Signal Processing 116 (2015) 55–67

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Unsupervised ridge detection using second order anisotropic Gaussian kernels

C. Lopez-Molina [a,b,*], G. Vidal-Diez de Ulzurrun [b], J.M. Baetens [b], J. Van den Bulcke [c], B. De Baets [b]

[a] Dpto. Automatica y Computacion, Universidad Publica de Navarra, 31006 Pamplona, Spain
[b] KERMIT, Department of Mathematical Modelling, Statistics and Bioinformatics, Ghent University, Coupure links 653, 9000 Ghent, Belgium
[c] Laboratory of Wood Technology, Department of Forest and Water Management, Ghent University, Coupure links 653, 9000 Ghent, Belgium

ARTICLE INFO

Article history:
Received 21 October 2014
Received in revised form
27 March 2015
Accepted 29 March 2015
Available online 7 April 2015

Keywords:
Ridge detection
Anisotropic Gaussian Kernel
Multiscale Gaussian kernel
Fungi imagery

ABSTRACT

We propose the use of the second derivative of Anisotropic Gaussian Kernels for ridge detection. Such kernels, which have proven successful in edge and corner detection, offer interesting advantages over isotropic kernels. In the case of ridge detection, these advantages include the increase of the sensitivity at junctions, as well as an improved characterization of blob-like artefacts. We do not only illustrate these advantages on synthetic images, but also perform a comparison on a new dataset for line detection, which is composed of 100 images of in vitro fungi.

1. Introduction

Line detection is one of the most fundamental procedures of low-level image processing. Ridges (bright lines on a dark background) and valleys (the opposite) usually hold critical information for the analysis of images, especially for the extraction of graph-like structures. This technique plays a prominent role in many automated processes, such as photogrammetry and remote sensing [1,2]. Line detection is also relevant for the analysis of biological or biomedical structures, including vessels or bronchi profiling and measurement [3,4]. Although such applications demand high-level information for accomplishing their goals, they usually rely on an initial phase of line characterization. In the remainder of this work, we refer to line detection as ridge detection, in order to align with the established nomenclature in the literature. Nevertheless, the adaptation of any ridge detection algorithm to valley detection is usually straightforward (see e.g. [5]).

Together with edges and corners, ridges are the most studied low-level features in the literature. The analysis of these three features is often coupled [6,7]. Also in this work we exploit the relationship between edges and ridges. This connection can be seen in many different ways, the most evident one being that a ridge is composed, at a very small scale, of two locally parallel step edges [2,8,9]. From an analytical point of view, edges are local maxima of the first order partial derivative of a signal, while ridges (resp. valleys) are local maxima (resp. minima) of the second order derivative.[1] Both notions can be formulated in similar

* Corresponding author.
E-mail addresses: carlos.lopez@unavarra.es (C. Lopez-Molina), guillermo.vidal@ugent.be (G. Vidal-Diez de Ulzurrun), jan.baetens@ugent.be (J.M. Baetens), jan.vandenbulcke@ugent.be (J. Van den Bulcke), bernard.debaets@ugent.be (B. De Baets).

[1] More detailed definitions of ridges can be found in the literature. We refer to [7] or [10] for deeper insights.

http://dx.doi.org/10.1016/j.sigpro.2015.03.024
0165-1684/

terms through the local analysis of the Jacobian or Hessian matrices of an image, leading to an evident relationship between both features [7,11]. An exhaustive analysis of this relationship can be found in [10,12] from a mathematical perspective, and in [13] from a topological perspective. From this fundamental relationship, it seems clear that the strategies used for detecting edges and ridges mainly differ in the order of differentiation applied to the original signal. In this work we elaborate on this relationship to produce a flexible ridge detector inspired by well-known first order differentiation kernels.

The analysis of edges and lines is so similar that there is some controversy on whether they are different concepts. This is partially due to the fact that no clear definition has been agreed upon for edges, leading to *ad hoc* or ground-truth-based characterizations [14]. For example, Papari and Petkov assumed that the edges in an image are *the set of lines that human observers would consent on to be the contours in that image* [15]. Since some humans actually mark up lines as edges, they conclude that *every line in the image should be regarded as a contour, although none of the lines is a boundary between two regions of different colors or textures* [15]. Also relevant is the fact described by Canny that boundaries between polyhedral objects manifest themselves as lines [16], which is also demonstrated by the hybrid edge profiles presented by Perona and Malik [17]. Similar observations have been reported for specific types of images, such as ultrasound scans [18], in which edges between tissues manifest themselves as peaks in brightness. Despite such controversy, we adhere to the widely accepted assertions by Lindeberg [7] on the characterization of edges and lines as maxima of the first and the second partial derivative, respectively.

Ridge detection methods often rely on the analysis of the first or second derivative of the images, which is usually extracted by filtering the image with kernels [12,19]. Other ridge detection techniques impose certain conditions on the processing or the images, or even demand the intervention of humans [2]. For example, path optimization or tracking techniques call for either the semi-supervised introduction of the endpoints of the segments, or the inclusion of a critical initial phase of endpoint selection [20,21]. Although some authors advocate the need for human intervention [2], we believe that this induces a severe, and often undesired, limitation for applied researchers. Alternatively, transformation-based methods (such as those using the Hough transformation) are not well conditioned to analyze complex scenes with intricate networks in which ridges merge, break and branch. An example of this is the Line Segment Detector (LSD) method by Grompone von Gioi et al. [22], in which the Hough transformation is used to detect line segments, mostly yielding straight segments. Despite the visually impressive results, the detected edges do not match the exact position of the silhouettes in the original images, since the Hough transformation results in a simplification of their traces. In this work we elaborate on the use of elongated kernels for the characterization of the second partial derivative of an image. These kernels, created as a second partial derivative of the Anisotropic Gaussian Kernels introduced by Shui and Zhang [23], are able to adapt to the local conditions of the ridges in terms of width, roundness and orientation. Moreover, we introduce a multiscale procedure that permits the fusion of the local results obtained with several kernels, so that the ridges at each region of the image are characterized by the most suitable kernels. Note that most authors of practical applications combine a phase of line detection with a subsequent phase of problem-aware line discrimination, which incorporates contextual knowledge. Such discrimination can be done in terms of the length of the ridge segments, their width or any other contextual hint, and involves very different classification techniques (see, e.g. [1,3,24]). In our case, we propose a context-unaware method for line detection, which is further customized for its application to fungal branch delineation for in vitro growth tracking. This customization is tested on a new dataset containing 100 images of fungi with hand-made ground truth.

The remainder of this work is organized as follows. In Section 2, we review the use of Isotropic Gaussian Kernels (IGKs) of different orders in the literature. Section 3 covers the use of Anisotropic Gaussian Kernels (AGKs), which are further applied to a multiscale ridge detection algorithm in Section 4. Section 5 includes an experimental validation with a new dataset of in vitro fungal images. Finally, Section 6 discusses some conclusions.

2. Gaussian kernels for low-level feature detection

Gaussian kernels are among the most employed tools for image processing, and have proven useful for a number of different tasks. The reasons for using such kernels range from their isotropy, steerability or decomposability properties [25,26] to the special characteristics related to their integration or differentiation. Additionally, the fast computation of their multidimensional extensions was given as an argument for their use during the early years of image processing [16]. It is generally agreed upon that Gaussian kernels are a very convenient option for the robust computation of both the first and the second derivative of a discrete signal, and consequently for the computation of its Jacobian and Hessian.

The study of Gaussian kernels can be subdivided according to their order of differentiation. The zeroth order kernels (i.e. Gaussian kernels) are used for regularization prior to signal processing. The reasons are diverse, and include their ability to eliminate Gaussian noise [16] and the fact that they produce no new artefacts (maxima or minima of the first derivative) in the image [27]. They form the core of the most employed scale-space in the literature, the Gaussian Scale-Space [7,28,29], and they have also been linked to other scale-spaces [30]. Another use is, for example, the approximation of the Laplacian of a signal by a difference of Gaussians (see [31]). First Order Isotropic Gaussian kernels (FOIGKs) have been used extensively as well, especially after the results obtained by Canny [16]. In his paper, Canny observed that the optimal kernel for 1D step edge detection under additive white Gaussian noise is similar to the negative first derivative of a Gaussian kernel.[2] Note that FOIGKs are not the only Gaussian

[2] In fact, Canny quantified the difference of performance between the optimal 1D kernel and the negative first derivative of a Gaussian to be about 20% [16], in terms of his penalty criteria.