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Image thresholding based on semivariance

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ABSTRACT

In this paper, an algorithm for image thresholding based on semivariance analysis is presented. The rationale of the approach is to binarize an image such that it best reproduces the original image variation across several spatial scales. The method can be alternatively viewed as one identifying the binary image that best approximate the overall level of edgeness measured across multiple scales in the original image. A comparison with seven other thresholding methods is presented for 2 synthetic images and 22 Non-Destructive Testing (NDT) grey level images. The results indicate that the proposed method is highly competitive. Performance of the proposed method in relation to the image content is also discussed.

1. Introduction

Thresholding is a major class of image segmentation techniques (Pal and Pal, 1993). Simply stated, image thresholding aims at separating foreground from background objects: foreground pixels having perceptually different grey level values than the background. Thresholding methods are often categorized into global or local methods (Wang et al., 2008). In global methods, a single threshold is determined for the entire image whereas the threshold depends on pixel position for local methods. Alternatively, thresholding methods can be divided into parametric or nonparametric methods (Bazi et al., 2007). Parametric methods associate each class with predefined statistical distributions. Nonparametric methods are distribution-free approaches and they rely on the optimization of one criterion (or a few numbers of). Yet, from another perspective (Sezgin and Sankur, 2004), they can be categorized according to the type of information used, i.e. histogram shape, clustering, entropy, attribute similarity, spatial, and local information (adaptive).

The large spectrum of thresholding applications is succinctly enumerated in Sezgin and Sankur (2004). Examples of applications domains are: document image analysis, scene processing for target detection, change detection, and segmentation for NDT applied to numerous image types: cell, ultrasonic, eddy current, thermal, tomography, endoscopic, etc. (for a detailed list, see Bazi et al., 2007; Sezgin and Sankur, 2004; Li et al., 2011; Zhang and Wu, 2011). With so diverse approaches and image types, the results of a thresholding technique strongly depend on how the image properties and content fulfill the method's assumptions (Wang et al., 2008). It is therefore not surprising that, for real-world images, different algorithms often produce different results when applied on a same image (Melgani, 2006; Sezgin and Sankur, 2004). There is simply no method able to achieve good performance for all kinds of images. Nevertheless, some methods perform better than other ones in a general setting. Based on a dataset of 40 NDT images, Sezgin and Sankur established that the methods of Kittler-Illingworth (KI) (Kittler and Illingworth, 1986) and Kapur et al. (1985) (KSW) are the ones achieving the best overall results (Table 7 in Sezgin and Sankur, 2004). The former uses cluster information whereas the latter is based on entropy information. The best method exploiting spatial information was the one of Abutaleb (1989) and ranked 11th. The popular Otsu (1979) method ranked 6th. Since the Sezgin and Sankur (2004) work, several other thresholding algorithms have been published (e.g. Wang et al., 2008; Bazi et al., 2007; Zhang and Wu, 2011; Coudray et al., 2010). In an attempt to resolve the constancy issue between thresholding methods, Melgani (2006) proposed a strategy based on the fusion of an ensemble of thresholding methods to derive a more robust threshold. Notably, Celebi et al. (2009) indicates that the performance of such a fusion algorithm, when applied to dermoscopy images, seems to depend on the choice of the selected thresholding methods composing the ensemble (although no comparative information is provided).

The vast majority of existing nonparametric methods for global thresholding rely on an optimization criterion applied in the radiometric domain. Notably, methods exploiting spatial information represent a small fraction of these methods (e.g. Pal and Pal, 1989; Abutaleb, 1989; Cheng and Chen, 1999; Beghdadi et al., 1995; Pham, 2007). Still, those using spatial information mostly

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take into account only immediate pixel neighborhood, hence probing a restricted range of spatial scales. This is rather remarkable as structural information plays an important role in human perception. In this paper, a novel algorithm for global grey level image thresholding exploiting spatial information is described. The method seeks to best reproduce in the binary image the spatial variability measured in the original image across scales. The algorithm is based on the image variogram. The variogram is a statistical tool providing a description of the scale and pattern of spatial variation within an image (Oliver et al., 1989).

The paper is organized as follows. Section 2 provides the rationale of the method followed by a detailed description of the proposed algorithm. Section 3 presents the data sets used to assess the method and the experimental results. The behavior of the algorithm in relation to image characteristics is discussed in Section 4. The conclusions are given in Section 5.

2. Methods

Bi-level image thresholding algorithms rely on the hypothesis that an image is composed of two components: the objects and the background. Most algorithms are based on the premise that both components can be isolated from each other by selecting an appropriate threshold in the gray-level domain (Tabbone and Wendling, 2003). However, from a human vision point-of-view, the spatial information definitely plays an important role in recognizing the two components from the structural patterns they exhibit in the image. This is in line with the philosophy of Wang et al. (2004): '*The main function of the human visual system is to extract structural information from the viewing field, and the human visual system is highly adapted for this purpose*.' If further evidence was needed, human validation through visual inspection is still a vital step to evaluate the quality of segmentation results (Zhang et al., 2008; Pal and Pal, 1993). From experiments, it can be observed that different threshold values applied on a same image will produce different spatial patterns in the resulting binary images. It is therefore the premise of the proposed method that the optimum thresholding result will be the one that best approximate the structural information contained in the original image. To concretize this idea, spatial pattern characteristics must be quantified in both the original and its binarized version. Our proposal is based on a well-recognized tool designed to describe spatial variation of an attribute of interest: the variogram. Under the Sezgin and Sankur (2004) categorization system, the proposed method falls under both the attribute similarity and spatial information groups.

2.1. Preliminaries

2.1.1. Semivariance

Semivariance measures the spatial variability of a variable at different scales, h (Jupp et al., 1989). It is defined as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [g(i) - g(i+h)]^2 \qquad (1)$$

where $g(i)$ is the variable value (grey level) at pixel location i and $N(h)$ is the number of pairs of observations separated by the distance lag, h. The function that relates γ to h is called a semivariogram (in the sequel, the term 'variogram' will always refer to 'semivariogram'). The variogram has long been used in geostatistical structural analysis to assess the spatial structure of a variable; it is a tool to quantify spatially correlated variation (Jupp et al., 1989). Specifically, the variogram describes the magnitude, spatial scale and general form of the variation (Oliver et al., 1989). It is worth noting that because of the relaxed condition on the stationarity assumption, the variogram can be used where auto-covariance doesn't (Oliver et al., 1989). Effectively, the so-called intrinsic hypothesis behind the variogram requires mean stationarity in increment.A typical variogram is shown in Fig. 1. The shape of a variogram curve is highly dependant on the image content. There are of three main descriptive feature associated with a variogram: the sill, the range, and the nugget. The sill is the variance at which the variogram flattens off, it is a measure of the overall variance. The absence of a sill reflects either a data trend or the fact that object sizes are greater than the scale probed. The range is the lag distance at which the sill is attained (or the lag distance at which there is a very small difference to reach the sill). The range value is linked to the size of the objects. The nugget variance is defined by the intercept of the variogram as h tends to 0. A non-null value is expected in the presence of uncorrelated noise. For white noise, the expected variogram is characterized by $\gamma(h = 0) = 0$ and $\gamma(h > 0)$ = constant. When the number of gray level values consist of only two values [$g(i) \in 0,1$], the resulting variogram is called indicator semivariance, $\gamma^I(h)$. Interestingly, $2\gamma^I(h)$ provides a measure of the transition frequency between the two components.

2.1.2. Pham's proposal

Pham (2007) has proposed a method for grey level image thresholding by minimizing the variograms of object and background pixels. The method seeks the threshold that minimizes the following criterion: $\Gamma(t) = \frac{1}{H}\sum_{h=1}^{H}[\gamma_B(h,t) + \gamma_o(h,t)]$, where $\gamma_B(h,t)$ and $\gamma_0(h,t)$ are respectively the variogram computed on the background and object pixels. The value of H is selected to probe the boundaries of objects and background pixels and therefore the value of H is small. Pham (2007) adopted a value of $H = 5$, hence $h = 1,2,\ldots, 5$.

2.2. Thresholding based on semivariance similarity: a new proposal

Let us binarize an image by setting all pixel values above a given threshold t to z_1, and all pixels that are equal or below that threshold to z_0. The underlying principle of the proposed algorithm is to threshold the original image and then adjusts the binarized values, z_0 and z_1, such that the semivariance of the bilevel image best approximates the ones of the original image over a wide range of values of h. Let $\gamma(h)$ denotes the semivariance of the original image at lag distance h, and $\gamma_{z_0,z_1}(h,t)$ the semivariance of its bilevel version. The sum of the square of the difference between the semivariance of both images, δ, can be used as a measure of 'goodness-of-fit' to quantify how well the bilevel image reproduces the spatial characteristics of the original image:

$$\delta(z_0, z_1, t) = \sum_h \left[\gamma(h) - \gamma_{z_0,z_1}(h,t)\right]^2 \qquad (2)$$

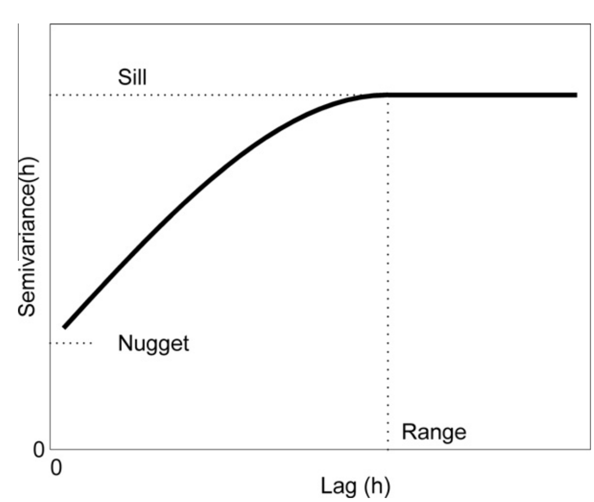

Fig. 1. Typical variogram showing sill, range and nugget points.