# Image Feature Detection Based on Phase Congruency by Monogenic Filters

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**Abstract:** The image brightness and contrast changes remain invariant when phase congruency changes. Specifically the monogenic filters, a new image feature detection method is proposed, which is based on phase congruency and the monogenic signal theory in this paper. The performances of Monogenic filters are excelled to that of Log-Gabor filters in theory, hence a greater amount of feature vectors are generated. Compared with the Log-Gabor filters, the most important advantage of Monogenic filters is that it performances with lower time and smaller memory space. The experimental result indicates that image features with Monogenic filters can not only overcome the limitations of Log-Gabor filters, but also improve the location accuracy and anti-noise ability with comparable or better performance.

**Key Words:** Image Feature Detection, Phase Congruency, Monogenic Filters, Riesz Transform

## 1 INTRODUCTION

In spatial domain, gradient based image feature detection methods, such as Log operator, Sobel operator, Canny operator and so on, are using difference operator to calculate the variation degree of gray image pixels gradient. These are mainly focus on step features and the results of feature detection are susceptible to the brightness and contrast of image[1]. However, in frequency domain, phase congruency gets to be a contrast and brightness invariant method and applicable for step edge, linear edge and roof edge feature detection. In addition, this method can be only according to phase congruency to determine the feature points with not making any prior assumption on the premise. For most images, it exhibits good robust properties, and then the thresholding problem is greatly eased.

Log-Gabor function is used as an accessible filter model that Field[2] proposed in 1987. Kovesi[3,4] developed phase congruency to 2D signal between 1996 to 1999. But due to the need for many times convolution operation, its computation is quite big, and the application of real-time systems is not suitable.

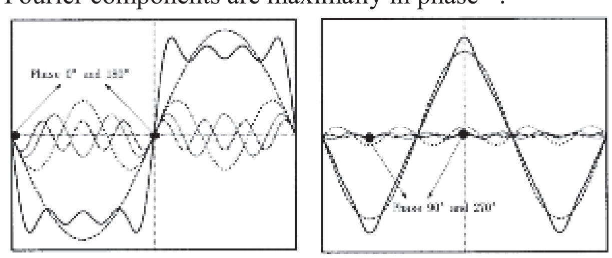
By the multiple resolution orientation, magnitude and phase, an analytic two-dimensional (2D) verbalizes from the one-dimensional (1D). Riesz transform is the founation of the approach mentioned above, but not is the Hilbert transform. And from solenoidal and irrotational vector fields, it can analytically deduce the monogenic signal[5].

This paper presents an improved method called Monogenic filters, which is a novel image feature detector based on phase information. Monogenic filters have many advantages over other Gabor based methods. one obvious advantage is that it has much lower space complexity and performance time. Log-Gabor filters need use dirigible filters to generate multiple orientation image features, but the monogenic signal is not like the Log-Gabor filters do.

## 2 phase congruency

### 2.1 PC Function

In the Fig.1, the signal is indicated by a solid line, the Fourier harmonic components are shown by some dotted lines and the solid points represent the feature points. In the step of square wave, each sinusoidal wave is at the same phase of 0 ° and 180 ° corresponding to the fall and rise edge respectively of the square wave, as shown in Fig1(a). At the peaks of the triangular wave, cosine components are 90 ° and 270 ° of the same phase corresponding to the negative peak and positive peak of the triangular wave, as shown in Fig 1(b) above. Also the step of the square wave and the peak of the triangular wave can be regarded as step edge and roof edge. Therefore, phase consistency method detects image feature through finding where the Fourier components are maximally in phase[6].



(a) square wave Fourier components    (b) triangular wave Fourier components

Fig.1: Construction of square and triangular waveforms from their Fourier series

The Fourier series expansion of a 1D signal, $I(x)$ , is generally described as[7]

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$$I(x)=\sum_n A_n\cos(n\omega x+\phi_{n_0})$$
$$=\sum_n A_n\cos(\phi_n(x)) \tag{1}$$

where $\phi_{n(x)}$ means in $x$ the local phase of the Fourier constituent.

With the signal $I(x)$ at some location $x$, the phase congruency[8] is defined as the terms of the Fourier series expansion

$$PC(x)=\max_{\bar{\varphi}(x)\in[0,2\pi]}\frac{\sum_n A_n\cos(\varphi_n(x)-\bar{\varphi}(x))}{\sum_n A_n} \tag{2}$$

Kovesi[9]proposed the phase congruency equation $PC(x)$. It shows a 2D signal over orientation $o$ and scale $n$ with the phase congruency to be defined.

$$PC(x)=\frac{\sum_o\sum_n W_o(x)\lfloor A_{no}(x)\Delta\Phi_{no}(x)-T_O\rfloor}{\sum_o\sum_n A_{no}(x)+\varepsilon} \tag{3}$$

where $\varepsilon$ is a small parameter for avoiding divised by zero and $T$ is the approximate noise effect, and $\Delta\Phi_n(x)$ is a responsive phase deviation among them. If it is positive, then $\lfloor\ \rfloor$ represents that the enclosed quantity is itself.

### 2.2 Local energy function

To calculate the certain points of maximum phase congruency identically with the methed of searching for peaks in the local energy function is an alternative to this. The local energy[10] is defined for a one-dimensional profile , $I(x)$ ,as

$$E(x)=\sqrt{F^2(x)+H^2(x)} \tag{4}$$

where $F(x)$ is the DC component eliminated signal $I(x)$, and $H(x)$ is the Hilbert transform of $F(x)$, which has a 90 degree phase shift of $F(x)$. Through convolving the signal with a quadrature couple of filters, it can typically obtain the components $F(x)$ and $H(x)$. Scaled by the total quantity of the Fourier amplitudes, the local energy is seemed equally to phase congruency, that is

$$E(x)=PC(x)\sum_n A_n \tag{5}$$

The relationship between local energy, phase congruency, and the summation of the Fourier amplitudes can be showed in Fig.2 geometrically.

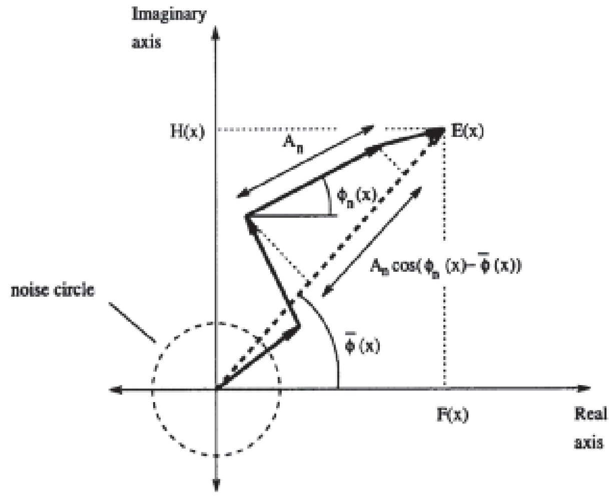



Fig.2: Geometrical relationship of local energy,phase congruency and the sum of the Fourier amplitudes

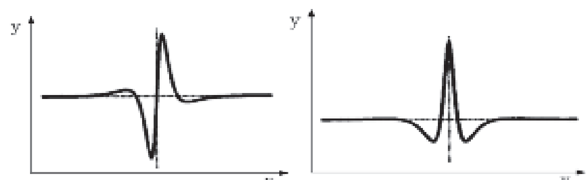
Adding one connected to one another vectors, the local Fourier components are plotted as complex ones. The sum of these components projected onto the real axis represent $F(x)$, the original signal with DC component removed, and the projected onto the imaginary axis represents $H(x)$.The magnitude of the vectors from the beginning to the end points are the sum of the local energy $E(x)$ [11].

## 3 log-gabor filters

In the logarithmic frequency domain, there is a Gaussian transfer function in the Logarithmic Gabor filters[12]. Creating the Large bandwidth filters in Log-Gabor filters are allowable, also in the even symmetric filter keeping a zero DC component in it. The transfer equation of Log-Gabor function in the linear frequency domain defined as

$$\xi(\omega)=e^{\frac{-(\log(\omega/\omega_0))^2}{2(\log(k/\omega_0))^2}} \tag{6}$$

At a scale $n$, make $M_n^o$ and $M_n^e$ represent the odd-symmetric (sine) and even-symmetric (cosine) filters, and Fig.3 illustrates the two kinds of wavelets.




(a) odd (b) even

Fig.3: Odd and even log-Gabor wavelets

Then the each quadrature couple of filters results conduct a response vector

$$[e_n(x),\ o_n(x)]=[I(x)*M_n^e,\ I(x)*M_n^o] \tag{7}$$

Giving a filter measure, the amplitude of the conversion is expressed by

$$A_n(x)=\sqrt{(I(X)*M_n^e)^2+(I(x)*M_n^o)^2} \quad (8)$$

and the phase is defined by

$$\varphi_n(x)=\tan^{-1}\left[(I(x)*M_n^o)/(I(x)*M_n^e)\right] \quad (9)$$

Summing the even filter convolutions, an evaluatation $F(x)$ can be conducted[13].

$$E(x)=PC(x)\sqrt{(\sum_n(I(x)*M_n^e))^2+(\sum_n(I(x)*M_n^o))^2} \quad (10)$$

Fig.4 shows the filtering process that applies Log-Gabor filters on a one-dimensional signal.

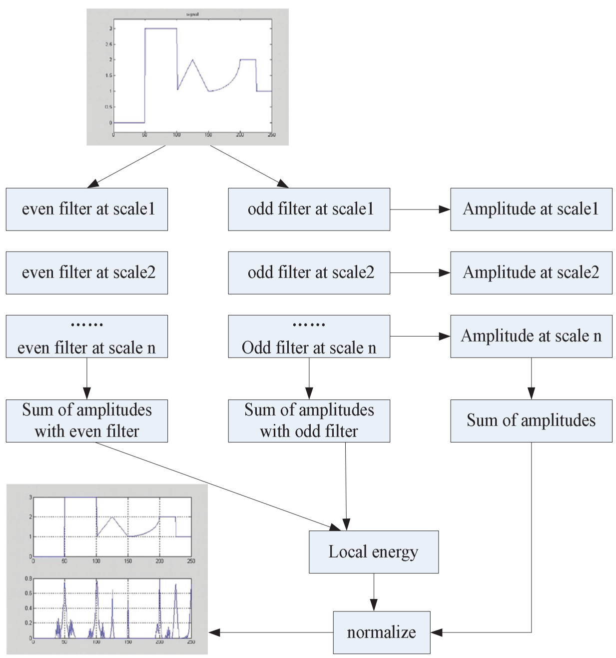



Fig.4: Application of Log-Gabor filters on a one-dimensional signal

Despite the high precision filtering cost, the computation time of the Log-Gabor pointed out above is very high as same as the storage space. Because Log-Gabor filters perform along six different directions and in four or more different scales, which Monogenic filtering mentioned latter would overcomes the limits of Log-Gabor filtering.

## 4 monogenic filters

### 4.1 Riesz Transform

Riesz transform combinates with a two- dimensional signal can conduct a novel signal, namely monogenic signal likewise the analytic signal. Therefore, the dimension choice is greatly proper applying for 2D signal[14]. Denoting the harmonic potential field as

$$\vec{g}(\vec{x})=(g_1(\vec{x}),g_2(\vec{x}),g_3(\vec{x}))^{\mathrm{T}}=\nabla\rho(x) \quad (11)$$

where $\nabla$ represents the three-dimensional gradient operator, $g_3(x_1,x_2,0)=f(x_1,x_2)$ is the boundary condition. The relation of $g_3(x_1,x_2,0)$ to the other two boundary conditions $g_1(x_1,x_2,0)$ and $g_2(x_1,x_2,0)$ conducts the description of the Riesz transform. The relations between $G_1$, $G_2$ ,and $G_3$

$$G_1(u_1,u_2,x_3)=\frac{iu_1}{q}G_3(u_1,u_2,x_3) \quad (12)$$

$$G_2(u_1,u_2,x_3)=\frac{iu_2}{q}G_3(u_1,u_2,x_3) \quad (13)$$

Therefore, if the fixed $x_3<0$, a harmonic potential field with its ingredients are related by (12) and (13).

$$\vec{g}_1(u_1,u_2,0)=\frac{iu_1}{q}\vec{g}_3(u_1,u_2,0)=\frac{iu_1}{q}F(u_1,u_2) \quad (14)$$

$$\vec{g}_2(u_1,u_2,0)=\frac{iu_2}{q}F(u_1,u_2) \quad (15)$$

Setting

$$F_R(u_1,u_2)=(\vec{g}_1(u_1,u_2,0),\vec{g}_2(u_1,u_2,0))^{\mathrm{T}} \quad (16)$$

then defining $\vec{u}=(u_1,u_2)^{\mathrm{T}}$ so that, $q=|\vec{u}|$, it obtains the equation with the frequency domain of the Riesz transformed signal[15]

$$F_R(\vec{u})=\frac{i\vec{u}}{|\vec{u}|}F(\vec{u})\overset{def}{=}H_2(\vec{u})F(\vec{u}) \quad (17)$$

Hilbert transform with two-dimensional generalized the Riesz transform $H_2$ function. In the following, the notation $\vec{x}=(x_1,x_2)^{\mathrm{T}}$ since $x_3=0$.

$$f_R(\vec{x})=-\frac{\vec{x}}{2\pi|\vec{x}|^3}*f(\vec{x})\overset{def}{=}\vec{h}_2(\vec{x})*f(\vec{x}) \quad (18)$$

where $\vec{h}_2$ is obtained by applying the derivative theorem of the Fourier transform to $F_2\{|\vec{x}|^{-1}\}=|\vec{u}|^{-1}$. Therefore, it has built up in the Riesz transform is a vector field is deduced based background Hilbert proper generalization of 2D transform[16].

### 4.2 The monogenic signal

Felsberg et alnoted that monogenic analytic signal composed by three orthogonal components[17]

$$f_M(x,y,s)=f_p(x,y,s)+f_x(x,y,s)+f_y(x,y,s) \quad (19)$$

Specifically, the local magnit $A$, orientation $\theta\in[0,\pi)$ and phase $\phi\in[0,2\pi)$ of a 2D signal can be computed by

$$\begin{cases} A(x,y,s)=\sqrt{f_p^2(x,y,s)+f_x^2(x,y,s)+f_y^2(x,y,s)} \\ \theta(x,y,s)=art\tan(f_y(x,y,s)/f_x(x,y,s)) \\ \varphi(x,y,s)=-sign(f_x(x,y,s)) \\ art\tan2(\sqrt{f_x^2(x,y,s)+f_y^2(x,y,s)}/f_p(x,y,s)) \end{cases} \quad (20)$$

According to the theory above, improving the Eq.20, a monogenic phase congruency detection method is proposed

$$PC(x,y,s) = W\left[1 - a\cos\left(\frac{E}{A_{\Sigma}+\varepsilon}\right) - \frac{T}{A_{\Sigma}+\varepsilon}\right] \tag{21}$$

Local energy is defined as

$$E = \sqrt{f_{p-\Sigma}^2 + f_{x-\Sigma}^2 + f_{y-\Sigma}^2} \tag{22}$$

Also, the sum of the local amplitudes is defined as

$$A_{\Sigma} = \sum_{s=1}^{n} A(x,y,s) \tag{23}$$

where $f_{p-\Sigma} = \sum_{s=1}^{n} f_p(x,y,s)$, $f_{x-\Sigma} = \sum_{s=1}^{n} f_x(x,y,s)$, $f_{y-\Sigma} = \sum_{s=1}^{n} f_y(x,y,s)$. $W$ represents the weight, $T$ is a noise threshold.

According to the monogenic phase congruency function as shown in Eq.3, As seen in the Eq.23, a monogenic signal is composed of three components, which are mutually orthogonal, to form feature vector. Here the definition of a monogenic feature vector is

$$V(x,y,s) = \left[Uf_p(x,y,s), Uf_x(x,y,s), Uf_y(x,y,s)\right]^T \tag{24}$$

where $U$ represents all components of feature point in the neighborhood. Eq.24 expresses that feature vectors are composed by row vectors of the three components.

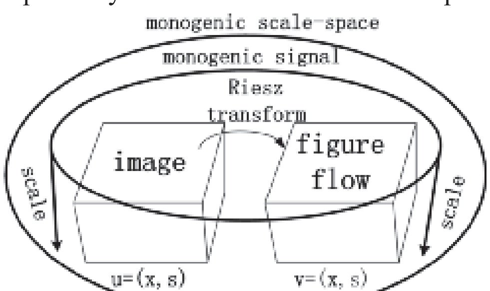



Fig.5: Relations between Riesz transform,monogenic signal,and monogenic scale-space

### 4.3 The monogenic filters

In fact, the image coordinate system by using the generalized transform calculation for Hilbert (relative to the preferred direction or arbitrary) axis in a not isotropic. Therefore, local phase and amplitude are dependent on local axis (or preference direction) of system error and signal direction angle[18]. The design of this problem is equivalent to the log Gabor filter (this is a complex domain impossible), or two-dimensional dispersion equation (which is impossible) solution, single gene screening is based on the Riesz transform, which is instead of the Hilbert transform is used in the Log-Gabor filter. The principle flow diagram of monogenic filtering process is shown in the figure 6 below:

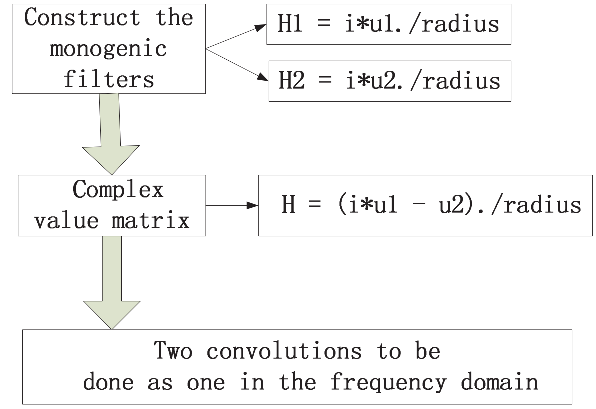
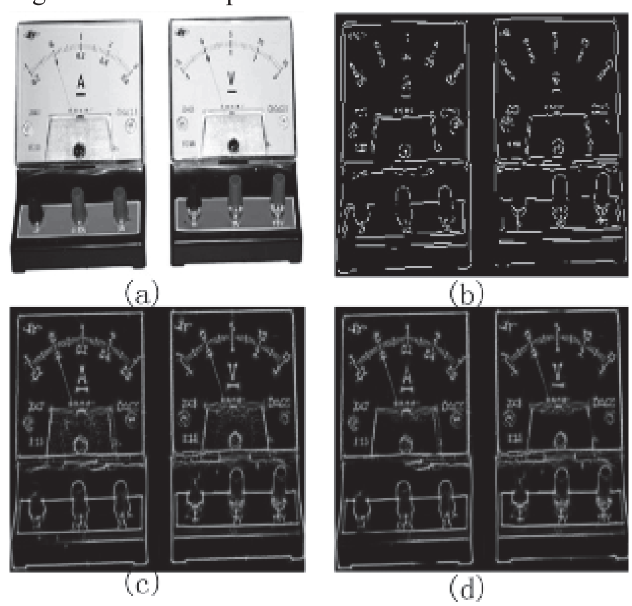



Fig.6: The flow diagram of monogenic filtering

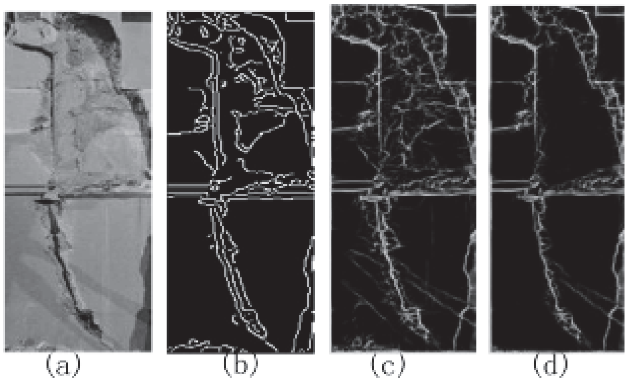
## 5 EXPERIMENTAL RESULTS AND ANALYSIS

To demonstrate the performance of the Monogenic filters by developing software in MATLAB 7.0, the Monogenic filtering is applied to two images and compared with the Log-Gabor filters. And Canny edge detection algorithm is the best of many edge detector. Select 6 orientations (0 °,30 °,60 °,90 °,120 °,150 °) Log-Gabor filters to extract features. The threshold of frequency spread is 0.5. 10 is appropriate number to control the spread spectrum transition phase congruency of Sigmoid function sharpness. Fig.7 and Fig.8 show the comparison results.




(a) original image (b) Canny operator (c) Log-Gabor filters (d) Monogenic filters

Fig.7: Comparison three algorithm detection results of ammeter and voltmeter




(a) original image (b) Canny operator (c) Log-Gabor filters (d) Monogenic filters

Fig.8: Comparison three algorithm detection results of bridge column cracks

As shown in Fig.7and Fig.8, Canny operator has some disadvantages: complex computation, false zero crossing, time consuming. Canny edge detection method dose not presents all information of the image and two-edges. Log-Gabor filters are more sensitive to small change in the contour of objects. The Monogenic filters produce more localized response function to features and allows a better detection in the details of the images than Canny operator and Log-Gabor filters.

Metric. F. is used to measure the pros and cons of different edge detection algorithm. Formula F is defined as:

$$F = \frac{1}{\max\{I_I, I_A\}} \sum_{i=1}^{I_A} \frac{1}{1+\alpha d^2(i)} \tag{25}$$

The metic F trends of the three detection algorithm with the change of signal to noise ratio are shown gin Figure 9. Monogenic filters have a stronger anti-noise capability, and its performance is better than the other two algorithms.

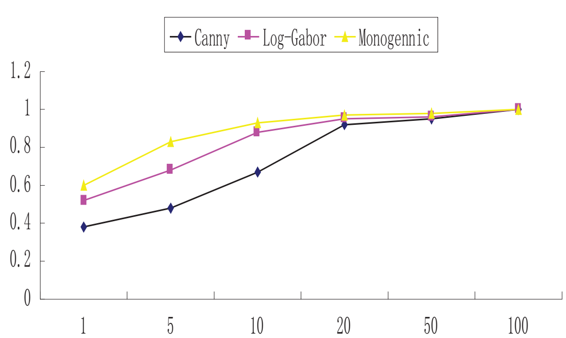



Fig.9: The metic F trends of the three algorithm

Experimental data show that the recognition of algorithm is precision and speed after much experimentation. This data is recorded as following table:

Table 1. The comparison of three methods between the complexity of time and space

| | algorithm | time/ms | space complexities | feature number |
|---|---|---|---|---|
| Image 1 | Canny | 3.41160 | 100 | n/a |
| | Log-Gabor | 2.63310 | 80 | 152 |
| | Monogenic | 0.95280 | 20 | 159 |
| Image 2 | Canny | 3.69030 | 100 | n/a |
| | Log-Gabor | 2.56830 | 80 | 148 |
| | Monogenic | 0.89570 | 20 | 155 |

As shown in Table.1, Canny operator and Log-Gabor filters are more time-consuming processing than Monogenic filters. It can be seen that the computation load of Canny operator and Log-Gabor filters are fairly high.Because of Log-Gabor filter enhancement needs 80 Gabor convolution filters on per image. However, because of monogenic signal that don't use directional Gabor filtering, the monogenic filtering method only requres 3 Log-Gabor filtering and 6 Riesz transform each image. This algorithm e noise of images restrained and the feature is more distinct after phase congruency.

## 6 CONCLUSION

In this paper, it has presented an alternative method, called monogenic filtering, which can avoid the limitation of Log-Gabor filtering, because it is itself a compact representation of the characteristics of almost no information loss and not using filters that can bemanipulated to create multi-orientation features. Experimental results show that the Monogenic filtering algorithm based on phase congruency and monogenic signal analysis are quite better to the application of real-time image processing systems than other methods. However, the of the monogenic scale-space's structure representation still needs further investigation to be completely understood.

## REFERENCES


[1] Marr D, Hildreth E C. Theory of edge detection[C]. Proceedings of the Royal Society, London B, 1980, 207:187-217.

[2] Morrone, M.C., and Owens, R.A. Feature detection from local energy[J]. Pattern Recognition Letters, 1987,6,303-313.

[3] Meng Yang, Lei Zhang, et al. Monogenic Binary Pattern (MBP): A Novel Feature Extraction and Representation Model for Face Recognition[C]. International Conference on Pattern Recognition,2010,2680-2683.

[4] Felsberg M., Sommer G. The monogenic signal[J]. IEEE Transactions on Signal Processing, 2001, 49(12), 3136-3144.
[5] Field, D. J. Relations between the statistics of natural images and the response properties of cortical cells[J]. Journal of The Optical Society of America A,1987,4,2379-2394.
[6] Kovesi P. Phase congruency:A low-level image invariant[J].Psychological Research, 2000, 64(2): 136-148.
[7] Xiao Z, Hou Z, Miao C, et al. Using phase information for symmetry detection[J]. Pattern Recognition Letters,2005,26:1985-1994.
[8] Owens, R. A. Feature-free images[J]. Pattern Recognition Letters,1994,15,35-44.
[9] Owens, R. A., Venkatesh, S., and Ross,J. Edge detection is a projection[J]. Pattern Recognition Letters,1989,9,223-244.
[10] Kovesi P. Image features from phase congruency[J]. Videre: Journal of Computer Vision Research,1999, 1(3):1-30.
[11] Kovesi P. Phase congruency detects corners and edges[C]. Proceedings of DICTA'03: The Australian Pattern Recognition Society Conference,2003
[12] Field D J, Nachmias J. Phase reversal discrimination[J]. Vision Research,1984,24(4):333-340.
[13] Z. T. Xiao, C. M. Guo. M. Yu. Research on log-gabor wavelet and its application in image edge detection[C]. In Proceedings: $6^{th}$ International Conference on Signal Process. Beijing, China, Aug. 2002:592-595.
[14] Canny J F. A computational approach to edge detection[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence,1986,8(6):679-698.
[15] Linguraru M G, Ballester M A G, Ayache N. A multiscale feature detector for morphological analysis of the brain[C]. Medical Image Computing and Computer-Assisted Intervention-MICCAI2003,2003.
[16] L.Zhang,L.Zhang,Z.Guo,andD.Zhang, Monogenic-LBP: A new approach for rotation invariant texture classification[J].Proc. ICIP,2010,2677– 2680.
[17] M. Felsberg and G. Sommer, Structure multivector for local analysis of images[J], Lecture Notes in Computer Science, 2001,2032:95– 106.
[18] Signal Process., vol. 49, no. 12, pp. 3136–3 144, 2001.Liu C, Sharan L, Adelson E H, et al. Exploring features in a bayesian framework for material recognition[C].Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on. IEEE, 2010: 239-246.