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Gradient-based enhancement of tubular structures in medical images

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ABSTRACT

Vesselness filters aim at enhancing tubular structures in medical images. The most popular vesselness filters are based on eigenanalyses of the Hessian matrix computed at different scales. However, Hessian-based methods have well-known limitations, most of them related to the use of second order derivatives. In this paper, we propose an alternative strategy in which ring-like patterns are sought in the local orientation distribution of the gradient. The method takes advantage of symmetry properties of ring-like patterns in the spherical harmonics domain. For bright vessels, gradients not pointing towards the center are filtered out from every local neighborhood in a first step. The opposite criterion is used for dark vessels. Afterwards, structuredness, evenness and uniformness measurements are computed from the power spectrum in spherical harmonics of both the original and the half-zeroed orientation distribution of the gradient. Finally, the features are combined into a single vesselness measurement. Alternatively, a structure tensor that is suitable for vesselness can be estimated before the analysis in spherical harmonics. The two proposed methods are called Ring Pattern Detector (RPD) and Filtered Structure Tensor (FST) respectively. Experimental results with computed tomography angiography data show that the proposed filters perform better compared to the state-of-the-art.

1. Introduction

Several important anatomical structures in the human body have a tubular shape, including blood vessels, airways in the lungs and structures of the nervous and digestive system. Imaging and analyzing these structures is important for diagnostic purposes. As an example, computer tomography angiography (CTA) is now a standard clinical tool for diagnosing coronary artery diseases (Marwan et al., 2014; Weustink and de Feyter, 2011) and pulmonary embolism (Hogg et al., 2006; Mos et al., 2009). Magnetic resonance angiography (MRA) is used clinically for imaging the cerebral vessels (Parker et al., 1998) as well as the renal and peripheral arteries (Dong et al., 1999; Prince et al., 1999).

Both CTA and MRA use contrast agents in order to increase the visibility of vessels with respect to surrounding tissue. This increased contrast has allowed physicians to perform a better assessment in the clinic. Despite this, the level of contrast might not be enough for performing automatic analyses. One reason for this is that adjacent structures to vessels can also be enhanced by contrast agents, which is for example the case of the heart chambers in coronary artery imaging. Another problem in patients is impeded flow of the contrast agent in diseased vessels, which results in lack of contrast in those areas. Additional issues include noise and low resolution, which can become a big hindrance for resolving small vessels. For these reasons, the automatic analysis of tubular structures from images acquired through CTA or MRA is still challenging.

In general, methods aiming at enhancing tubular structures in medical images are referred to as vesselness filters. These filters are useful in many medical image analysis applications. For example, some vessel segmentation methods include preprocessing steps for enhancing the vessels on images acquired through computed tomography or magnetic resonance angiography (CTA or MRA) in order to improve their results (cf. Lesage et al. (2009); Rudyanto et al. (2014) for a description of methods that follow this approach). Moreover, some state-of-the-art centerline extraction algorithms are also based on vesselness measurements (e.g., Yang et al., 2012; Schaap et al., 2009). From a clinical perspective, vesselness filters are also appealing, since they could be used for obtaining high quality images at low radiation doses in CTA.

An ideal vesselness filter should comply with at least the following requirements: both vessels and bifurcations should be enhanced, “bright” and “dark” vessels should be distinguished and the measurement should be scale- and rotation-invariant. In addition, more

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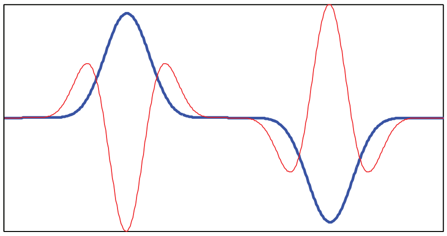

Fig. 1. Synthetic model of a 1D bright followed by a dark vessel (in blue) and the corresponding second order derivative (in red). The second order derivative can have peaks not only at the middle of the vessels but also at other locations. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

advanced requirements for an ideal filter include distinguishing between vessels and bifurcations, centerline delineation and vessel segmentation.

The most popular vesselness filters are based on the Hessian (Frangi et al., 1998; Li et al., 2003; Sato et al., 1998; Xiao et al., 2011; 2013; Yang et al., 2014). These methods take advantage of the fact that ideal bright vessels have negative (positive) peaks on the second derivative across of "bright" ("dark") vessels and such a derivative is almost null along the vessel. These methods combine the eigenvalues of the Hessian at multiple scales into a single vesselness measurement.

For example, the method proposed by Frangi et al. (1998) computes vesselness as:

$$V_i = \left[1 - e^{\left(-\frac{R_A^2}{2\alpha^2}\right)}\right] e^{\left(-\frac{R_B^2}{2\beta^2}\right)} \left[1 - e^{\left(-\frac{S^2}{2c^2}\right)}\right] \tag{1}$$

or $V_i = 0$ if $\lambda_1 > 0$ or $\lambda_2 > 0$, where $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3|$ are the eigenvalues of the Hessian at the scale i, α, β and c are parameters, S is the Frobenius norm of the Hessian, and R_A and R_B are computed as:

$$R_A = \frac{|\lambda_2|}{|\lambda_1|} \tag{2}$$

$$R_B = \frac{|\lambda_3|}{\sqrt{|\lambda_2 \lambda_1|}} \tag{3}$$

Finally, the method computes vesselness as the maximum V_i estimated at different scales i.

Despite its success, the use of second order derivatives makes the Hessian-based vesselness filters very sensitive to overshooting artifacts. This problem can be better understood through the 1D example of Fig. 1. Assume, without loss of generality, that one is interested in bright vessels. Then, positive peaks of the second order derivative can safely be discarded. However, if not treated carefully, the negative peaks of the second order derivative that are not related to vessel peaks can easily lead to artifacts as shown in the figure. In higher dimensions, the second order derivative in all possible directions is encoded within the Hessian matrix. It is not difficult to show that the overshooting problem in 1D also affects the Hessian in higher dimensions. As in the 1D case, positive eigenvalues of the Hessian can safely be discarded for bright vessels. However, the Hessian can have negative eigenvalues at locations not related to vessels peaks, which can lead to errors in the vesselness estimation. Related to the Hessian, vesselness methods based on the the analysis of the shape operator (also known as Weingarten map) have also been proposed (Armande et al., 1996; Prinet et al., 1996). Unfortunately, these methods require not only second but also first order derivatives. Thus, the aforementioned problems also affect these methods. A different approach estimates the Hessian as the gradient of the regularized gradient field (Bauer and Bischof, 2008), where such a regularization is performed through gradient vector flow (Xu and Prince, 1998). However, this method also require second order derivatives.

In the last few years, alternative vesselness measurements have been proposed to tackle the problems of using second order derivatives. A first family of such methods estimates vesselness from an analysis on the gradient field. An interesting approach is based on the analysis of the flux of the gradient on the surface of local spheres (Vasilevskiy and Siddiqi, 2002). The main hypothesis of the method is that such a flux attains its maximum at the centerline of the vessels. Efficient implementations of this method have been proposed (Law and Chung, 2009). This approach has been extended to oriented variants with reported better results than the original non-oriented approach (Benmansour and Cohen, 2011; Law and Chung, 2008; Law et al., 2012, 2013; Xiao et al., 2013).

A different method that uses the gradient analyzes the eigendecomposition of the gradient structure tensor (GST) in order to enhance vessel-like structures (Agam et al., 2005; Agam and Wu, 2005). Linked to this approach, Wiemker et al. (2013) use a modified version of the GST for vesselness estimation. This approach is discussed in detail in Section 2 since it is very related to the method we propose in that section.

Intensity values have also been used for vesselness estimation. Moments of the intensity values have been used as an alternative to the Hessian (Hernández Hoyos et al., 2006; Nemitz et al., 2007). These methods could have difficulties in regions with strong adjacent structures, such as the heart chambers. Similar to that approach, Cetin et al. (2013) compute tensors from the intensity values, which can be analyzed for detecting vessel-like structures. Moreover, Qian et al. (2009) use patterns of the intensity profile for vesselness estimation. Also, model-fitting of the intensity profiles have been proposed (Friman et al., 2010; Wörz and Rohr, 2007).

Another family of methods uses a bank of oriented filters that combined can yield a probability map that can be used for vesselness (Auvray et al., 2009). A very related approach is the use of orientation scores (Hannink et al., 2014). Furthermore, diffusion filtering have been used for enhancing vessels, e.g. Cañero and Radeva (2003); Krissian (2002); Manniesing et al. (2006). Unfortunately, these last-mentioned methods rely on the estimation of the Hessian at different scales.

More recently, alternative machine learning techniques based on features of the image intensity and gradient (Zheng et al., 2011, 2012) have also been proposed as alternatives to Hessian-based methods. Indeed, the performance of these methods depends on the adequacy of the training data with respect to the application, and on the set of features used in the computations.

An approach related to the method proposed in Section 3 is the one by Rivest-Hénault and Cheriet (2013). This method analyzes second order derivative distributions through spherical harmonics at different scales. Unlike that method, our approach is not exposed to the problems of using second order derivatives and, on top of that, it is able to analyze multiple scales by performing all the computations at a single scale. The reader is referred to review papers for a more extensive list of approaches, e.g., Lesage et al. (2009) or Kirbas and Quek (2004).

In this paper, we propose two methods for determining vesselness using the gradient. At an intermediate step, a modified version of the GST, which is suitable for vesselness estimation, is introduced. We refer to this method as filtered structure tensor (FST). Building on top of this approach, the proposed method analyzes the spherical harmonics expansion of the local orientation distribution of the gradient, which is more appropriate than the FST for analyzing vessels with bifurcations. Since this method looks for ring patterns in the local orientation distribution, we refer to this method as ring pattern detector (RPD).

The paper is organized as follows. Section 2 proposes the modified version of the GST for vesselness estimation (FST). Section 3 describes