

EDGE DETECTION AND LINKING USING WAVELET REPRESENTATION AND IMAGE FUSION

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ABSTRACT

This paper presents an innovative way to combine edge detection and linking using the wavelet representation and image fusion. We describe how to detect and link edges in connection to horizontal and vertical orientations selectivity of the human visual system. We develop a framework with three stages: decomposition, recomposition, and fusion. In recomposition stage, we reconstruct both horizontal and vertical details to form input images for fusion stage. The output image of framework matches to contrast sensitivity paradigm of human visual system. In addition, our framework integrates both linear and nonlinear wavelet constructions in a single application. The framework is applied to 512x512, 8-bit gray scale images and results are presented.

Keywords: edge detection, edge linking, HVS, wavelets, image fusion

1 INTRODUCTION

This paper extends our previously developed framework in [1]. Edge detection is a common approach for detection of meaningful discontinuities in gray levels. Edge detection algorithms typically are followed by linking procedures to assemble edge pixels into meaningful edges. Edge linking procedures consist of linking edge segments separated by small breaks and deleting isolated short segments. An edge is a set of connected pixels that lie on the boundary between two regions. Automatic boundary detection within an image is a challenging task [2]. Figure 1 shows an example of the boundary detection problem. Humans are very good as their visual system makes this task possible within a moment whereas considerable efforts are required for machines to replicate the same or somewhat nearer. To tackle this problem we develop a framework for edge detection and linking in the wavelet domain. Our framework exploits horizontal and vertical orientations selectivity of the human visual system and consists of three stages: decomposition, recomposition, and fusion. From output of the decomposition stage, we recombine (reconstruct) horizontal and vertical details in the recomposition stage. The fusion stage outputs a fused image of both horizontal and vertical recomposed orientations using wavelets again.

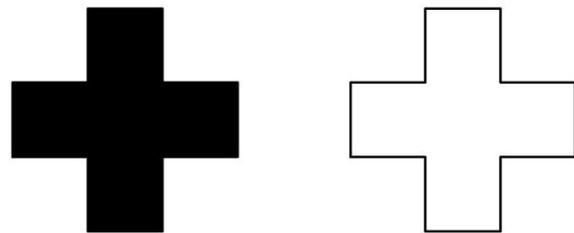


Figure 1: Example (left) input and (right) output images.

1.1 Motivations and Contributions

The contrast sensitivity for a grating in the oblique orientations is lower than that for a grating presented either horizontally or vertically [3], [4]. The wavelet coefficients have high amplitude around the edges and the wavelet representation discriminates orientations [5]. We choose horizontal and vertical details for edge detection. Image fusion combines information from various sensors or by the same sensor in many measuring contexts [6]. Therefore, image fusion is a nearly optimal choice for linking both horizontal and vertical orientations. Our main contribution in this paper is the introduction of a recomposition stage to bridge

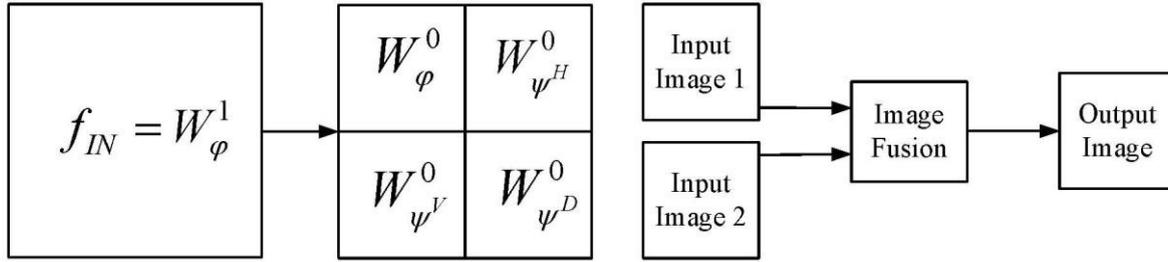


Figure 2: (Left) Wavelet decomposition [7], and (right) image fusion process.

decomposition and fusion stages. Therefore, the theme of our edge detection and linking framework (EDLF) is to link both horizontal and vertical orientations in connection with sensitivity to human visual system (HVS). Other contributions are: choice of wavelets at decomposition/recomposition and fusion stages and an integration of both linear and non-linear (lifting-based) wavelet constructions in a single application.

The paper outline is as follows. In Section 2, we present related research and mathematical preliminaries for wavelets and image fusion. We describe EDLF in Section 3, and implement it using MATLAB in Section 4. Finally, we conclude our paper in Section 5.

2 PRELIMINARIES

2.1.1 Related Research

The wavelet representation [5] for an image corresponds to a decomposition of the image into a set of independent frequency bands: approximation and three spatial: horizontal, vertical, and diagonal (oblique) orientations. Brannock found discrete wavelet transform very useful in edge detection [2].

Sweldens proposed lifting-based biorthogonal wavelet constructions [8] and emphasized that lifting yields a faster implementation of the wavelet transform [9].

The principle of image fusion using wavelets is to merge the wavelet decompositions of original images using fusion methods applied to approximations coefficients and details coefficients. Use of discrete wavelet transform (DWT) in image fusion was almost simultaneously proposed by Li et al. [10] and Chipman et al. [11], See [12] for an excellent review of image fusion and references by Goshtasby. The current techniques using wavelets in image fusion are reviewed by Piella [13] and mainly deal with fusion of multisensor images [14], [15], [6].

The edge linking approaches generally fall in spatial domain and deal with the use of masks to detect gray level discontinuities and enjoy a long history [16], [17], [18]. From literature, we found no trace of any deliberate effort made to fuse

recomposed horizontal and vertical details for edge linking. The diagonal detail coefficients are suppressed due less sensitivity of HVS to oblique orientations. Our proposed edge detection and linking framework differ with usual implementations as it deals with a single input image or more precisely image data from the visible spectrum.

2.2 Wavelets and Image Fusion

The notion $L^2(\mathbb{R}^2)$, where \mathbb{R} is the set of real numbers, denotes finite energy functions $f(x,y)$ in $L^2(\mathbb{R}^2)$; and x, y are in \mathbb{R} . In two dimensions, a two-dimensional scaling function, $\varphi(x,y)$, and three two-dimensional wavelets, $\psi^H(x,y)$, $\psi^V(x,y)$, and $\psi^D(x,y)$, are required. These wavelets measure functional variations – intensity or gray-level variations for images – along different directions: $\psi^{H,V,D}$ measure variations along Horizontal, Vertical, and Diagonal. The DWT of $f = f(x,y)$ of size $M \times N$ is:

$$W_{\varphi}(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f \varphi_{j_0, m, n} \quad (1)$$

$$W_{\psi^i}(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f \psi_{j, m, n}^i \quad (2)$$

where j, m, n, M, N are in \mathbb{Z} , $i = \{H, V, D\}$, j_0 is an arbitrary starting scale and the coefficients W_{φ} define an approximation of f at scale j_0 . \mathbb{Z} denotes the set of integers. The coefficients in Eq. 2 above add horizontal, vertical, and diagonal details, See Fig. 2, for scales $j \geq j_0$. The $\varphi_{j, m, n}$ and $\psi_{j, m, n}^i$ define scaled and translated basis functions as:

$$\varphi_{j, m, n}(x, y) = 2^{j/2} \varphi(2^j x - m, 2^j y - n)$$

$$\psi_{j, m, n}^i(x, y) = 2^{j/2} \psi^i(2^j x - m, 2^j y - n)$$

Given W_{φ} and W_{ψ^i} , f is obtained via the inverse DWT as:

$$f = \frac{1}{\sqrt{MN}} \sum_m \sum_n \{W_{\varphi}^{j_0} \varphi_{j_0} + \sum_i \sum_{j=j_0}^{\infty} W_{\psi^i}^j \psi_j^i\} \quad (3)$$

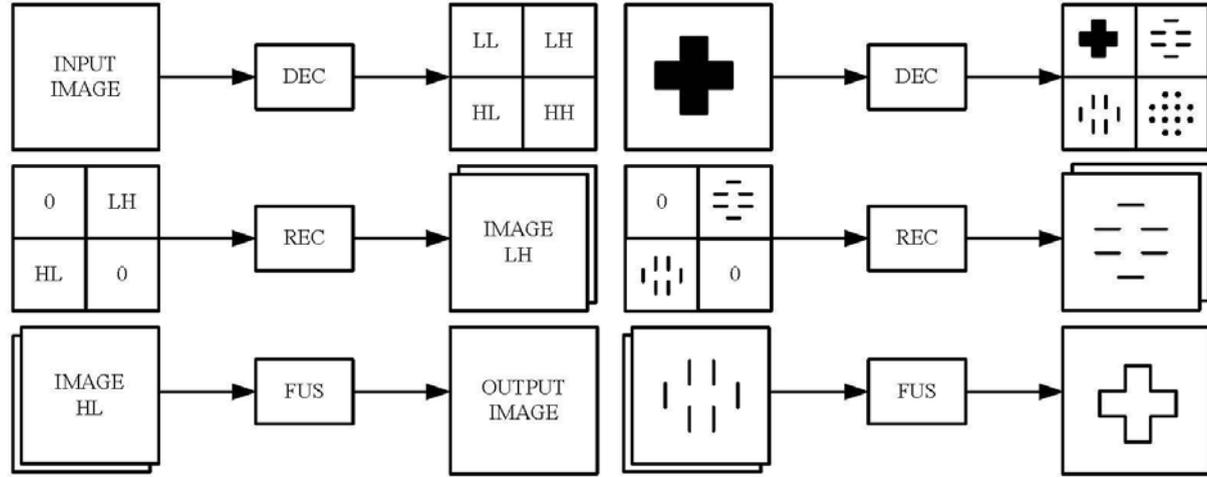


Figure 3: (Left) The framework block diagram: (Top to bottom) DEComposition, REComposition, and FUSion stages. The output (input) of recombination (fusion) stage are two images. (Right) The framework application to our example image in Fig. 1.

Figure 2 shows a simple block diagram of image fusion process. Both images undergo wavelet based decomposition again in this stage. A recombination follows after coefficients selection using Eq. 3. The fusion parameter selection rule, based on absolute maximum of horizontal and vertical coefficients is [19]:

$$W_{\varphi} = \begin{cases} W_{\psi^h}, & |W_{\psi^h}| \geq |W_{\psi^v}| \\ W_{\psi^v}, & \text{otherwise} \end{cases} \quad (4)$$

3 THE FRAMEWORK

The EDLF works on following algorithm:

- In the decomposition-stage, we decompose the input image into four quarter-size output images using Eqs. 1 and 2, See Fig. 2 for starting scale $j_0 = 1$.
- In the recombination-stage, both horizontal and vertical details are recombined using Eq. 3 as:

$$f_{H,V} = \frac{1}{\sqrt{MN}} \sum_m \sum_n \sum_{i=H,V} \sum_{j=j_0}^0 W_{\psi^i}^j \psi_j^i \quad (5)$$

- Both images, $f_{H,V}$, from above step are decomposed again as in the first step to obtain wavelet coefficients and are fused using Eq. 4. The output image is reconstructed finally as an approximation using Eq. 3 as:

$$f_{OUT} = \frac{1}{\sqrt{MN}} \sum_m \sum_n W_{\varphi}^0 \phi_{j_0} \quad (6)$$

Figure 3 shows EDLF and application of our algorithm to the example image in Fig. 1. We use composite images, except for the input image, for visibility. We limit ourselves to just one level of decomposition and recombination. A generalization follows a natural extension, See Fig. 4, of algorithm to levels $j_0 > 1$. We, then, remove diagonal details and approximation becomes input to the next level of decomposition hierarchy and the algorithm iterates. We found an experimental limit of $j_0 = 2$ or 3 for our proposed framework. Decomposition further will not provide any better results.

4 EXPERIMENTAL RESULTS

The framework implemented in MATLAB [20], [21] and experiments were carried out using a set of ten 512x512, 8-bit gray scale images. Figure 5 shows framework application to the Lena image using the Haar wavelet. The input image was decomposed in decomposition-stage. Both horizontal and vertical

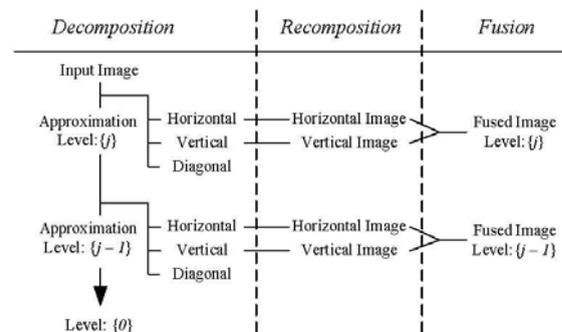


Figure 4: Decomposition, recombination, and fusion tree.

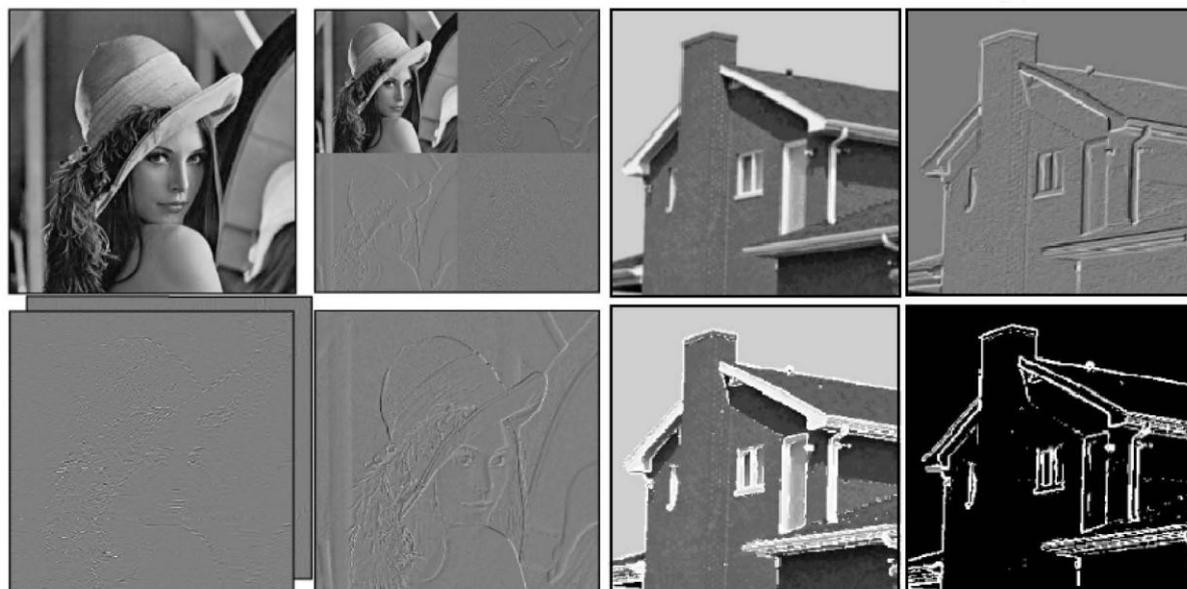


Figure 5: (Left) The framework application to Lena image: (clockwise from top-left) input image, output of the decomposition-stage: (again clockwise from top-left) approximation, horizontal, diagonal, and vertical details, output of the fusion-stage, and recomposed horizontal and vertical detail images. (Right) Application of framework to image segmentation: (clockwise from top-left) input, output, binary, and superimposed images.

details were recomposed in the recombination stage. The recomposed images were fused using wavelets again in the fusion-stage. In this scenario, with one level of decomposition/recomposition (D/R) and use of the same wavelet basis for D/R and fusion stages, we found an application that closely matched the contrast sensitivity paradigm [3], [4] of HVS. Therefore, edge detection and linking was achieved automatically using the wavelet representation and image fusion in connection with horizontal and vertical orientations selectivity of HVS.

Figure 5 also shows an application of proposed EDLF to the thresholding process. The binary subimage is a gray scale image with pixel values corresponding to minimum and maximum in the input house image. Thresholding was performed by suppressing a range of pixel values calculated from background of the output image. With the introduction of recombination-stage, our proposed framework integrates two novel wavelet constructions, known as first-generation (linear) and second generation (non-linear) wavelets, in a single application, See Fig. 6. Here we used Haar and lifted Haar wavelets in D/R and fusion stages respectively.

We observed the output image was degraded in quality due removal of diagonal details. This degradation was observed clearly for level $j - k$ and beyond, where $k > 2$. The algorithm performed equally well at levels $j_0 = 1$ or 2 for noise-free images, and better results found at level $j_0 = 2$. The method resulted into a poor output when dealing with images contained overwhelming number of

Table 1: Framework Mutual Information Results

Image #	Mutual Information (Bits)			
	Haar	Haar & Lifting	Lifting	
01	1.6603	1.1417	1.2091	1.2361
02	1.6665	1.1667	1.2658	1.3041
03	1.8115	1.1655	1.2941	1.3793
04	1.1847	0.9090	1.0283	0.9897
05	0.8957	0.7109	0.7623	0.7641
06	1.7191	1.2320	1.2696	1.2819
07	1.4080	1.0593	1.1893	1.1887
08	1.9867	1.3617	1.5206	1.5944
09	2.0058	1.1846	1.2396	1.3539
10	1.2625	0.9894	1.0646	1.0161
Mean	1.5601	1.0921	1.1843	1.2108

objects. The manual thresholding process was very time consuming and a better way to remove isolated discontinuities needed.

Mutual information, a natural measure of dependence between random variables, was first used for image fusion assessment in [22] as the image fusion performance metric. Table 1 shows performance assessment results for input images. For Lena image we found mutual information measures as: 1.6603 (1.2361) bits when we used the Haar (lifted-Haar) wavelet in D/R and fusion stages; and 1.1417 (1.2091) bits when we used the Haar (lifted-Haar) and lifted-Haar (Haar) wavelets in D/R and fusion stages. Therefore our framework combined both linear and non-linear wavelet constructions in a



Figure 6. The framework application to an MRI image: (left) input image and (right) output image.

single application. From the mean value under columns with heading “Haar & Lifting” we observed better results achieved when lifted-Haar wavelet was used in D/R instead of fusion stage.

5 CONCLUSION

We have proposed three stages edge detection and linking framework using wavelets and image fusion. The framework was implemented in MATLAB and applied to 512x512, 8-bit gray scale images, in connection with horizontal and vertical orientations selectivity of the human visual system. The detection and linking of edges found very natural and straightforward operation in the wavelet domain. We have made an attempt to integrate both linear and nonlinear wavelet constructions, in a single application. Our proposed framework has introduced a recomposition-stage to bridge two well-established multiresolution technologies: the wavelet representation and image fusion. In addition, our framework has created flexibility for the choice of wavelets at decomposition/recomposition and fusion stages, and the lifting scheme.

In our opinion, the output of framework could be closely related to pre-attentive human visual perception [23], [24] as described by Mallat [5]. The presented framework output could also be used to learn statistical models [25], [26] for various visual patterns in images [27]. In future, we shall enhance our framework to object modeling for computer vision applications.

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