Gabor Features in Image Analysis

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***Abstract*—In applications of computer vision and image analysis, Gabor filters have maintained their popularity in feature extraction for almost three decades. The original reason that draw attention was the similarity between Gabor filters and the receptive field of simple cells in the visual cortex. A more practical reason is their success in many applications, e.g., face detection and recognition, iris recognition and fingerprint matching, where Gabor feature based methods are among the top performers. The derivation of Gabor features is elegant through the fundamental domains of signal processing: space (time) and frequency. Topped with many practical and computational advantages we will see their use also in future applications.**

***Index Terms*—Gabor filter, Gabor feature, image analysis, image processing, computer vision.**

I. Introduction

Features constructed from responses of Gabor filters, Gabor features, have been particularly successful in many computer vision and image processing applications. In biometrics, for example, Daugman's iris code [1] is the golden standard for iris recognition, Gabor features are among the top performers in face recognition (e.g., [2]) and fingerprint matching [3]. Gabor features extract local pieces of information which are then combined to recognise an object or region of interest. The first breakthrough was the dynamic link architecture (DLA) by Lades et al. [4] which introduced the concept of "Gabor jets". Wiskott et al. extended the method to elastic bunch graph matching (EBGM), which can be used to detect and recognise objects such as human faces [5]. Usage of Gabor features can be justified by solely their success in the existing applications, but often the argument that they model the simple cell response function in the mammalian visual cortex [6] is the main motivation, and this old adage is continuously resurrected [7]. It is intriguing why still, 25 years after the Daugman's milestone paper in [6], features based on Gabor filter responses perform remarkably well in many modern problems and applications of computer vision and image processing.

II. Gabor features

A the core of Gabor filter based feature extraction is the 2D Gabor filter function [8]:

$$\begin{aligned} \psi(x,y) &= \frac{f^2}{\pi\gamma\eta} e^{-\left(\frac{f^2}{\gamma^2}x'^2 + \frac{f^2}{\eta^2}y'^2\right)} e^{j2\pi f x'} \\ x' &= x\cos\theta + y\sin\theta \\ y' &= -x\sin\theta + y\cos\theta \ . \end{aligned} \tag{1}$$

In the spatial domain (Eq. (1)) the Gabor filter is a complex plane wave (a 2D Fourier basis function) multiplied by an origin-centred Gaussian (Fig. 1). f is the central frequency of the filter, θ the rotation angle, γ sharpness (bandwidth) along the Gaussian major axis, and η sharpness along the minor axis (perpendicular to the wave). In the given form, the aspect ratio of the Gaussian is η/γ. This function has the following analytical form in the frequency domain

$$\begin{aligned} \Psi(u,v) &= e^{-\frac{\pi^2}{f^2}\left(\gamma^2(u'-f)^2 + \eta^2 v'^2\right)} \\ u' &= u\cos\theta + v\sin\theta \\ v' &= -u\sin\theta + v\cos\theta \ . \end{aligned} \tag{2}$$

In the frequency domain (Eq. (2)) the function is a single real-valued Gaussian centred at f (Fig. 1). The Gabor filter in (1) and (2) is a simplified version of the general 2D form devised by Daugman [6] from the Gabor's original 1D "elementary function" [9]. The simplified version enforces a set of filters self-similar, i.e. scaled and rotated versions of each other ("Gabor wavelets"), regardless of the frequency f and orientation θ.

Gabor features, referred to as Gabor jet, Gabor bank or multi-resolution Gabor feature, are constructed from responses of Gabor filters in (1) or (2) by using multiple filters on several frequencies f_m and orientations θ_n. Frequency in this case corresponds to scale information and is thus drawn from [10]

$$f_m = k^{-m} f_{max}, \ \ m = \{0, \ldots, M-1\} \tag{3}$$

where f_m is the mth frequency, $f_0 = f_{max}$ is the highest frequency desired, and $k > 1$ is the frequency scaling factor. The filter orientations are drawn from [10]

$$\theta_n = \frac{n2\pi}{N}, \ \ n = \{0, \ldots, N-1\} \tag{4}$$

where θ_n is the nth orientation and N is the total number of orientations. Scales of a filter bank are selected from exponential (octave) spacing and orientations from linear spacing.

From the analytical point of view of a bank of filters, the parameters f_{max}, k, M, N, γ and η are redundant, and therefore equations of parameter selection can be defined [11]. The most intuitive parametrisation is achieved by defining the function envelope cross point at $p = 0.5$, i.e. two filter Gaussians cross on the half magnitude. This value has been experimentally tested and it provides sufficient "shiftability" [12], [13], i.e. information loss is moderate even if important input content falls between two filters. The cross point parameter p is fixed and the adjustable parameters are now the highest frequency f_{max}, number of frequencies m and number of orientations n. The bandwidths γ and η are automatically set using the formula in [11]. Example configurations are shown in Fig. 2.

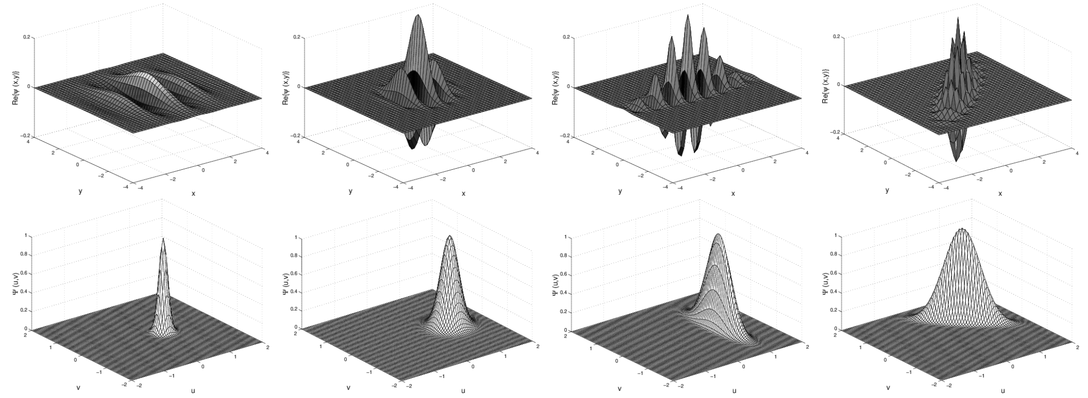

Figure 1. 2D Gabor filter functions in the spatial domain (top, real part only) and frequency domain (bottom). Parameter settings from the left: $(f = 0.5, \theta = 0°, \gamma = 1.0, \eta = 1.0)$; $(f = 1.0, \theta = 0°, \gamma = 1.0, \eta = 1.0)$; $(f = 1.0, \theta = 0°, \gamma = 2.0, \eta = 0.5)$; $(f = 1.0, \theta = 45°, \gamma = 2.0, \eta = 0.5)$.

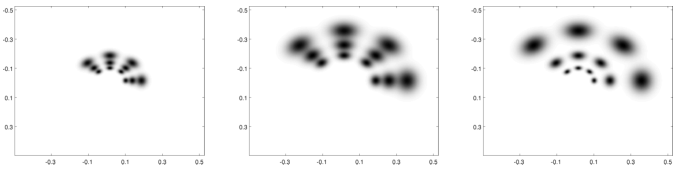

Figure 2. Examples of multi-resolution Gabor filter banks in the frequency domain: (a) $m = 4$ orientations and $n = 3$ frequencies, (b) the base frequency f_{max} increased, (c) the frequency scaling factor k increased.

A. Feature extraction

Raw features are the complex-valued responses of a set of multi-resolution Gabor filters as illustrated in Fig. 3. Using a classifier, as simple as Gaussian mixture models in the facial feature detector in [14], the features can be effectively used to detect and recognise complex real world structures in images.

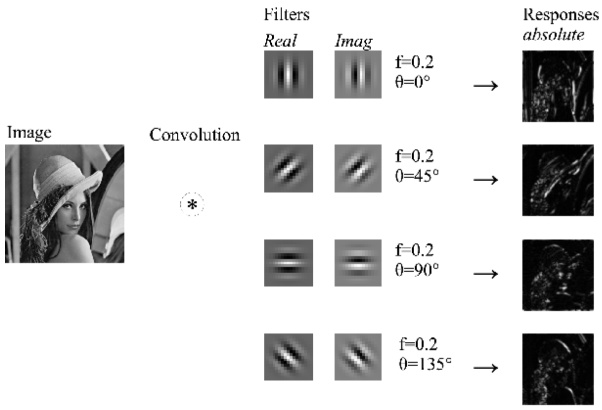

Figure 3. Feature extraction using a bank of Gabor filters.

III. Conclusions

Use of Gabor filters in feature extraction can be justified by biological findings in vision systems, natural image statistics and success in existing applications. Elegance of their derivation and easy of use promotes their usage also in future applications.

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