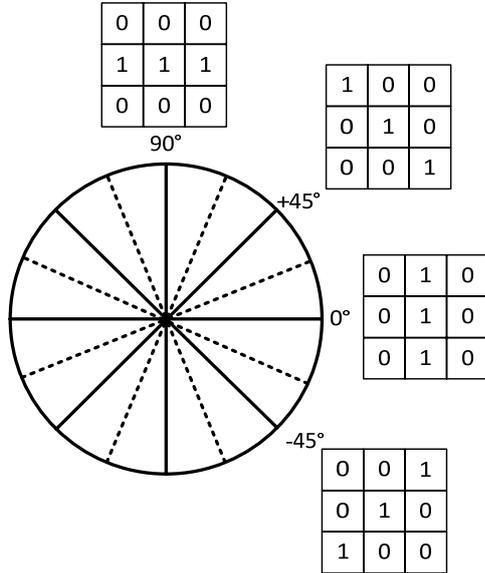


Figure 4. Edge directions are quantized to one of the four directions (0, -45, +45, 90) shown with full lines. Decision boundaries are shown with dashed lines. Masks used for non-maximum suppression are shown for each direction.



Figure 6. Detected edges



Figure 7. Input (left) and output (right) of false edges cleaning step.

F. False edges cleaning

As can be seen from Figure 6 some false edges are left in the final map. This can be avoided by setting larger threshold but in that case small details will be lost as well. Another way is to employ double thresholding scheme. Looking at the final edge map we can see that false edges are usually short edges disconnected from properly detected objects. False edges rate can be reduced with very simple cleaning scheme which can be applied iteratively. In first step we sum all pixels in 3x3 window around our test pixel. If this sum is less than 3 then this means that this pixel is alone or it is end of some detected edge but it is certainly not in the middle of some detected edge and in that case this pixel is set to 0 in the output map. By this step all lonely detections will be deleted. In other iterations filtering window is progressively increased (5x5, 7x7 ...) cleaning larger portions of detected edges. In our testing we have used 4 step cleaning scheme with following window sizes 3x3, 5x5, 7x7 and 9x9. Result of false edge cleaning process is shown on Figure 7.

V. RESULTS AND DISCUSSION

We have tested our algorithm for 3 different noise strengths without any parameter adjustments. Edges were extracted from multiplication of the second and third level of stationary wavelet transform. Comparisons with Canny edge detection algorithm are presented. Parameters of Canny algorithm were adjusted to obtain the best detection for introduced noise level.

Presented comparisons show that our result is comparable with result of Canny algorithm best suited for applied noise while other settings of Canny algorithm exhibits either significantly smaller detection rate or significantly larger false detection rate.



Figure 8. Detected edges for input image without any noise. Top-left (proposed algorithm), top-right (Canny with default parameter set), bottom-left (Canny tuned for middle noise $\sigma_n = 0.01$), bottom-right (Canny tuned for strong noise $\sigma_n = 0.1$)

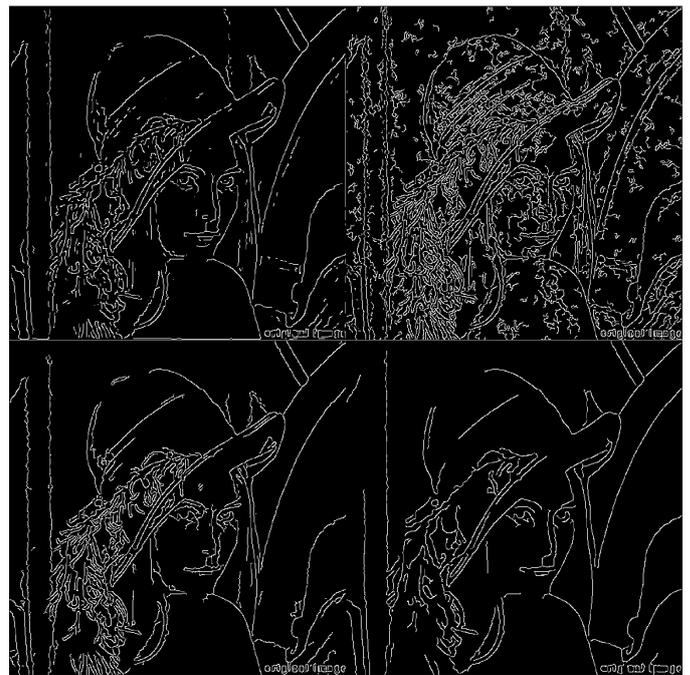


Figure 9. Detected edges for input image with Gaussian noise of middle strength $\sigma_n = 0.01$. Top-left (proposed algorithm), top-right (Canny with default parameter set), bottom-left (Canny tuned for middle noise $\sigma_n = 0.01$), bottom-right (Canny tuned for strong noise $\sigma_n = 0.1$)

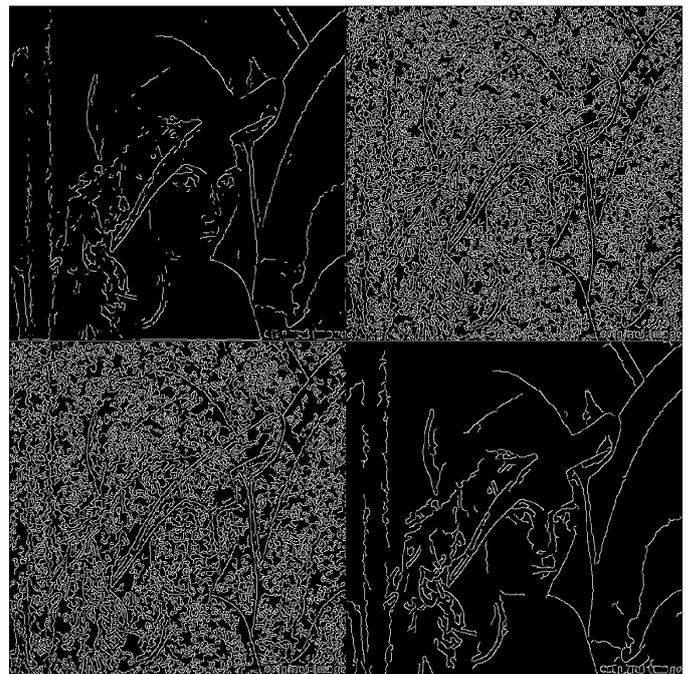


Figure 10. Detected edges for input image with strong Gaussian noise $\sigma_n = 0.1$. Top-left (proposed algorithm), top-right (Canny with default parameter set), bottom-left (Canny tuned for middle noise $\sigma_n = 0.01$), bottom-right (Canny tuned for strong noise $\sigma_n = 0.1$)

VI. CONCLUSION AND FUTURE WORK

We have presented a complete algorithm based on stationary wavelet decomposition and scale multiplication. Parameter adjustment process has been made automatic by estimation of noise strength using diagonal wavelet details in each decomposition level. We have shown that our algorithm performs well for different noise levels achieving good detection rate while keeping false detection minimal without need for manual parameter adjustments.

In the current algorithm edges were extracted from multiplication of the second and third level details of stationary wavelet decomposition. For stronger noise higher levels are needed for efficient noise suppression. Also if there is no noise good edges can be extracted from lower levels (multiplication of the first and second) enabling better localization. Automatic detection of the best level for edge extraction will be interesting feature that we plan to explore.

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