2DSBG: A 2D SEMI BI-GAUSSIAN FILTER ADAPTED FOR ADJACENT AND MULTI-SCALE LINE FEATURE DETECTION

Baptiste Magnier, Ghulam Sakhi Shokouh,
Louis Berthier, Marcel Pie, Adrien Ruggiero and Philippe Montesinos

EuroMov Digital Health in Motion, Univ Montpellier, IMT Mines Ales, Ales, France

ABSTRACT

Existing filtering techniques fail to precisely detect adjacent line features in multi-scale applications. In this paper, a new filter composed of a bi-Gaussian and a semi-Gaussian kernel is proposed, capable of highlighting complex linear structures such as ridges and valleys of different widths, with noise robustness. Experiments have been performed on a set of both synthetic and real images containing adjacent line features. The obtained results show the performance of the new technique in comparison to the main existing filtering methods.

***Index Terms*—** Bi-Gaussian, Semi-Gaussian, Ridges.

1. INTRODUCTION AND MOTIVATIONS

The detection of features in images is a computationally intensive process and remains a primary step in many low-level computer vision tasks. Linear structures (ridges, edges, etc.) are widely used features in various computer vision applications. To detect these linear structures, numerous filtering approaches are implemented. The optimal approach is chosen based on how to retain the maximum amount of desired information, whilst removing the noise to obtain an optimal segmentation result depending on the application. To that end, linear structure detection techniques require the analysis of the first or second order derivative of the images, which is obtained by filtering the image using a kernel convolution [1, 2]. The derivative's order, the type of kernel, and their related parameters control which feature type is aimed to be detected. Gaussian kernels are the most popular and widely used filtering techniques due to their useful isotropy, steerability and decomposability properties related to the implementation of integration and differentiation in images [3]. The zeroth order Gaussian kernels G are used for regularization [4]:

$$G(\sigma, x) = \frac{1}{\sqrt{2\pi}\sigma} \cdot \mathrm{e}^{-x^2/2\sigma^2}, \text{ with } \sigma \in \mathbb{R}_+^*,\ x \in \mathbb{R}, \quad (1)$$

where σ represents the standard deviation. The first and second order Gaussian kernels are commonly used for linear structure detection. However, these kernels are prone to noise, relative to both the derivative order and the σ parameter. Gaussian multi-scale is the primary method in multi-scale feature detection [5]. These techniques are mostly based on the eigen-decomposition of the Hessian matrix [6, 5, 7, 8].

Meanwhile, steerable filters of second order (SF_2) are an elegant technique to capture ridge information; they are generated by the linear combination of basis filters [3] such as the second derivative of the Gaussian G'' in one dimension (1D):

$$G''(\sigma, x) = \frac{x^2 - \sigma^2}{\sigma^4} \cdot \mathbf{e}^{\frac{-x^2}{2\cdot\sigma^2}}, \text{ with } \sigma \in \mathbb{R}_+^*,\ x \in \mathbb{R}. \quad (2)$$

To improve the precision of the detection, elongated oriented filters were designed in terms of a better compromise between noise rejection and localization accuracy [9, 10, 11]. Then, to extract line feature, the Second-Order Anisotropic Gaussian Kernel (SOAGK) can be applied in two dimensions (2D):

$$\text{SOAGK}\,(\sigma, \sigma_s, x, y) = \frac{x^2 - \sigma^3}{2\pi\sigma^5\sigma_s} \mathrm{e}^{-\frac{1}{2}\left(\frac{x^2}{\sigma^2} + \frac{y^2}{\sigma_s^2}\right)}, (\sigma, \sigma_s) \in \mathbb{R}_+^* \times \mathbb{R}_+^*. \quad (3)$$

The choice of $\sigma_s > \sigma$ enables to build a narrow filter, then the filter is oriented to extract ridges, as illustrated in Fig. 1(b).

The second order Gaussian kernels are even and the filter's coefficients distant from the filter center have opposite signs; they correspond to the filter support which unfavorably gets enlarged when the σ parameter is growing. Indeed, this enlargement yields robustness against noise but on the other hand exposes the defect of the second order Gaussian filtering. Therefore, an empirical trade off when adjusting the parameter's configuration is unavoidable in conventional manner. In particular, adjacent linear structures of different widths cannot be accurately extracted with this type of support. The proposed solution consists in seizing the properties of both a precisely orientable filter (Semi-Gaussian) and an adjustable filter under certain conditions of adjacent linear structures. As a result, a new filter is generated, named 2D-Semi-Bi-Gaussian filter (2DSBG). The 2DSBG rigorously minimizes the interference of adjacent line features while retaining adequate line feature information thanks to the fine-tuning of σ and the scale ratio parameter, as detailed below.

(a) SF_2 (b) SOAGK (c) SDSG (d) 2DSBG , $\rho = 0.5$

Fig. 1. 2D discrete filters of second order steered at 0° and 20°. For the derivative part G'' or BG'' in (d), $\sigma = 3.91$ whereas for (b)-(d), the anisotropic parameter $\sigma_s = 5 \cdot \sigma$.

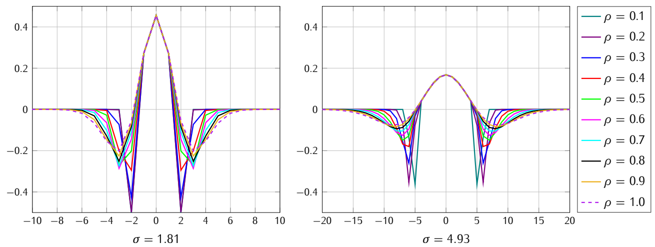
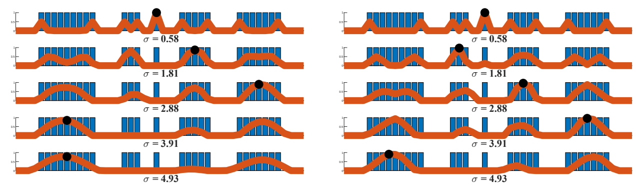


Fig. 2. Discrete second derivatives of bi-Gaussians in 1D computed using different parameters ρ, see Eqs. (4) and (5).



(a) Convolution with G'' (b) Convolution with BG'', $\rho = 0.5$

Fig. 3. Ridge highlighting in 1D for different scales σ. G'' and BG'' convolutions are used in (a) and (b) respectively. The blue bars represent the original signal containing separated ridges while the convolved signals are plotted in orange and the maximum of each signal is displayed by black circles.

2. PROPOSED APPROACH: 2DSBG

The objective is to detect several line features in an image at different unknown positions and orientations. The detection procedure is formulated as a rotational matched filtering.

2.1. Bi-Gaussian Filter

The second order Gaussian G'' (Eq. (2)) is useful to determine the location of linear structures [6, 5, 11, 12]. However, this simple Gaussian kernel relies on only one parameter to determine its shape: σ. This denotes one of the main well-known drawbacks of the Gaussian filter. Due to the length of its support, this is therefore not sufficient to differentiate between adjacent or closely related structures, especially when the σ value is large [13]. Consequently, linear structures cannot be suitably separately detected without any delocalization or fusion due to the regularization filter [14], as illustrated in Fig. 3(a). To address this drawback, the main idea is to transform the initial Gaussian filter into a bi-Gaussian, which combines the merits of the Gaussian and the Rectangular kernels. The benefits of this kernel are that it has a scale ratio able to clearly separate adjacent structures and at the same time, the Gaussian part gives it robustness against noise. To tune the BG'' filter, a σ_b parameter allows us to play on the width and the sharpness of the curves on both sides of the central part [13]. To simplify, a parameter ρ is defined as the scale ratio:

$$\rho = \frac{\sigma_b}{\sigma}. \tag{4}$$

A ρ value ranging in $]0, 1]$ improves the detection of peaks, especially for adjacent contours by making the bi-Gaussian kernel narrower. The influence of ρ value is studied in the next section. The second order bi-Gaussian filter is expressed as follows:

$$BG''(\sigma, \sigma_b, x) = \begin{cases} \rho^2 \cdot G''(\sigma_b, x - \sigma_b + \sigma) & \text{if } x \leq -\sigma \\ G''(\sigma, x) & \text{if } |x| < \sigma \\ \rho^2 \cdot G''(\sigma_b, x + \sigma_b - \sigma) & \text{if } x \geq \sigma. \end{cases} \tag{5}$$

When $\rho = 1$, the BG'' filter is equivalent to the 2nd derivative of the Gaussian G''. The Fig. 2 shows the 1D normalized BG'' filters for different values of σ and ρ. This filter's shape behaves in an opposite manner to Ziou's filter which is very sharp in the middle, but contains the large length of its support [15][8]. For the multi-scale step, the highest filtered value is retained along the different scales (see [8][12]). The Fig. 3(b) illustrates the application of the BG'' filter at different scales on a 1D signal containing different ridges of variable widths. The convolved signals are plotted, and the maximum of the signal is displayed where each ridge is tied to a specific scale (width of value 1, 3 5, 7 and 9). Contrary to the Gaussian kernel in Fig. 3(a), the BG'' best fits the signal along the different scales, revealing the great interest of this filter shape.

2.2. 2DSBG: 2D Semi Bi-Gaussian Filter

The proposed technique consists in combining a bi-Gaussian and a Semi-Anisotropic Gaussian filter which can be steered [16, 17, 12]. The main idea of the developed filter is to consider: (i) close and parallel neighboring ridges and linear feature and (ii) paths (i.e. ridges or valleys) crossing each pixel. To innovate, the proposed filter can detect close and parallel narrow bended ridges of different widths in two different directions thanks to the semi bi-Gaussian capacities.

It is inspired by the SDSG (Second-Derivative of a Semi-Gaussian [12]) where the main idea is to "*cut*" the second order anisotropic Gaussian kernel (Eq. (3)) using a Heaviside function and, then, steer this filter in all directions around the considered pixel: from 0 to 360°. Mathematically, the SDSG filter is defined by the combination of:

- a semi-Gaussian $\mathcal{G}$ for the smoothing, vertically truncated by a Heaviside function H, for $\sigma_s \in \mathbb{R}_+^*$ and $x \in \mathbb{R}$: $\mathcal{G}(\sigma_s, x) = H(x) \cdot \mathbf{e}^{-x^2/2 \cdot \sigma_s^2}$,
- a second derivative of a Gaussian G'' horizontally.

The proposed 2D filter substitutes the second order derivative of a Gaussian G'' for a second order derivative of a bi-Gaussian BG'' presented in Eq. (5): it is composed of Semi-Gaussian and bi-Gaussian operators. Note that for $\rho = 1$, the 2DSBG filter becomes the SDSG filter, see Fig. 1(c)-(d).

To adapt the multi-scale strategy, the response of the filter for different scaling parameters is configured - and the maximum value among the different filter responses can be selected [17]. When this new filter is steered towards the linear structure direction, the σ_s parameter allows an elongated smoothing in the line direction, whereas the σ captures the line structure strength (Eq. (5)). Then, the line structure strength is calculated using a local directional maximization/minimization (see [12]).

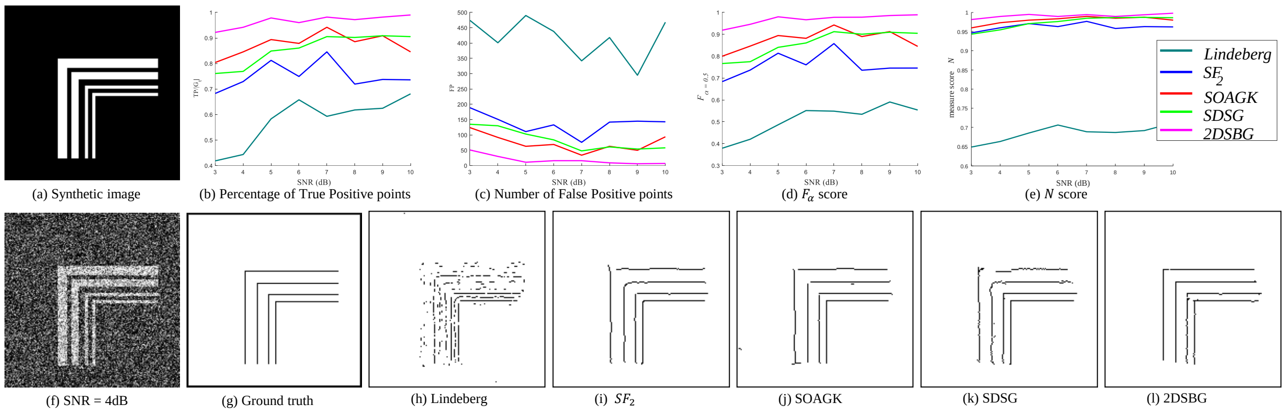


Fig. 4. Evaluation of the ridge extraction techniques on synthetic images corrupted by a Gaussian noise between SNR=10dB and SNR=3dB ($\sigma_s = 5 \cdot \sigma$ for SOAGK, SDSG and 2DSBG). On the bottom: visualization of the best segmented images at SNR=4dB.

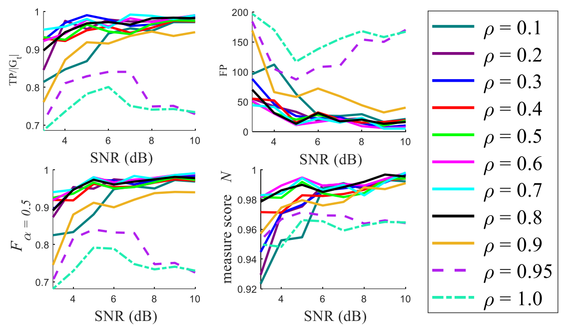


Fig. 5. Estimation of the best ρ parameter of the 2DSBG on synthetic images corrupted by a Gaussian noise ($\sigma_s = 5 \cdot \sigma$).

3. EXPERIMENTAL EVALUATION AND RESULTS

The proposed technique is evaluated on a set of both synthetic and real images-containing complex linear features such as close adjacent lines and ridges with varied scales. Datasets containing fungi images with manually annotated ground truth G_t are used [11]. To evaluate the linear structure extraction, the *Normalized Figure of Merit* method [18] called N is employed. Thus, N calculates a standardized dissimilarity score; the closer the evaluation score is to 1, the more the linear structure is qualified as suitable. On the contrary, a score close to 0 corresponds with poor contour detection.

The aim here is to get the best contour map in a supervised way. Theoretically, to be objectively compared, the ideal contour map must be the one for which the supervised evaluation gets the highest score [18, 19]; and the overall quality is expressed in terms of the F_α-measure with α=0.5 [19].

In this context, the 2DSBG filter is compared with 4 other multi-scale linear feature extraction techniques via filtering, namely: Lindeberg [5], SF_2 [3], SOAGK [11], and SDSG [12]. Evaluation scores for synthetic cases are presented in Figs. 4(b)-(e) for percentage of true positive, false negative points, F_α and N measures respectively. In most cases, scores achieved by 2DSBG are superior to those of other techniques, showing the reliability of the proposed filter. Fig. 5 shows that the optimum parameter ρ for the 2DSBG belongs to $[0.5, 0.7]$ and its reliability increases when ρ<1, compared to the SDSG filter (corresponding to ρ=1). Thus, the prominence of the proposed 2DSBG filter is confirmed in Fig. 4(l), where the Linderberg and SF_2 present the worst results with adjacent linear features because of their unadjustable kernel. The SDSG obtains desirable results for the close and narrowly bent contours, but undesirable results in the case of wider contours due to the sensitivity of the second-order kernel. The SOAGK and 2DSBG produced broken lines when applied to thick and thin linear structures respectively. However, the fractures obtained with 2DSBG are very small and recoverable via post-processing.

The results obtained with real images of fungus in Fig. 6 indicate that Linderberg's method and especially the SF_2 produce erroneous contours and thus have a low segmentation quality. Although SDSG has been able to detect most of the contour details as well as the bent and narrow structures, it also generated erroneous points due to its second-order noise sensitivity. Accordingly with the previous performance results, the 2DSBG clearly extracts the most contours, especially in the case of narrow and adjacent lines, with barely any erroneous points. Note that the evaluation score here could be influenced by the hand annotated mispositioned ground truth, as detailed in [20] for supervised evaluations.

4. CONCLUSION

2DSBG, a new filter for multi-scale linear features extraction in images, constructed from bi-Gaussian and second-order semi-Gaussian filters is presented. This filter exploits the advantages of the bi-Gaussian for the detection of adjacent linear features, as well as the qualities presented by semi-Gaussian kernels for the analysis of bent and complex linear structures. Experiments on synthetic and real images were performed, allowing us to find the optimal parameter configuration ($\rho\in[0.5, 0.7]$), and thus confirming the novelty and merit of the 2DSBG over the existing filtering methods.

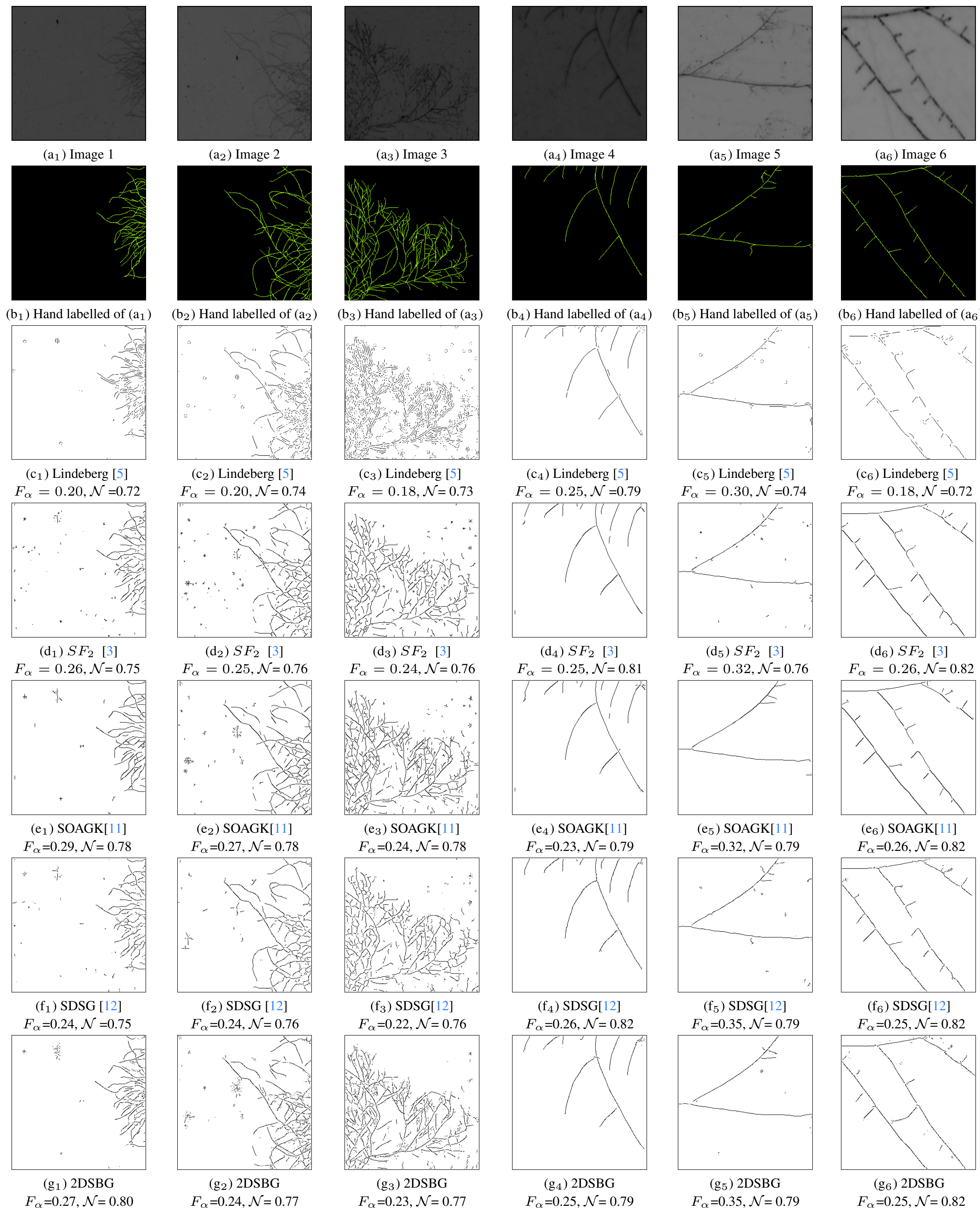


Fig. 6. Images of size 300×300. Comparison of the proposed filter-2DSBG with the four state-of-the-art filters in the detection of linear structures in real fungus images. Parameters for SOAGK, SDSG and 2DSBG filters are the same: $\sigma_s = 5 \cdot \sigma$.

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