A Novel Image Edge Detection Method Using Simplified Gabor Wavelet

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Abstract. The Edge Detection is used in wide range of applications in image processing such as object detection, recognition, automated inspection of machine assemblies, diagnosis in medical imaging and topographical recognition. An efficient algorithm for extracting the edge features of images using simplified version of Gabor Wavelet is proposed in this paper. Conventional Gabor Wavelet is widely used for edge detection applications. Due do the high computational complexity of conventional Gabor Wavelet, this may not be used for real time application. Simplified Gabor wavelet based approach is highly effective at detecting both the location and orientation of edges. In this approach, Simplified Gabor Wavelet features are employed for two different scales and four different orientations. The results proved that the performance of proposed Simplified version of Gabor wavelet is superior to conventional Gabor Wavelet and other edge detection algorithm. And also the required run time for proposed work is faster than all other edge detection methods.

Keywords: Gabor wavelet, Simplified Gabor wavelet, edge detection, Peak Signal to Noise ratio.

1 Introduction

Edges are predominant features in images and their analysis and detection are an essential goal in computer vision and image processing [1].Edge detection is one of the key stages of image processing and objects recognition [2]. An edge is defined by a discontinuity in gray level values. In other words, an edge is the boundary between an object and the background. The shape of edges in images depends on many parameters: geometrical and optical properties of the object, the illumination conditions, and the noise level in the images [3].

Research in automatic edge detection has been active because of this topic's wide range of applications in image processing, such as automated inspection of machine

N. Meghanathan et al. (Eds.): CCSIT 2012, Part I, LNICST 84, pp. 620–630, 2012.

assemblies, diagnosis in medical imaging, and topographical recognition [4]. Edge detection is a very difficult task. When viewing an image, humans can easily determine the boundaries within that image without needing to do so consciously. However, no single edge-detection algorithm, at present, has been devised which will successfully determine every different type of edges [5].Many edge detection algorithms have been proposed and implemented. These algorithms differ from each other in many aspects such as computational cost, performance and hardware implementation feasibility.

Simplified version of Gabor Wavelets (SGW) is proposed in this work, whose features can be computed efficiently and can achieve better performance for edge detection. Proposed SGWs can replace the GWs for real time applications.

1.1 State of the Art

An edge is in general a border which separates the adjacent zones of image having distinct brightness. The development of an edge detector is often based on a specific characteristic of the image [6].First generation of edge detection algorithms are represented by Gradient operators such as Sobel's, Robert's and Prewitt's operator[7].The drawbacks of these operators are their inability to detect weak edges and their inability to detect weak edges and their poor performance in the presence of noise. Compass operators are enhanced version of the gradient operators. More computations are required in the compass operators in order to detect more edges and produce better results [2].

Another well known operator, based on the occurrence of zero crossings after applying LOG filter is Marr's operator, known as Laplacian of Gaussian [7]. Since not all zero-crossings correspond to edges, some false edges may be introduced. Canny's operator [1] is one of the most widely-used edge detection algorithms in the computer vision community because of its performance. In this algorithm, edge pixels are detected based on first derivative of that pixel. In addition, two thresholds are applied to remove false edges. The problem with this operator is that these two thresholds are not easily determined and low threshold produces false edges, but a high threshold misses important edges.

Brannock and Weeks [3] have proposed an edge-detection method based on the discrete wavelet transform (DWT), which combines DWT with other methods to achieve an optimal solution to edge-detection algorithm. Y.P.Guan [8] has proposed a multiscale wavelet edge detection algorithm for lip segmentation. In noiseless images with high contrast, Canny's edge detection has proven to be very successful [1].But that algorithm is not efficient for noisy image. For noisy images, Lu and Zhang has proposed algorithm to detect diagonal edge information, based on the wavelet transform with shifted coefficients [3].

The section 2 describes conventional Gabor Wavelet and edge detection using Gabor wavelets. Section 3 describes about proposed methodology of this work. Section 4 discusses about the obtained results and conclusion the work.

2 Conventional Gabor Wavelet

Gabor Wavelets (GWs) [9] are commonly used for extracting local features for various applications such as object detection, recognition and tracking. The human visual system can be viewed as composed of a filter bank. The responses of the respective filters can be modeled by Gabor functions of different frequencies and orientations. The Gabor features have been found to be particularly appropriate for texture representation and discrimination and have been successfully applied to texture segmentation, face recognition, handwritten numerals recognition, and fingerprint recognition. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave as follows:

$$G(x,\ y)=\exp\left[-\frac{x^2+y^2}{2\sigma^2}\right]\exp[j\omega(x\cos\theta + y\sin\theta)] \tag{1}$$

Where σ is the standard deviation of the Gaussian function in the x- and y-directions and ω denotes the spatial frequency. Family of Gabor kernels can be obtained from eqn.(1) by selecting different center frequencies and orientations. These kernels are used to extract features from an image.

2.1 Edge Detection Using Conventional Gabor Wavelet

Gabor wavelets can effectively abstract local and discrimination features. In textural analysis and image segmentation, GW features have achieved outstanding results, while in machine vision, they found to be effective in object detection, recognition and tracking. The most useful application of the Gabor Wavelets is for edge detection [10].For given an input image I(x, y), the Gabor Wavelet features are extracted by convolving I(x,y) with G(x,y) as in equation (2).

$$\Phi(x,\ y) = G(x,\ y) \otimes I(x,\ y) \tag{2}$$

Where ⊗ denotes the 2-D convolution operation [8]. The Gabor wavelets (GWs) respond strongly to edge if the edge direction is perpendicular to the wave vector (ω cos θ, ω sin θ). When hitting an edge, the real and imaginary parts of Φ(x, y) oscillate with the characteristic frequency in- stead of providing a smooth peak.

3 Proposed Work

The computation required for Gabor Wavelet based feature extraction is very intensive. This in turn creates a bottleneck problem for real time processing. Hence, an efficient method for extracting Gabor features is needed for many practical applications.

3.1 Simplified Gabor Wavelets

Wei Jiang.et.al.[9]have proposed that the imaginary part of a Gabor filter is an efficient and robust means for edge detection. The imaginary part of a GW is as in equation (3):

$$S(x, y) = \exp\left[-\frac{x^2 + y^2}{2\sigma^2}\right]\sin\left[\omega(x\cos\theta + y\sin\theta)\right] \tag{3}$$

Edges can be detected by using this simplified Gabor Wavelet. Set of Simplified Gabor kernels can be obtained from eqn. (3) by selecting different center frequencies and orientations. These kernels are used to extract features from an image. This method is known as Simplified Gabor wavelet.

3.2 Shape of an SGW

The equation for 1-D Gabor Wavelet is shown in equation (4).

$$s(x) = \frac{1}{2\prod\sigma^2}\exp\left[-\frac{x^2}{2\sigma^2}\right]\sin(\omega x) \tag{4}$$

The values of imaginary part of 1-D GW are continues one. Its values are quantized to a certain number of levels. The same number of quantization levels is used for the positive and the negative values of the Gabor function because it is antisymmetrical [4]. For 2-D cases, the imaginary part of a 2-D GW, with the gray-level intensities representing the magnitudes of the Gabor function.

3.3 Determination of Quantization Levels

The determination of the quantization levels for an SGW is the same as that in [10]. One of the quantization levels of the SGW is set to zero. As the imaginary part of a Gabor function is antisymmetrical, the number of quantization levels for the positive and negative values are equal and are denoted as n_1. Then, the total number of quantization levels is $2n_1+1$. Suppose that the largest magnitude of the GW is A, the corresponding quantization levels for positive levels and negative levels are as in equation (5)

$$q_+(k) = \frac{A}{2n_1+1}.2k\ .\quad q_-(k) = -\frac{A}{2n_1+1}.2k \tag{5}$$

where $k = 1. . . n_1$. These SGWs are then convolved with an image to extract the SGW features at different center frequencies and orientations to form a simplified Gabor jet.

3.4 Determination of the Parameters

The values of important parameters for the GWs or SGWs are determined for edge detection, which are the values of ω, σ, and θ. Edges of an image can be detected in different directions, by setting different values for θ [11]. Computational can be reduced by setting four values for θ.Hence, the number of orientations used in this proposed work is four,i.e.,θ_k=kπ/4 for k=0,1,2,3.As edges are very localized feature of an image, the value of ω should be small when compared to that for face recognition[4]. So, in this proposed work edges can be detected efficiently by setting ω = 0.3 π and 0.5π.

3.5 Efficient Edge Detection Using SGWs

Edge detection can be done efficiently by using SGWs of two different scales (ω) and four different orientations (θ). The convolution of an SGW of scale ω and orientation θ with the image I(x,y) generates the SGW features and is denoted as $\phi'_{\omega,\theta}(x_c, y_c)$ .The resulting SGW feature $\phi''_{\omega,\theta}(x_c, y_c)$ at a pixel position (x_c, y_c) is equal to the absolute maximum of the eight $\phi'_{\omega,\theta}(x_c, y_c)$, i.e.,

$$\phi''_{\omega,\theta}(x_c, y_c) = \max\{\phi'_{\omega i,\theta j}(x_c, y_c), i = 0,1 and j = 0,\ldots,3\} \tag{6}$$

where ω_0 = 0.3 π, ω_1 = 0.5 π, and θ_j = jπ/4, for j = 0, . . . , 3. The SGW feature $\phi'_{\omega,\theta}(x_c, y_c)$ is computed by convolving the image I(x, y) with the SGW whose patterns are dependent on the scale ω and the orientation θ. As edges are much localized in an image, so the window size of the patterns is either 3 × 3 or 5 × 5. The SGWs are formed using two levels of quantization for the positive and the negative magnitudes of the GWs.These two quantization levels are denoted as q1 and q2 with q2 > q1 for positive magnitudes and the corresponding quantization levels for the negative magnitude are −q1 and −q2, respectively. Two different scales and four different orientations are adopted for this proposed work. The required computation for a $\phi'_{\omega,\theta}(x_c, y_c)$ is not more than 2 multiplications and 22 additions. Hence the computational cost is very lower than conventional Gabor Wavelet [11].

4 Result and Discussion

The performance of the proposed SGW based approach with different scales and different orientations are evaluated. Then relative performance with the use of the GW features and the SGW features will be compared. Finally, performance of the Canny, Sobel, Robert, and Prewitts and conventional Gabor wavelet operators are compared with SGW based Edge Detection Algorithm.

4.1 Performance Analysis of SGWs with Different Quantization Levels for Edge Detection

The effect of the number of quantization levels on edge detection using Simplified Gabor Wavelet can be evaluated using three, five and seven quantization levels. In this analysis, the coins images and cameraman images are used as shown in Fig.1 and

Fig 2. The edge detection results based on SGW with ω=0.3π and three different quantization levels for coin image are shown in Fig.1(a) - 1(d).And for the same image, result for ω=0.5 π and three different quantization levels are shown in Fig.1(e) - 1(g). Fig.2(a)-2(g) shows the results for cameraman image for ω=0.3π and ω=0.5π with three different quantization levels.

From Fig.1 and Fig. 2, the performance of edge detection using SGWs of five and seven quantization levels are better than three quantization levels, while the performances of five and seven quantization levels are very similar. More computation can be required for higher number of quantization levels. Hence, five quantization levels are chosen in this proposed work.

4.2 Performance Analysis of SGWs with Different Scales for Edge Detection

The most promising performance in terms of accuracy and computation can be achieved by using SGWs with five quantization levels, which is proved in Sec 4.1. This section evaluates the effect of SGWs with five quantization levels and with different scales ω=0.125 π, ω=0.3 π, ω=0.5 π and ω=0.65 π. The edges of the cameraman image and coins image based on SGW features of the four different scales are shown in Fig 3 and Fig 4. The edge detection results based on SGW with five quantization levels and four different scale ω=0.125π, ω=0.3π, ω=0.5π and ω=0.65π. of cameraman image are shown in Fig 3(a) - 3(e). And the Fig. 4(a)-4(e) shows the results of coin image for ω=0.125π, ω=0.3π, ω=0.5π and ω=0.65π with five different quantization levels. From this comparison, two scales ω=0.3π, ω=0.5π can be identified for better performance.

4.3 Comparing the Performance of SGWs with other Edge Detection Algorithms

The performance of SGWs based edge detection algorithm are compared with some conventional edge detection algorithms, such as Canny, Sobel, Prewitt, Robert and conventional Gabor Wavelet methods. In order to get best performance, the SGWs with two scales ω=0.3π, ω=0.5π, four orientation $\theta = \{0, \pi/4, \pi/2, 3\pi/4\}$, and five quantization levels are used for this comparision.Fig.5 shows the results of various edge detection algorithm for cameraman image, coins image, Angiogram brain image and pears image. This result comparison proved that proposed Simplified Gabor Wavelet is an efficient algorithm for all type of images.

4.4 Comparison of Quantitative Analysis for SGWs with Other Edge Detection Algorithms

The performance comparison was discussed in last section. The Quantitative measures for all the edge detection algorithm is described in this section. For quantitative analysis of the proposed method performance measures for cameraman image such as average run time and PSNR are calculated and are tabulated in Table 1 and Table 2

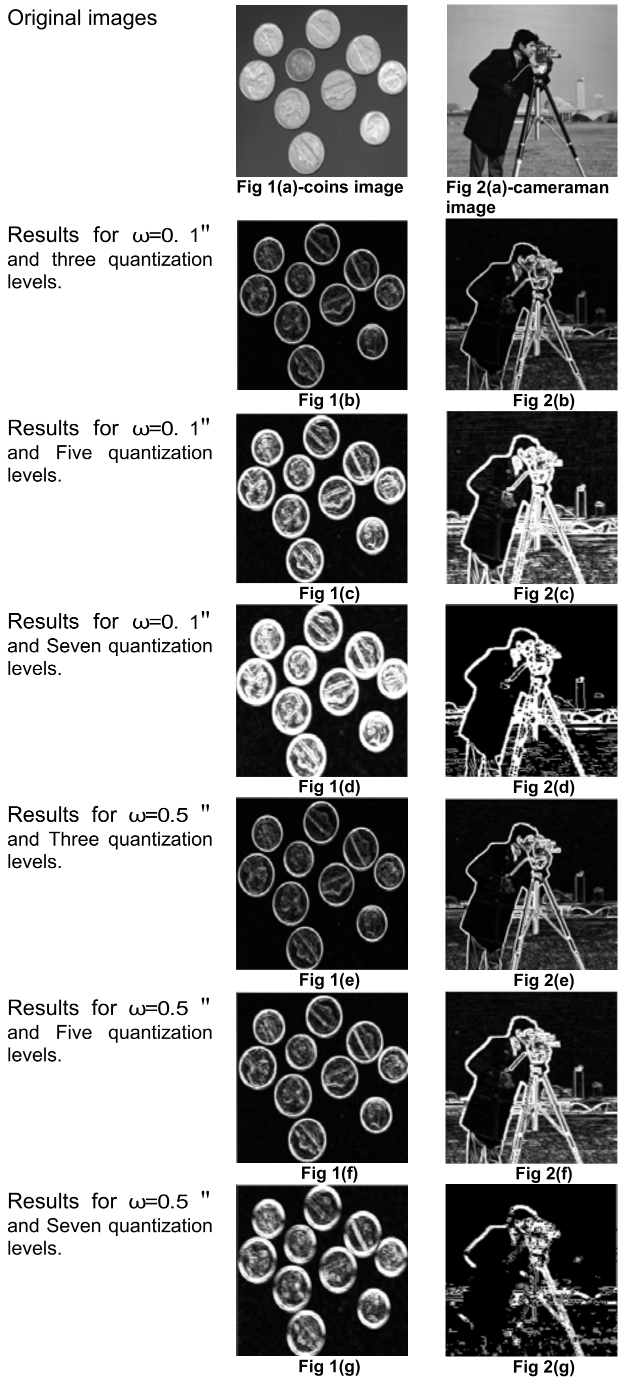

Fig. 1&2. SGW based edge results for different quantization levels

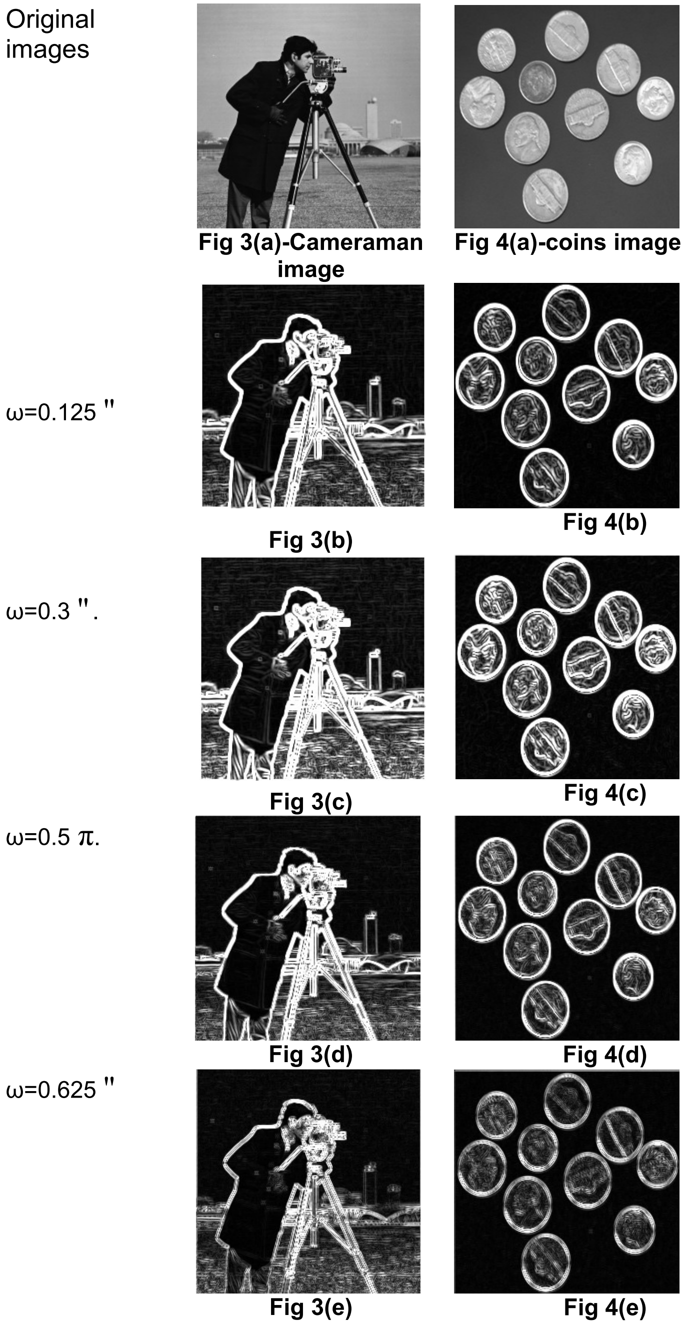

Fig. 3&4 SGW based edge detection results for different values of ω

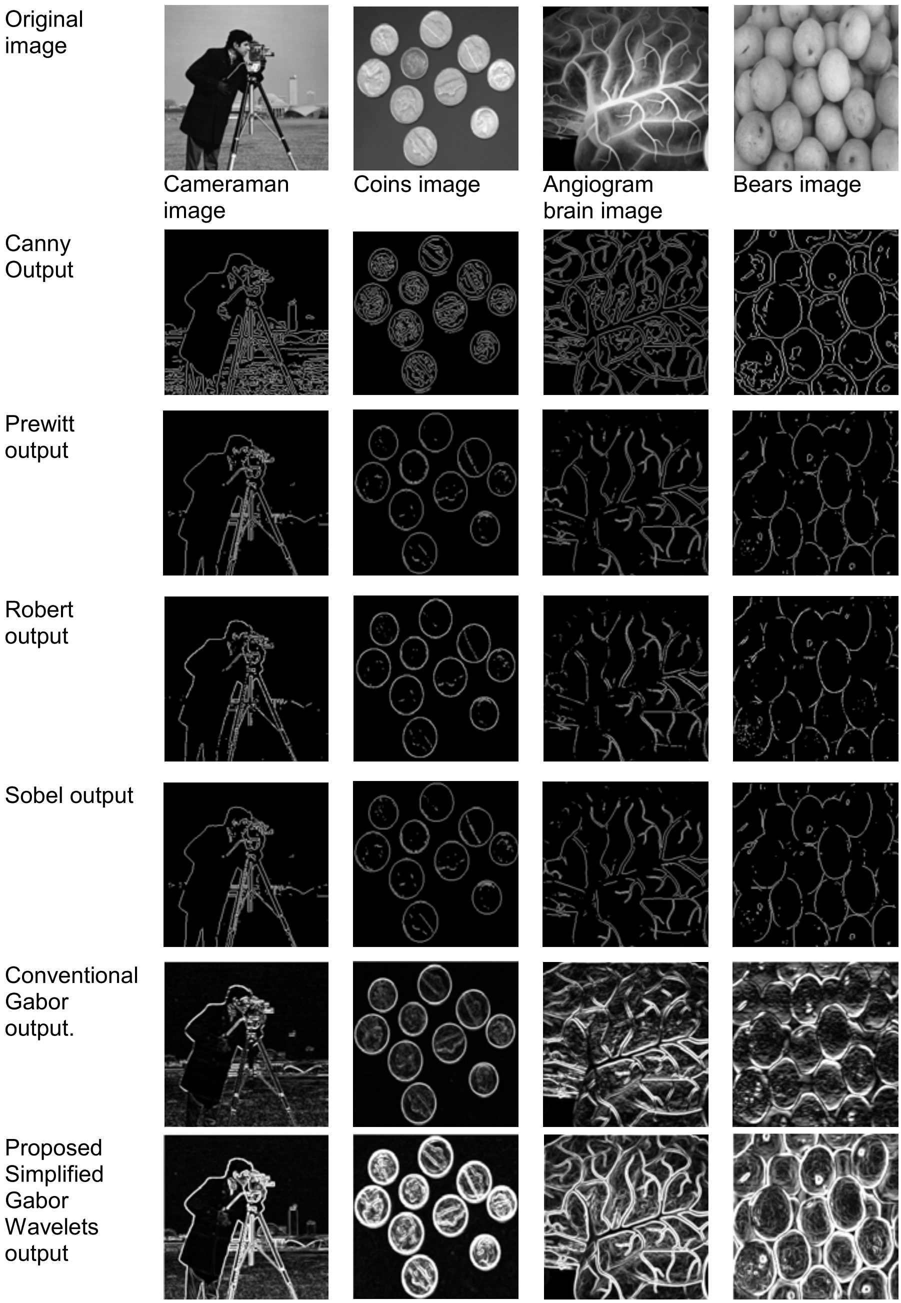

Fig. 5. Comparison of Simplified Gabor Wavelet results with different algorithms

for different edge detection algorithms respectively. The average runtime required by SGWs is compared with other conventional methods. This comparison is tabulated in Table1. The run time required by SGW based edge detection algorithm is smaller than that required by conventional Gabor Wavelet and Canny edge detection methods. The average run time is similar to that of Prewitt and Roberts's method, but compared with their performances the proposed Simplified Gabor Wavelet is superior to all other methods.

Table 1.

S.No	Algorithm	Run Time
1	Canny	76.5 ms
2	Prewitt	23.4 ms
3	Roberts	21.8 ms
4	Sobel	78 ms
5	Gabor Wavelet	47 ms
6	Simplified Gabor Wavelet	31 ms

Peak Signal to Noise Ratio is measured between edge images of original image and noisy image. In this PSNR measure, Gaussian noise is added to the original image and that is considered as noisy image. PSNR values for different algorithms are compared with proposed SGW based edge detection. Those measures are tabulated in Table.2.

Table 2.

S.No	Algorithm	PSNR in db
1	Canny	8.45
2	Prewitt	17.45
3	Roberts	16.61
4	Sobel	17.77
5	Gabor Wavelet	25.23
6	Simplified Gabor Wavelet	33.41

From this quantitative analysis the proposed Simplified Gabor Wavelet based edge detection provides better performance than other conventional methods. Fast run time of proposed work realize that it is most suited for real time application.

5 Conclusion

In this paper, an efficient algorithm for edge detection using simplified version of Gabor Wavelets is proposed. Proposed work is based on the conventional Gabor wavelet, but it can detect more edge pixels than the conventional one. The various experiments prove that proposed algorithm clearly outperforms other edge detection methods. The proposed algorithm very effectively used for biomedical images also. The results prove that the edge features of angiographic brain images using proposed Simplified Gabor Wavelet are better than other conventional methods. The quantitative measures show that proposed SGW based edge detection is fast and better PSNR than other conventional methods. The performance comparisons and quantitative analysis proves that the proposed Simplified Gabor Wavelet based edge detection is very much suited for real time applications.

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