HBT Filter and Logarithmic Transform Based Edge Detection – A Modified Approach

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***Abstract*— A modified edge detection algorithm has been presented here that uses logarithmic transform and Hyperbolic Tangent (HBT) filter. The proposed algorithm incorporates Logarithmic transform along with Luminance and Contrast-Invariant Edge Similarity Measure algorithm for edge detection. The proposed algorithm gives a good quality edge detection of images with improved SSIM value and almost equal or higher PSNR values.**

***Index Terms*— Edge-Detection, HBT filter, Logarithmic Transform, Structural Similarity, Similarity Measure.**

I. Introduction

Accurate detection of edges is not possible most of the times due to contrast and noise sensitivity, and uneven illumination. Classical Gradient-Magnitude (GM) methods for edge detection [3] depend on edge strength and they usually do not detect weaker edges. Angle-based (AN) methods, which are based on the computation of the cosine of the projection angles between neighborhoods and predefined edge filters, can be used for detecting valid edges regardless of their magnitude, , but they are sensitive to noise and uneven illumination [5]. Same problem is faced by local thresholding of images because they tend to inhibit edges in regions of low luminance.

Smoothing as a pre-processing step is required by optimal step-edge detectors such as Canny's Gaussian first derivative (GFD) [3] filter to reduce noise. This smoothing process makes weak edges harder to detect. A method proposed by Kovesi [4] represents images in the frequency domain and edges correspond to the points of maximum phase congruency. Phase Congruency (PC) methods are invariant to contrast and illumination changes, but gives poor edge localization.

An edge detection algorithm has been proposed by Saravana Kumar et al. [1] that give better result than GM and AN method. Their method gives better edge localization and is more robust in the presence of varying illumination, contrast and noise level. It is based on edge similarity measure between image neighborhoods and directional finite impulse response (FIR) with hyperbolic tangent (HBT) profiles.

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Drawback of this method is that the final edge-detected images do not have enough structural similarity with the original image.

This paper proposes a modified edge detection algorithm that uses HBT filter and Logarithmic transform that preserves structural similarity with the original image and gives better edge detection. Consequently, a better Structural Similarity Index (SSIM) can be achieved compared to the conventional edge detection techniques as well as the edge detection based on edge similarity measure. Compared to the edge detection using similarity measure, the Peak Signal-to-Noise ratio (PSNR) will be almost equal or higher for the proposed method. A drawback of the proposed method compared to edge similarity measure algorithm is that latter gives a better edge detection in the case of contrast variant and noisy images. But still the proposed method gives an acceptable result in the case of noisy and contrast variant images. Smoothening as a preprocessing step can be applied in the case of noisy images to get better edge-detection and yield higher structural similarity. The proposed algorithm gives better results for noiseless and luminance variant images.

II. Edge Detection using HBT Filter

The edge detection method using similarity measure proposed by Sarvana Kumar et al. [1] obtains an optimal estimate of image edges by using principal component analysis (PCA). PCA is applied to a set of local neighborhoods b_i of size $n \times n$ to generate n^2 eigenvectors $\{e_i, 1 \le i \le n^2\}$ each of size $n \times n$. A neighborhood b_i can be expressed as

$$b_i = m + \sum_{j=1}^{n^2} u_{ij} e_j ,$$

where the average over all local neighborhoods is

$$m = \frac{1}{N} \sum_{i=1}^{N} b_i$$

and u_{ij} is the projection of b_i –m onto the j^{th} eigenvector e_j.

The eigenvector pair has similar profiles but is orthogonal. The number of zero crossings in the eigenvectors increases from eigenvector pair e2 - e3 to e6 - e7 and beyond, indicating that the eigenvectors corresponding to smaller values of Eigen values capture higher frequency information of the local neighborhoods and, hence, are more susceptible to noise. Two eigenvectors e2 and e3 are considered for edge detection since they most accurately approximate the gray-level variation in local neighborhoods. Since e_2 and e_3 have blurred

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step edge profiles and can be approximated by $\hat{e}_2$ and $\hat{e}_3$ given by $\hat{e}_2 = \alpha_{21} h_1 + \alpha_{22} h_2$ and $\hat{e}_3 = \alpha_{31} h_1 + \alpha_{32} h_2$, where $\{\alpha\}$ are weights, h_2 is orthogonal to h_1, and h_1 is the HBT profile

$$G_W = \frac{1 - e^{-\sigma_W (x+y)}}{1 + e^{-\sigma_W (x+y)}}$$ for $|x|, |y| \le W$ and 0 otherwise.

The region of support for G_W is limited by window size W to ensure edge localization.

The FIR filter pair h_1 and h_2, is obtained by sampling GW at integer locations (x_d, y_d) within [-W, W]. The weights α_{ij} are determined by projecting both e_2 and e_3 onto h_1 and h_2, i.e. $\alpha_{ij} = \langle e_i, h_j \rangle / \langle h_j, h_j \rangle$. The parameter σ_W defines the steepness of the profile at zero crossing and its relationship to filter support. σ_W for a given filter width W is determined such that the HBT filter pair can best approximate the natural step edges in an image. This is done by selecting σ_W for a given W such that its corresponding total approximation error is minimized. The approximation error is given as $\varepsilon_i = \| e_i - \hat{e}_j \| / \| e_j \|$ and the total approximation error is given as $\varepsilon_{total} = \varepsilon_2 + \varepsilon_3$. The edge detection using edge similarity measure uses cosine measure R_i with regularization parameter γ and an empirically determined constant c. It is given by,

$$R_i = \frac{\langle b_i - \bar{b}_i + c\gamma, g \rangle}{\| b_i - \bar{b}_i + c\gamma \| . \| g \|}$$

An estimate $\hat{\gamma}$ of regularization parameter γ is given by

$$\hat{\gamma} = \frac{median(Y_i : 1 \le i \le N)}{0.6745},$$

where $$Y_i = \sqrt{\frac{1}{n^2} \sum_{j=1}^{n^2} [b_i(j) - \bar{b}_i]^2}$$

i=1,2,….,N.

III. Logarithmic Transform Domain

The logarithmic transform domain [2] affords us the ability to view the frequency content of an image. The transformation is applied to the image in the frequency domain. This is done in two steps. The first step requires the creation of a matrix to preserve the phase of the transformed image. This will be used to restore the phase of the transform coefficients. The next step is to take the logarithm of the modulus of the transform coefficients as follows:

$$\hat{X}(i, j) = \ln(|X(i, j)| + \lambda)$$

where λ is some shifting coefficient. The shifting coefficient is used to keep from running into discontinuities. To return the coefficients to the standard transform domain, the signal is exponentiated and the phase is restored. This approach can be extended by using the following operator/function:

$$\hat{X}(i, j) = \gamma \ln(\eta |X(i, j)| + \lambda)$$

IV. Proposed Edge Detection Method

Significant visual information resides at mid to high spatial frequencies. Visually significant image details such as edges, lines and textures typically contain high frequency. The HBT filter and edge similarity measure with regularization parameter [1] along with logarithmic transform [2] has been applied to the image in frequency domain that attenuates low frequency components. The details of the modified edge-detection method are as follows:

Step 1: Apply the Fourier transform to the given image **f**. The Fourier transform of an image is given as

$$\boldsymbol{F}(\boldsymbol{u},\boldsymbol{v}) = \frac{1}{\boldsymbol{MN}} \sum_{\boldsymbol{x}=0}^{\boldsymbol{M}-1} \sum_{\boldsymbol{y}=0}^{\boldsymbol{N}-1} \boldsymbol{f}(\boldsymbol{x},\boldsymbol{y}) \boldsymbol{e}^{-\boldsymbol{j}2\boldsymbol{\pi}(\boldsymbol{ux}/\boldsymbol{M}+\boldsymbol{vy}/\boldsymbol{N})}$$

Step 2: Compute the Fourier spectrum and the phase angle of the Fourier transform. The Fourier spectrum $|\boldsymbol{F}(\boldsymbol{u},\boldsymbol{v})|$ and the phase angle $\boldsymbol{\phi}(\boldsymbol{u},\boldsymbol{v})$ of the Fourier transform is given as

$$|\boldsymbol{F}(\boldsymbol{u},\boldsymbol{v})| = \left[\boldsymbol{R}^2(\boldsymbol{u},\boldsymbol{v}) + \boldsymbol{I}^2(\boldsymbol{u},\boldsymbol{v})\right]^{1/2}$$

$$\boldsymbol{\phi}(\boldsymbol{u},\boldsymbol{v}) = \tan^{-1}\left[\frac{\boldsymbol{I}(\boldsymbol{u},\boldsymbol{v})}{\boldsymbol{R}(\boldsymbol{u},\boldsymbol{v})}\right]$$

where ***R(u, v)*** and ***I(u, v)*** are the real and the imaginary parts of ***F(u, v)***, respectively.

Step 3: Apply the logarithmic transform to the Fourier spectrum, $|\boldsymbol{F}(\boldsymbol{u},\boldsymbol{v})|$. The logarithmic transform domain [2] affords us the ability to view the frequency content of an image. The transformation is applied to the image in the frequency domain. This is done in two steps. The first step requires the creation of a matrix to preserve the phase of the transformed image. This will be used to restore the phase of the transform coefficients. The next step is to take the logarithm of the modulus of the transform coefficients as follows

$$\hat{\boldsymbol{F}}(\boldsymbol{u},\boldsymbol{v}) = \boldsymbol{\gamma} \ln(\boldsymbol{\eta} |\boldsymbol{F}(\boldsymbol{u},\boldsymbol{v})| + \boldsymbol{\lambda})$$

where γ, $\boldsymbol{\eta}$ and $\boldsymbol{\lambda}$ are parameters, that are computed empirically.

Step 4: Apply the luminance and contrast invariant edge similarity measure algorithm to $\hat{\boldsymbol{F}}$ to get the similarity map $\hat{\boldsymbol{R}}$.

Step 5: Apply the inverse logarithmic transform of $\hat{\boldsymbol{R}}$. Inverse logarithmic transform is done as follows

$$\boldsymbol{R}'(\boldsymbol{u},\boldsymbol{v}) = (\exp(\hat{\boldsymbol{R}} / \boldsymbol{\gamma}) - \boldsymbol{\lambda}) / \boldsymbol{\eta})$$

$$\bar{\boldsymbol{R}}(\boldsymbol{u},\boldsymbol{v}) = \boldsymbol{R}'(\boldsymbol{u},\boldsymbol{v}) \cdot \boldsymbol{e}^{\boldsymbol{j\phi}(\boldsymbol{u},\boldsymbol{v})}$$

Then apply the inverse Fourier transform on $\bar{\boldsymbol{R}}(\boldsymbol{u},\boldsymbol{v})$ to get ***R(x, y)***.

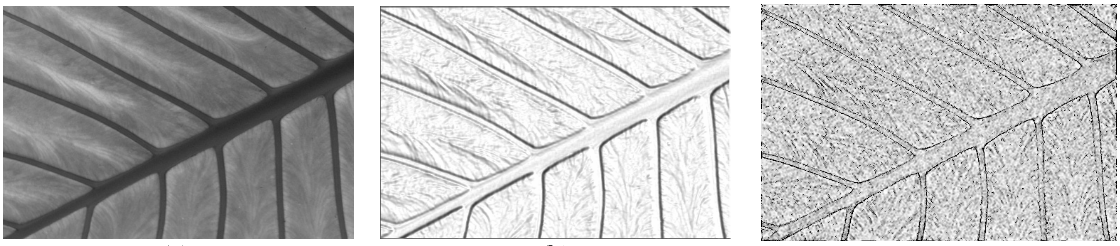
Step 6: Apply Lucy-Richardson Algorithm [6, 7] (this is an optional step) to **R** to reduce the noise and take the absolute value of the result.

(a) (b) (c)

Fig 1. Comparison of outputs for lena.tif image. (a) Original Image. (b) Edge-detected image using edge similarity measure. (c) Edge-detected image using proposed method.

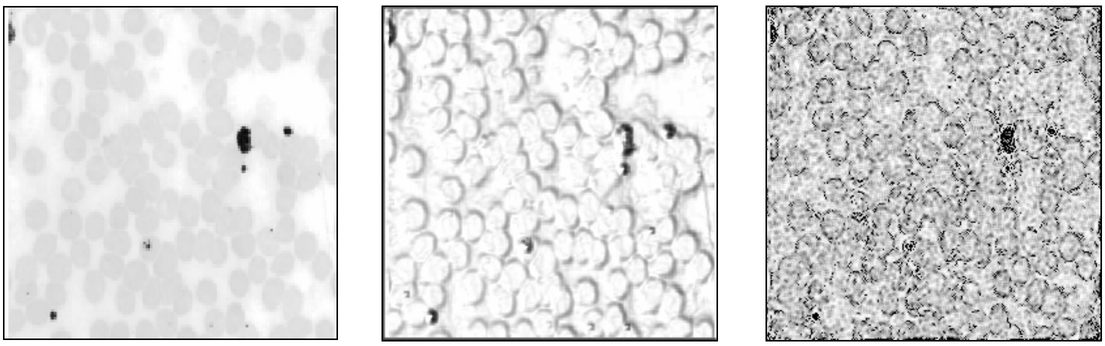
(a) (b) (c)

Fig 2. Comparison of outputs for tree.tif image. (a) Original Image. (b) Edge-detected image using edge similarity measure. (c) Edge-detected image using proposed method.



(a) (b) (c)

Fig 3. Comparison of outputs for aila.tif image. (a) Original Image. (b) Edge-detected image using edge similarity measure. (c) Edge-detected image using proposed method.

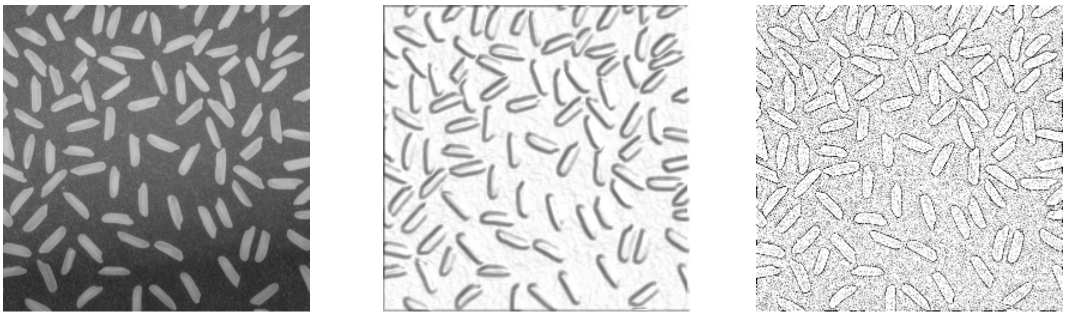


(a) (b) (c)

Fig 4. Comparison of outputs for cell.tif image. (a) Original Image. (b) Edge-detected image using edge similarity measure. (c) Edge-detected image using proposed method.

(a) (b) (c)

Fig 5. Comparison of outputs for coins.png image. (a) Original Image. (b) Edge-detected image using edge similarity measure. (c) Edge-detected image using proposed method.



(a) (b) (c)

Fig 6. Comparison of outputs for rice.png image. (a) Original Image. (b) Edge-detected image using edge similarity measure. (c) Edge-detected image using proposed method.

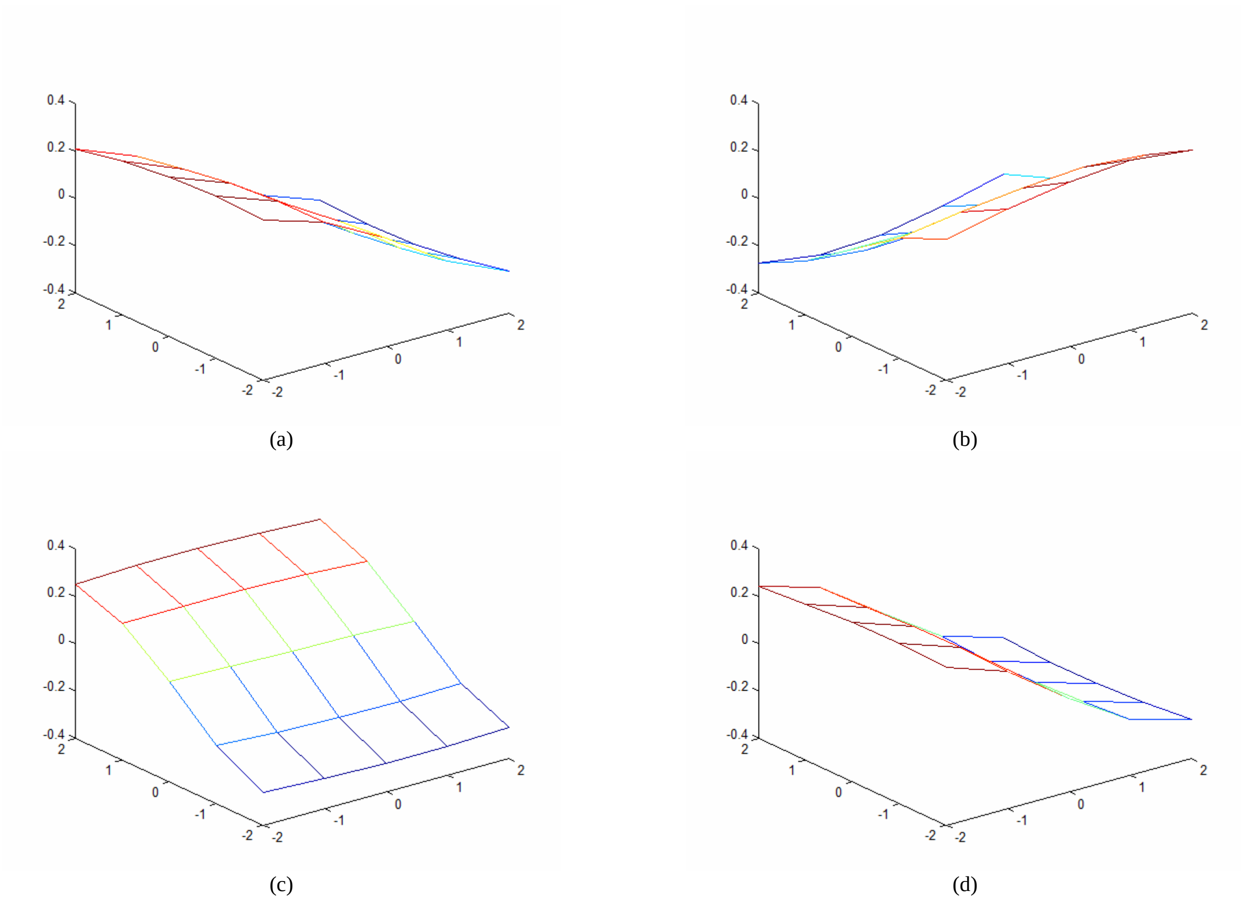
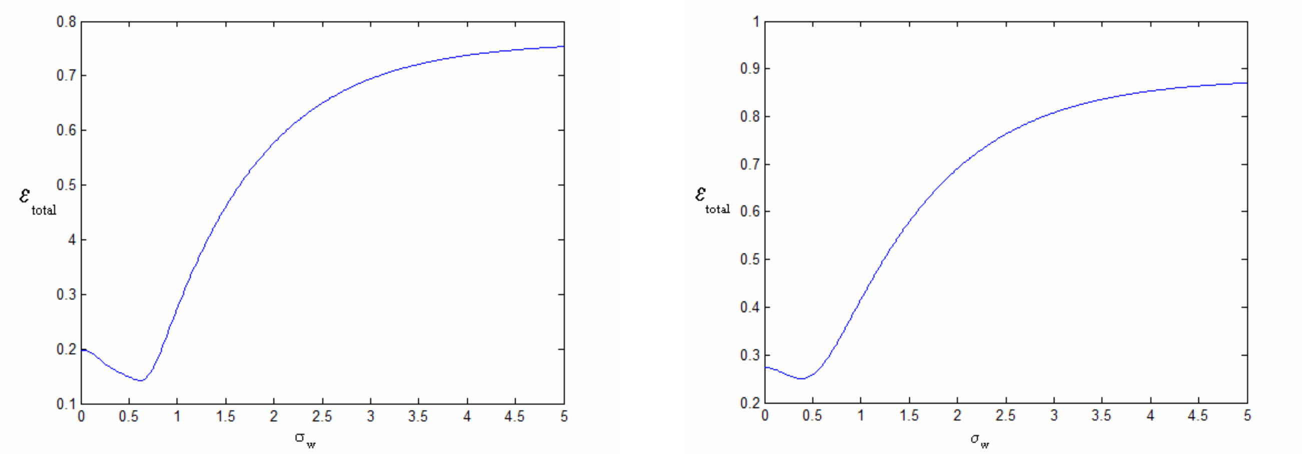


Fig 7. Least-square estimates of PCA eigenvectors using HBT filters (a) and (b) are PCA Eigen vectors of second and third largest Eigen values in spatial domain for Lena image; (c) and (d) corresponding values in the frequency domain.



(a) (b)

Fig 8. (a) σW values in spatial domain (b) σW value in frequency domain

TABLE I
Comparison of PSNR, SSIM, Luminance (I), Contrast (C) and Structure (S) values

	Luminance/Contrast Invariant Edge Similarity Measure					Edge Detection Using HBT Filter and Logarithmic Transform							
	PSNR	SSIM	Lum (I)	Cont (C)	Struc (S)	PSNR	SSIM	Lum (I)	Cont (C)	Struc (S)	η	γ	λ
Rice	5.725	-0.191	0.794	0.999	-0.241	6.344	0.183	0.812	0.961	0.235	1.2	10	2
Lena	5.495	0.02	0.765	0.977	0.027	5.552	0.199	0.764	0.999	0.261	1.2	10	2
Coins	4.898	-0.322	0.789	0.998	-0.409	4.948	0.0013	0.752	0.986	0.002	1.2	10	1.5
Aila	6.402	0.047	0.802	0.962	0.0615	6.872	0.167	0.807	0.985	0.211	1.2	10	2
Cell	16.623	0.086	0.999	0.788	0.108	19.424	0.307	0.999	0.927	0.331	1.2	10	2
tree	6.932	.011	0.84	0.888	0.014	8.3	0.277	0.872	0.964	0.33	1.2	10	2

Step 7: Take the complement of the result obtained from the previous step and save it in a variable, say **gneg**.
Step 8: Apply the image adjustment (imadjust) operation to **gneg** to get the image **A** with clear edges.
Step 9: Apply the Wiener filter and image adjustment operation (this is an optional step) to **A** in the case of noisy and contrast variant images to get better result.

V. RESULTS AND DISCUSSION

The similarity feature of the proposed method is compared with luminance and contrast invariant edge similarity measure algorithm [1]. The proposed method was applied to six standard images namely *Lena, Tree, Aila, Cell, Coins* and *Rice* shown in fig 1, 2, 3, 4, 5 & 6 respectively. The comparison results are displayed in Table I in terms of SSIM and PSNR values, where *Lum*, *Cont* and *Struc* stands for Luminance, Contrast and Structure, respectively.

It can be seen that PSNR values are almost similar; however, there is remarkable improvement in their SSIM values, especially in its structural component. The tree and cell images are noisy and contrast variant images. In these two images the ninth step is applied. In all the other images sixth step has been applied. Figure 7 shows the comparison of the second and the third largest eigenvectors of the PCA analysis in the spatial domain and frequency domain. Figure 8 shows the comparison of σ_W in the spatial and frequency domain.

VI. CONCLUSION

A modified edge detection algorithm has been presented in this paper which gives a better edge-detection while preserving the structural similarity with the original image. Logarithmic transform and HBT filter has been employed in the proposed method for yielding better result. As mentioned earlier, a drawback of this method is that, in the case of contrast variant and noisy images, edge-detection algorithm based on similarity measure gives better result. Our future research will be focusing on how to improve the performance of the proposed method in the case of noisy and contrast variant images.

REFERENCES

[1] G Saravana Kumar, Sim Heng Ong, Surendra Ranganath and Fook Tim Chew, “A Luminance and Contrast-Invariant Edge-Similarity

Measure", IEEE Transactions on Pattern Analysis and Machine Intelligence, 28(12), 2006, 2042-2048.

[2] Sos S. Agaian, Blair Silver and Karen A. Panetta, "Transform Coefficient Histogram-Based Image Enhancement Algorithms Using Contrast Entropy", IEEE Transactions on Image Processing, 16(3), 2007, 741-758.

[3] J. Canny, "A Computational Approach to Edge Detection", IEEE Transactions on Pattern Analysis and Machine Intelligence, 8, 1986, 679-698.

[4] P. Kovesi, "Phase Congruency: A Low Level Image Invariant", Psychological Research, 64, 2000, 136-148.

[5] W. Frei and C.C. Chen, "Fast Boundary Detection: A Generalization and a New Algorithm," IEEE Trans. Computers, vol. 26, pp. 988-998, 1977.

[6] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 2nd ed. Englewood Cliffs, NJ: Prentice-Hall, 2002, ISBN: 0-201-18075-8.

[7] Anil K. Jain, "Fundamentals of Digital Image Processing", 1st Ed., Prentice Hall, Pearson Education, 1989.

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