Palm Print Image Enhancement using Monogenic Wavelet

Enhancement of palm print image after image acquisition is an important step in constructing a palm print biometric recognition system. Enhancement of palm print image is important to extract out features which are more accurate than those extracted from a raw image. Pre-processing of image enhances the accuracy while matching with other palm prints in a database of millions. False Acceptance Rate (FAR) and False Rejection Rate (FRR) factors show tremendous improvement if the image, whose features needs to be extracted, is pre-processed properly. Hence image enhancement before extracting features plays a crucial role in constructing a highly accurate biometric recognition system.

The technique used here for enhancing the image is based on phase congruency. Phase congruency was developed by Peter Kovesi to extract out the features based on edge detection. Canny edge detection has a drawback that it produces double edges of thin ridges giving false information. Phase Congruency, on the other hand, highlights a single response on thin edges of palm print.

The importance of phase congruency is emphasized by considering the following features:

1. Phase congruency is invariant to illumination.
2. Phase congruency has no dimensions.
3. Its value lies in the range 0 to 1 , where higher value of phase congruency indicates a more distinctive and crucial feature.

Phase Congruency around point x, is given as follows:

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

Where, numerator denotes the local energy of signal and the denominator denotes the summation of the amplitudes of its Fourier Components.

Phase Congruency analysis using Monogenic Wavelets:

Phase congruency can be obtained over a band of frequencies rather than at a single frequency as its value will always be 1 at a particular frequency. To extract out minute features of palm print needs analysis in time and frequency which is spatially localised. The concept of phase congruency helps in extracting out spatially localised frequency information and the use of wavelets becomes ideal in such situations. Computing the analytic signal out of input signal helps in extracting phase information. Monogenic signal, which is obtained from Riesz transform (a vector valued extension of Hilbert transform in multiple dimensions) is a generalization of analytic signal in higher dimensions.

The monogenic equivalent of a 2D real image can be expressed as follows:

$$f_M(x_1, x_2) = \begin{bmatrix} f(x_1, x_2) \\ f_{R_1}(x_1, x_2) = R_1(x_1, x_2) * f(x_1, x_2) \\ f_{R_2}(x_1, x_2) = R_2(x_1, x_2) * f(x_1, x_2)) \end{bmatrix}$$

Where R1 and R2 are Riesz Filters. The above three components of the vector f_M can be utilized to evaluate instantaneous amplitude, frequency and phase.

The local Monogenic phase and orientation is expressed as follows:

$$\phi(x_1, x_2) = \tan^{-1}\left(\frac{\sqrt{f_{R_1}(x_1, x_2)^2 + f_{R_2}(x_1, x_2)^2}}{f(x_1, x_2)}\right)$$

$$\theta(x_1, x_2) = \tan^{-1}\left(\frac{f_{R_2}(x_1, x_2)}{f_{R_1}(x_1, x_2)}\right)$$

Where Φ varies from $(\frac{-\pi}{2}, \frac{\pi}{2})$ and Θ varies from $(0,\pi)$.

The amplitude of Fourier components is evaluated at different scales of wavelet and a portion of the frequency spectrum is captured at that particular scale. It is given by:

$$A_n(x_1, x_2, s) = \sqrt{f(x_1, x_2, s)^2 + f_{R_1}(x_1, x_2, s)^2 + f_{R_2}(x_1, x_2, s)^2}$$

and the energy of the image for N scales is given by :

$$E(x_1, x_2) = \sqrt{[f_{sum}(x_1, x_2)]^2 + [f_{R1\,sum}(x_1, x_2)]^2 + [f_{R2\,sum}(x_1, x_2)]^2}$$

where,

$$f_{sum}(x_1, x_2) = \sum_{s=1}^{N} f(x_1, x_2, s)$$

$$f_{R1\,sum}(x_1, x_2) = \sum_{s=1}^{N} f_{R_1}(x_1, x_2, s)$$

$$f_{R2\,sum}(x_1, x_2) = \sum_{s=1}^{N} f_{R_2}(x_1, x_2, s)$$

Thus the phase congruency at a spatial location (x_1, x_2) is defined as follows:

$$PC(x_1, x_2) = \frac{E(x_1, x_2)}{\sum_{s=1}^{N} A_n(x_1, x_2, s)}$$

Wavelet Selection:

The wavelet applied is a monogenic extension of a real 2D log Gabor Isotropic Wavelet. It is defined as follows:

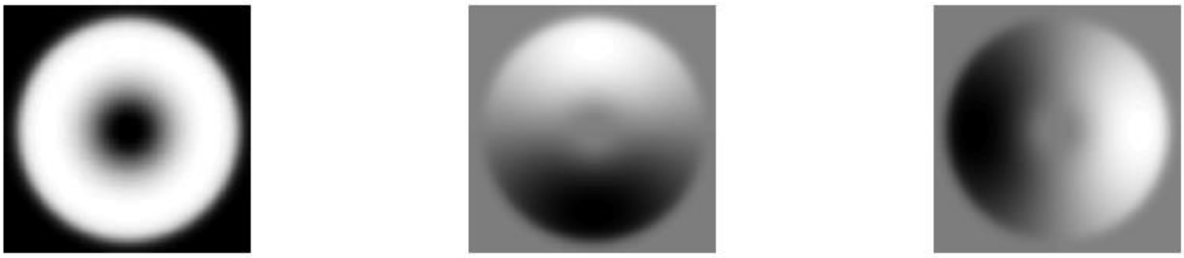
$$G(u_1,u_2) = \exp \frac{-\left(log\left(\frac{\sqrt{(u_1)^2+(u_2)^2}}{\omega_0}\right)\right)^2}{2\left(log\left(\frac{\zeta}{\omega}\right)\right)^2}$$

where u_1 and u_2 are frequency components, ω0 is the centre frequency and ζ is the scaling factor of bandwidth.

The advantage of using 2D Log-Gabor wavelet is as follows:

1. It is an isotropic wavelet and hence the directionality is represented by the signal's monogenic nature.
2. It has zero DC component
3. It has Gaussian shaped Response around the logarithmic frequency.
4. By utilizing minimum number of scales of wavelet, it is possible to achieve a broader spectrum range which in turn sets no limitation to the maximum bandwidth.

The real 2D isotropic Log Gabor wavelet along with its Riesz components together form the monogenic wavelet. The radial response profile of the 2D Log Gabor wavelet and its corresponding Riesz components is shown as follows:

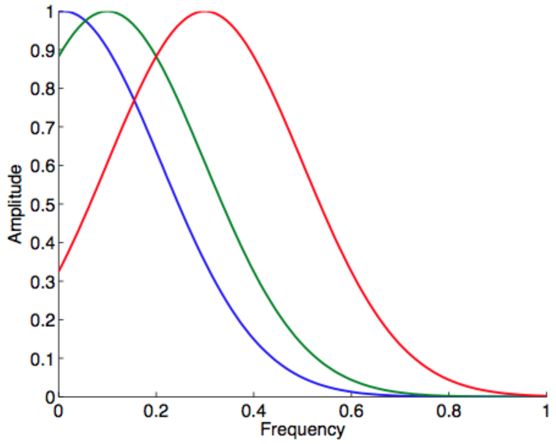


(a) (b) (c)

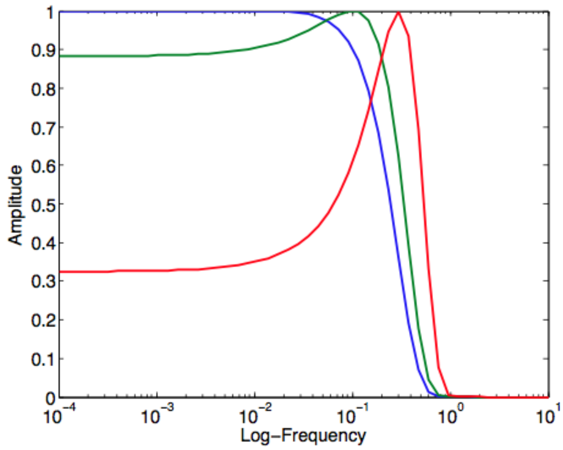
(a) Isotropic log-Gabor wavelet response

(b) and (c) corresponding Riesz wavelets filter responses

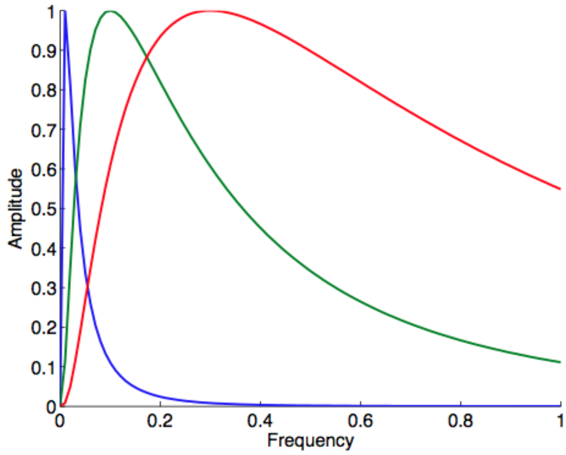
The amplitude v/s Frequency as well as amplitude v/s Log Frequency response for the Gabor and Log Gabor wavelet is as follows:



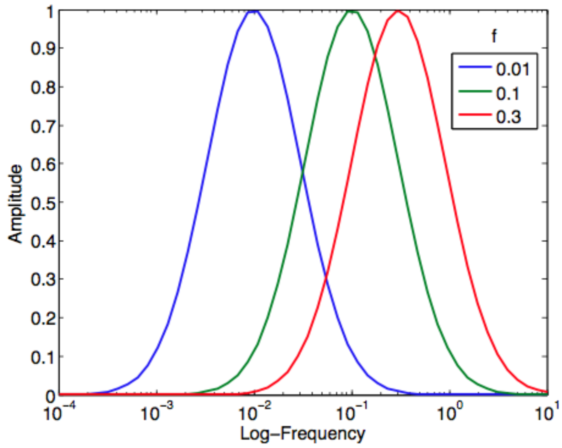
(a) Gabor - Linear Frequency



(b) Gabor - Log Frequency



(c) Log-Gabor - Linear Frequency



(d) Log-Gabor - Log Frequency

The above response clearly indicates a bandpass response of Log Gabor wavelet, supressing the DC component and is very much suitable for phase congruency.

The following is the result of application of Monogenic Wavelet over the extracted palm image for image enhancement: