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Comparative Analysis of Wavelet-Based Scale-Invariant Feature Extraction Using Different Wavelet Bases

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Abstract

In this paper, we present comparative analysis of scale-invariant feature extraction using different wavelet bases. The main advantage of the wavelet transform is the multi-resolution analysis. Furthermore, wavelets enable localization in both space and frequency domains and high-frequency salient feature detection. Wavelet transforms can use various basis functions. This research aims at comparative analysis of Haar, Daubechies and Gabor wavelets for scale-invariant feature extraction. Experimental results show that Gabor wavelets outperform better than Haar, Daubechies wavelets in the sense of both objective and subjective measures.

Keywords: *Haar, Daubechies wavelets, Gabor wavelets, Feature extraction, salient feature detection*

1. Introduction

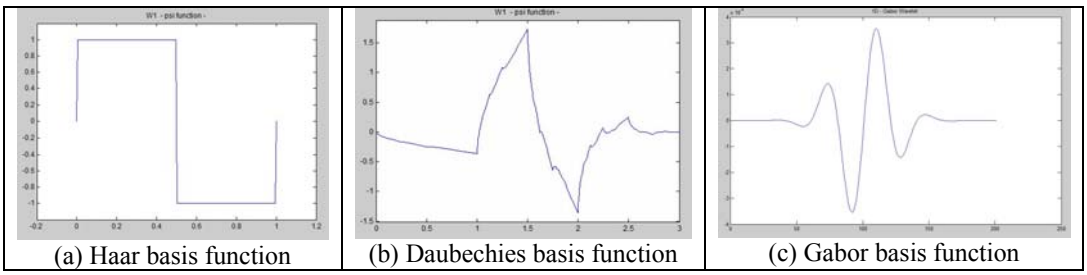
Extraction of image feature has been an active area in the object recognition research for decades. Feature extraction is based on the local property of an image. Many existing methods utilize Harris corner detectors [1], difference of Gaussian (DoG) [2], and the behavior of local entropy [3], to name a few. The description of the detected image features is based on the properties of the associated local regions, the simplest solution being the grey-level histogram. Lowe has proposed scale-invariant feature transform (SIFT), which provides distinctive, stable, and discriminating features [1], [4].

The main advantage of using such SIFT is the simplicity due to the unsupervised nature. However, the SIFT method is practically classified into semi-supervised since it requires a certain degree of supervision. In this paper propose a more efficient approach when the image feature detector uses supervised learning. It is clear that the semi-supervised methods are the most suitable for the cases where the object instance remains the same, such as in the interest point initialization for object tracking [5], but they cannot tolerate appearance variation among different instances of the object class on the local level. Local features can be computed to obtain an image index based on local properties of the image. These local features, which need to be discriminated enough to “summarize” the local image information, are mainly based on filtering, sometimes at different image scales. These kinds of features are too time-consuming to be computed for each pixel of the image. Therefore the feature extraction is limited to a subset of the image pixels, the interest points, where the image information is supposed to be the most important [6],[7],[8],[9]. In this paper, comparative

analysis of wavelet transform using Haar, Daubechies and Gabor wavelets for evaluating performance of scale-invariant feature extraction.

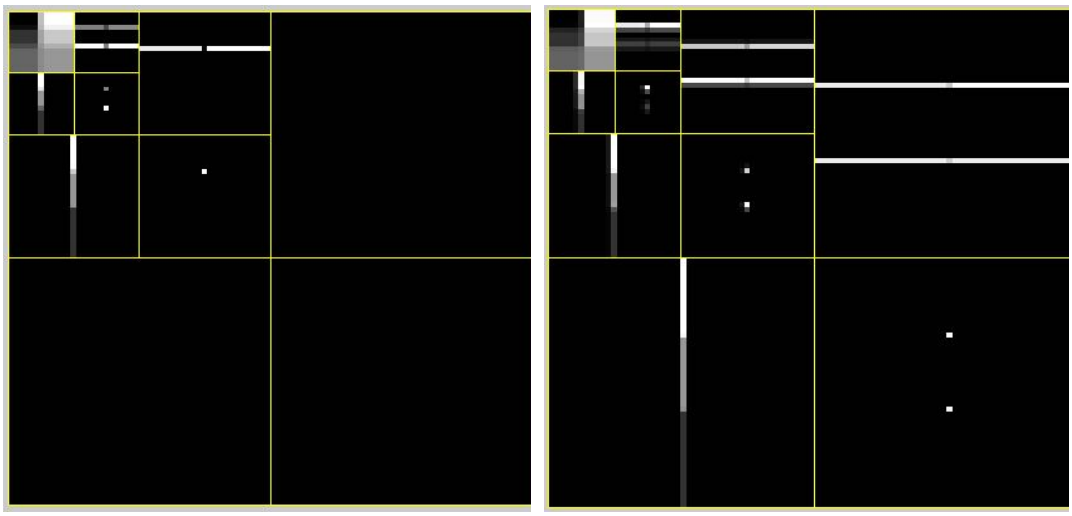
2. Comparison of Feature Extraction Performance Using Different Wavelet Bases

The wavelet transform can selectively use various basis functions. In this section, we compare two orthogonal basis functions including Daubechies and Haar wavelets. Gabor wavelet is Gaussian enveloped basis functions that are orthogonal -like basis functions.



(a) Haar basis function (b) Daubechies basis function (c) Gabor basis function

Figure 1. Different wavelet bases (a) Haar wavelet basis function, (b) Daubechies basis function, (C) Gabor wavelet basis function.



(a) (b)

Figure 2. Level-3 DWT representation of sample image (a) Haar DWT (b) Daubechies DWT

2.1. Feature extraction using the Haar and Daubechies wavelet

The discrete wavelets transform (DWT) decomposes an input signal into low and high frequency component using a filter bank. Daubechies, Haar wavelet, which characteristics the filter bank, has important properties of orthogonality, linearity, and completeness. We can repeat the DWT multiple times to multiple-level resolution of

different octaves. For each level, wavelets can be separated into different basis functions for image compression and recognition

Figure 2, shows the result of multi-resolution expansion using Haar, Daubechies wavelets. The wavelet transform can be used to represent a two-dimensional (2D) signal by the 2D resolution decomposition procedure, where an image is repeatedly decomposed into an approximation and several detail components at each level. In Figure 2, Level-3 wavelet decomposition of a sample image is shown. A Sample image is first decomposed into four sub-images including one approximation (low-frequency part of the signal) and nine details (high-frequency part of the signal) images. The approximation image is again decomposed into four sub-images. In the experiment, we use Haar, Daubechies-4(db4) wavelets to obtain Level-3 wavelet decomposition [10].

In order to construct the wavelet pyramid, we decide the number of Haar, Daubechies coefficients and approximation levels. We would like to extract salient points from any part of the image where "something" happens in the image at any resolution. A high wavelet coefficient (in absolute value) at a coarse resolution corresponds to a region with high global variations. The properly chosen length of the Haar, Daubechies wavelet and the number of the approximation levels provides the optimum local key points or features [11].

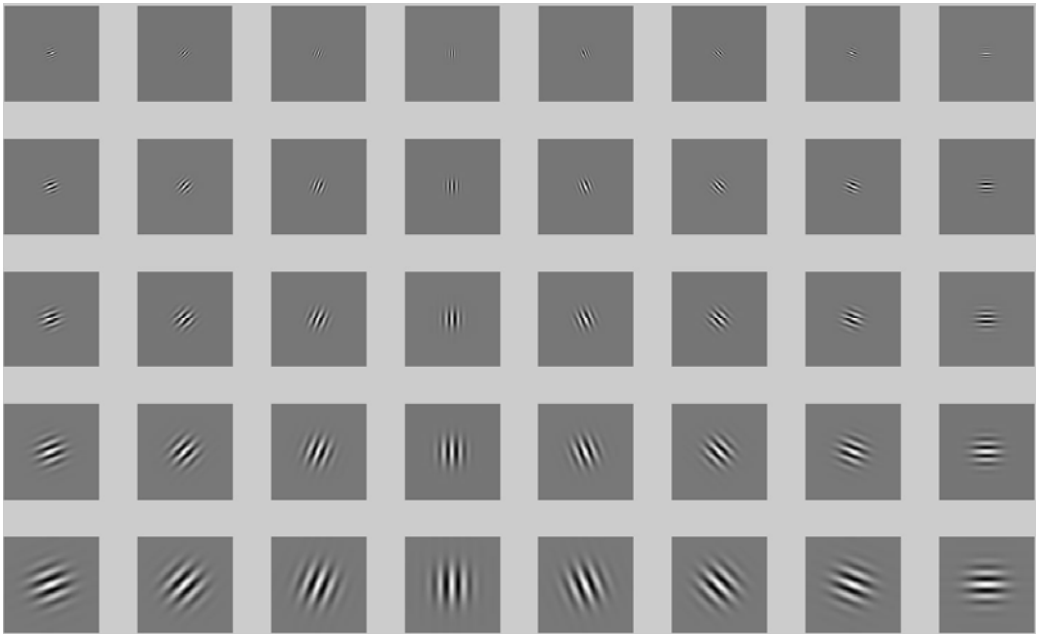


Figure 3. Gabor function for different values representation of real part

2.2. Feature extraction using Gabor wavelet

The Gabor wavelet transform uses a set of Gaussian enveloped basis functions that are orthogonal-like basis functions [12]. Gabor wavelets provide analysis of the input signal in both spatial and frequency domains simultaneously.

$$\psi(x,y,\omega_0,\theta)=\frac{1}{2\pi\sigma^2}e^{-((x\cos\theta+y\sin\theta)^2+(-x\sin\theta+y\cos\theta)^2)/2\sigma^2}[e^{i(\omega_0 x\cos\theta+\omega_0 y\sin\theta)}-e^{-\omega_0^2\sigma^2/2}], \quad (1)$$

where x, y define the pixel position in the spatial domain, ω_0 the radial center frequency, θ the orientation of the Gabor wavelet, and σ the standard deviation of Gaussian function along the x and y-axes. In addition, the second term of the Gabor wavelet, $e^{-\omega_0^2\sigma^2/2}$, compensates for the DC value because the cosine component has nonzero mean (DC response) while the sine component has zero mean.

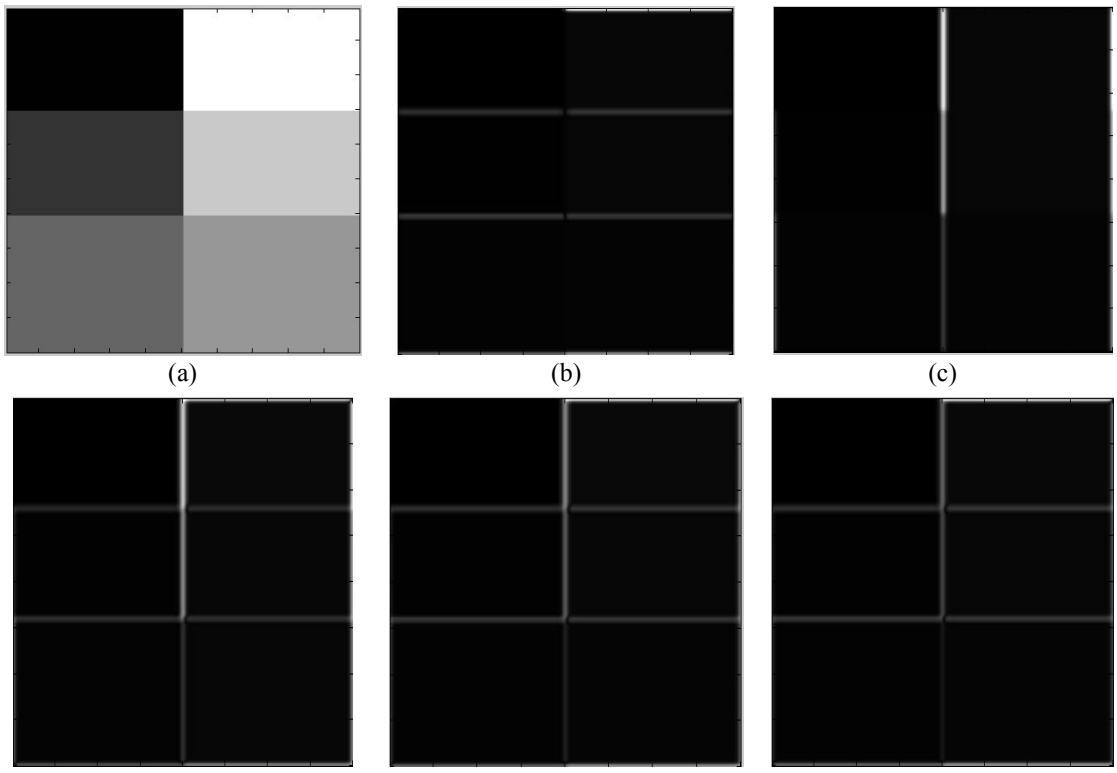


Figure 4. (a) Original image, (b) π, (c) $\pi/2$, (d) $\pi/4$, (e) $\pi/6$, (f) $\pi/8$.

As the half-amplitude bandwidth of the frequency response is about 1–1.5 octaves along the axes [13], the relationship between σ and ω_0 can be derived to be

$$\sigma=\kappa/\omega_0 \text{ where } \kappa=\sqrt{2In2}\left(\frac{2^{\Phi}+1}{2^{\Phi}+1}\right) \quad (2)$$

where Φ is the bandwidth in octaves. The Gabor representation of an image can be derived from the convolution of the image and the Gabor wavelets. Let $G(x,y)$ denote the image, then the convolution of $G(x,y)$ and $\psi(x,y,\omega_0,\theta)$ is defined as follows:

$$C_{\psi G}(x,y,\omega_0,\theta)=G(x,y)*\Psi(x,y,\omega_0,\theta) \quad (3)$$

where * denotes the convolution operator, and $C_{\psi G}(x, y, \omega_0, \theta)$ is the convolution result corresponding to the Gabor wavelet at radial center frequency ω_0 and orientation θ. With a set of ω_0 and θ, we obtain a multi-hierarchical Gabor representation of the image $G(x, y)$.

The effect of the DC term becomes negligible when the parameter σ, which determines the ratio of the Gaussian window width to wavelength, has sufficiently large values. In most case, one would use Gabor wavelets of five different scales, $\omega_0 = \{0, ..., 4\}$ and eight orientations, $\theta = \{0, ..., 7\}$ The parameter values of wavelength, orientation, phase offset, aspect ratio, and bandwidth are given for the Gabor function. Edge operator shows the salient feature of texture and Gabor energy operation is robust for isolated line, edge, and contours.

The Gabor wavelets respond strongly to edges if the edge direction is perpendicular to the wave vector $(\omega_0 \cos\theta, \omega_0 \sin\theta)$ .When hitting an edge, the real and imaginary parts of $C_{\psi G}(x, y, \omega_0, \theta)$ oscillate with the characteristic frequency instead of providing a smooth peak. Nevertheless, the magnitude of the response can provide a measure of the image's local properties [14][15].

Figure 5. Gabor energy filtering

3. Experiment Results

The results show that orthogonal basis function of Haar, Daubechies wavelet is in complex background and rough texture. However, for orthogonal-like basis function of Gabor wavelet, noise and rough texture of the edge are removed hence image feature can be extracted.

Figure. 6. Original Image

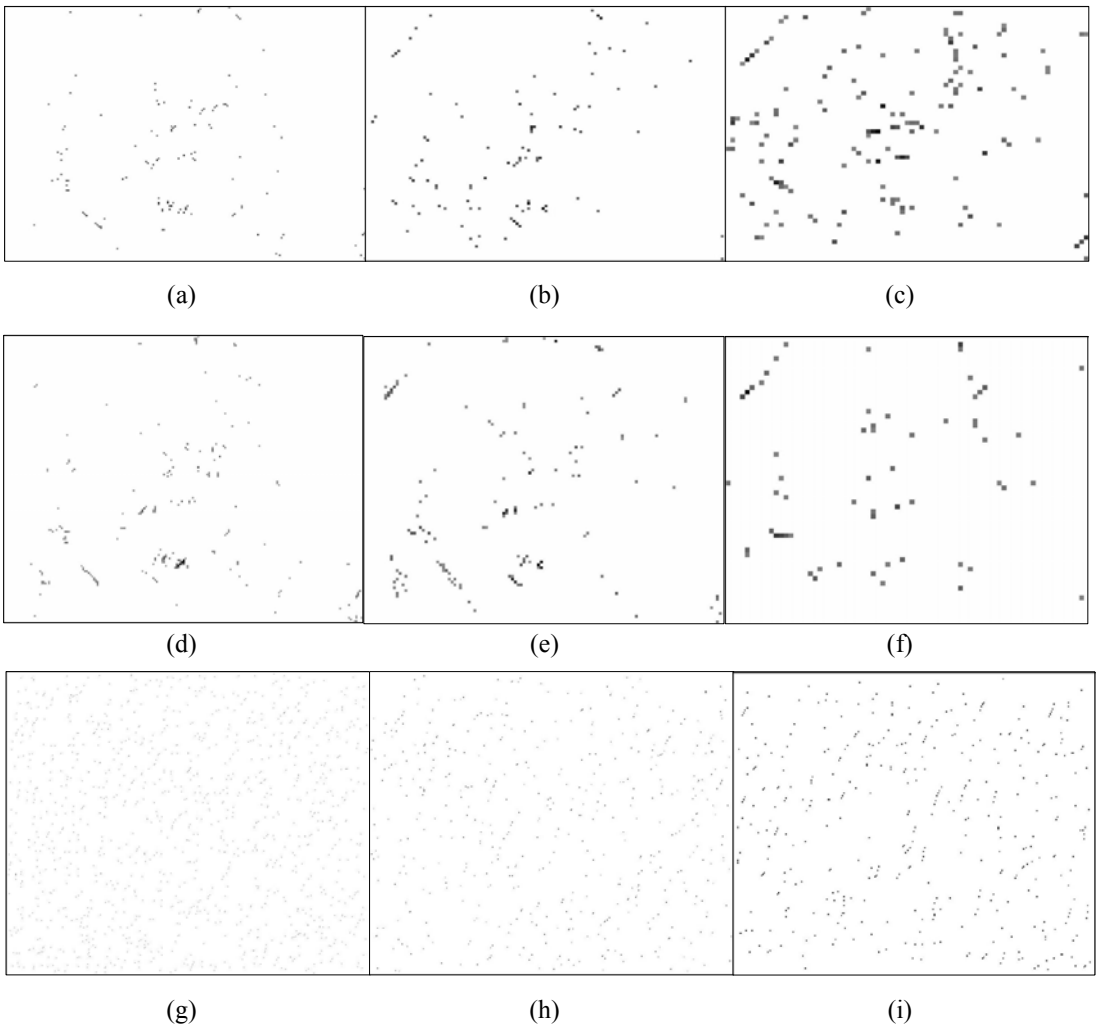
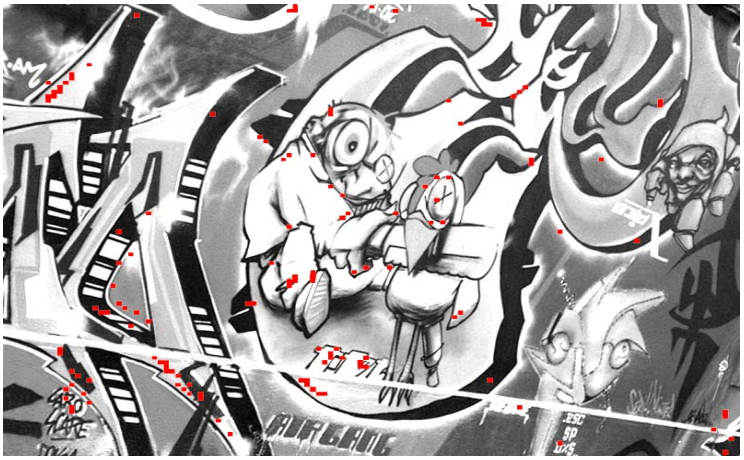
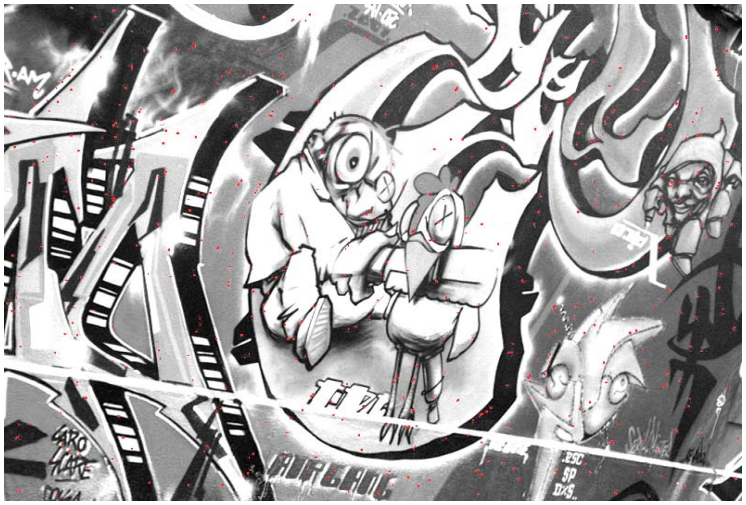


Figure. 7. Scale-invariant salient points (image size 1: 4/3 : 1/4) (a), (b), (c) Haar features, (d), (e), (f) Daubechies features,(g), (h), (i) Gabor features.

(a)



(b)



(c)

(d)

(e)

(f)

Figure 8. Experimental results: (a),(d) Haar features, (b),(e) Daubechies features, (c),(f) Gabor feature

5. Conclusion

We presented a salient feature detector based on wavelets. We used the Haar transform for point extraction, which is simple but may lead to bad localisation. Daubechies wavelets avoid this drawback, but are not symmetric. Since orthogonality is not required in our approach, we could extend it to other wavelets that are compactly supported and symmetric. Wavelets are also attractive to extract image features. These local features would be more related to our salient points. Gabor feature is a good representation method for local image. But the dimension of the feature vector is prohibitively large. The results show that of Haar, Daubechies wavelet and Gabor wavelet respond to contours and edges. However, noise and rough texture of the edge are removed hence image feature. Gabor wavelet basis function extracts image feature more efficiently than Haar, Daubechies, basis function in wavelet bases.

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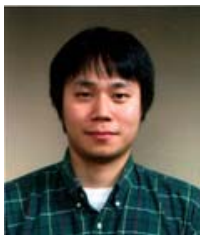

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