

Rotation and Scaling Invariant Texture Classification Based on Gabor Wavelets

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Keywords:

Abstract

2 Gabor Feature Extraction

1 Introduction

$$\psi_{\omega, \theta}(x, y) = \frac{1}{\pi\sigma} e^{-\left(\frac{(x \cos \theta + y \sin \theta)^2}{\sigma_x^2} + \frac{(-x \sin \theta + y \cos \theta)^2}{\sigma_y^2}\right)} \left[e^{i(\omega x \cos \theta - \omega y \sin \theta)} - e^{-\frac{\omega \sigma}{\sigma}} \right] \quad 1$$

$$\sigma = \kappa / \omega$$

$$\kappa = \sqrt{\left(\frac{\phi_+}{\phi_-}\right)} \quad \phi$$

$$Y_{\omega, \theta}(x, y) = f(x, y) * \psi_{\omega, \theta}(x, y) \quad 3$$

$$\sigma_{\omega\theta} = \sqrt{\frac{\sum_y \sum_x (Y_{\omega\theta}(x,y) - \mu_{\omega\theta})^2}{N_W \cdot N_H}}$$

$$Y_{\omega\theta} = [Y_{\omega\theta}(0,0) \dots Y_{\omega\theta}(N_H-1, N_H-1)]^T$$

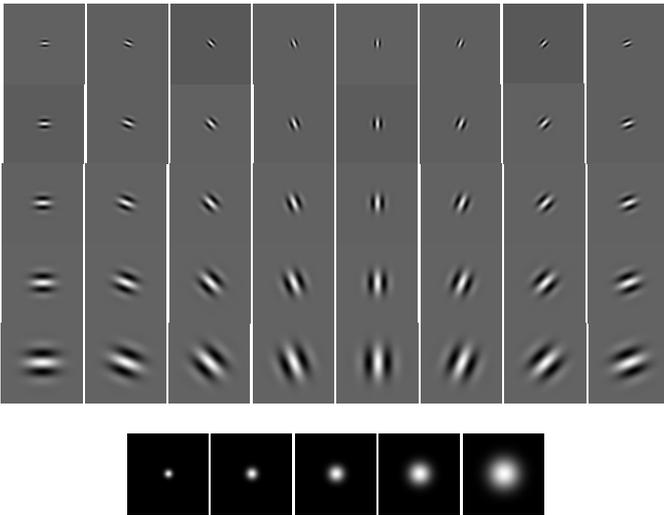
$$P = [\mu_{\omega\theta} \ \sigma_{\omega\theta} \ \mu_{\omega\theta} \ \sigma_{\omega\theta} \ \dots \ \mu_{\omega_m \theta_n} \ \sigma_{\omega_m \theta_n}]^T$$

P

$\omega \quad \theta \quad Y_{\omega\theta}$

$$Y = [Y_{\omega_1 \theta_1}^T \ Y_{\omega_2 \theta_2}^T \ \dots \ Y_{\omega_m \theta_n}^T]^T$$

m n



P

$\mu_{\omega\theta}$

P

θ_i

$$P = [\mu_{\omega_1 \theta_1} \ \sigma_{\omega_1 \theta_1} \ \mu_{\omega_2 \theta_2} \ \sigma_{\omega_2 \theta_2} \ \dots \ \mu_{\omega_m \theta_n} \ \sigma_{\omega_m \theta_n}]^T$$

$\mu_{\omega\theta}$

$\omega \quad \theta$

ω

θ

Fig. 1:

$$\pi/4 \quad \sqrt{2}\pi/4 \quad \pi/2 \quad \sqrt{2}\pi/4 \quad 3\pi/4$$

$$\pi/4 \quad \pi/2$$

3 Rotation and Scaling Invariant Feature Representation and Texture Classification

$$Y_{\omega\theta} \quad \mu_{\omega\theta}$$

$\sigma_{\omega\theta}$

$$\mu_{\omega\theta} = \frac{\sum_y \sum_x Y_{\omega\theta}(x,y)}{N_W \cdot N_H}$$

$$P_{\omega_i} = [\mu_{\omega_i \theta_1} \ \sigma_{\omega_i \theta_1} \ \mu_{\omega_i \theta_2} \ \sigma_{\omega_i \theta_2} \ \dots \ \mu_{\omega_i \theta_n} \ \sigma_{\omega_i \theta_n}]^T$$

θ_j

ω_i

$\mu_{\omega_i \theta_j}$

P_{ω_i}

$$P'_{\omega_i} = [\mu_{\omega_i \theta_{j_1}} \ \sigma_{\omega_i \theta_{j_1}} \ \mu_{\omega_i \theta_{j_2}} \ \sigma_{\omega_i \theta_{j_2}} \ \dots \ \mu_{\omega_i \theta_{j_n}} \ \sigma_{\omega_i \theta_{j_n}}]^T$$

P'_{ω_i}

P'_{ω_i}

$$P = [P'_{\omega_1} \ P'_{\omega_2} \ \dots \ P'_{\omega_m}]^T$$

$$P'_{\omega_i}$$

μ

σ

$$P = [\mu \ \sigma \ P'_{\omega_1} \ P'_{\omega_2} \ \dots \ P'_{\omega_m}]^T$$

P

$$D = \sum_i D_i + D$$

$$\left(\begin{array}{cc} () & () \end{array} \right) \quad () \quad ()$$

References

Recognition Rate (%)	Set I	Set II	Set III
Gabor Wavelets			
GW+ Circular Shift [11]			
GW+ Adaptive Circular Orientation Normalization			
Intensity Values			
GW+ Adaptive Circular Orientation Normalization + Intensity Values	95.7		
GW+ Intensity Values+Elastic Inter-Frequency Searching		89.6	
GW+ Adaptive Circular Orientation Normalization+Elastic Inter-Frequency Searching + Intensity Values			80.1

Table 1:

	Radon transform [7]	Lgo-polar wavelet energy signature [12]	Standard wavelet packet energy signature [13]	Our method
Recognition Rate (%)				99.2

Table 2:

5 Conclusion

Image Understanding 57 *CVGIP*

Pattern Recognition 29

Pattern Recognition 35

24 *Pattern Recognition Letters*

24 *Pattern Recognition Letters*

Neural Networks 14 *IEEE Trans.*

Letters 27 *Pattern Recognition*

Neural Networks 14 *IEEE Trans.*

Pattern Recognition Letters 27

Intell. 25 *IEEE Trans. Pattern Anal. Machine*

Intell. 15 *IEEE Trans. Pattern Anal. Machine*