Monogenic orientation-based blood flow estimation in high-frequency ultrasound imaging — Source link

Adrian Basarab, Didier Vray, Denis Kouame

Published on: 01 Oct 2012 - Internaltional Ultrasonics Symposium

Topics: Orientation (computer vision)

Monogenic orientation-based blood flow estimation in high-frequency ultrasound imaging

Adrian Basarab, Didier Vray, Denis Kouamé

10.1109/ULTSYM.2012.0084

Monogenic orientation-based blood flow estimation in high-frequency ultrasound imaging

Adrian Basarab[1], Didier Vray[2], Denis Kouamé[1]

[1]Université de Toulouse, IRIT, UMR CNRS 5505, France
[2]Université de Lyon, CREATIS ; CNRS UMR5220 ; Inserm U1044 ; INSA-Lyon ; Université Lyon 1, France

***Abstract* — Classical blood flow estimation techniques are based on the Doppler effect, but suffer from several limitations: inadequate estimations of low velocities, limited spatial resolution and impossibility to estimate flows perpendicular to the beam axis. In a recent work, the velocity was related to the texture orientation in spatiotemporal planes extracted from an ultrasound 2D+t volume. This texture orientation was previously estimated using a bank of orientated Gabor filters. This represents one of the major drawbacks of this method, as the accuracy of the estimates is directly linked to the angular step between two consecutive filters. We propose a novel velocity estimation method, based on the same assumption that a moving target leaves a trace in the spatio-temporal plane, generating an orientation of the texture related to its velocity. In our approach, we propose to estimate this orientation using the framework of the monogenic signal and thus to avoid the large amount of Gabor filters classically used.**

***Index Terms* — velocity estimation, flow estimation, monogenic signal, orientation estimation, high-frequency ultrasound imaging.**

I. INTRODUCTION

Due to its real-time nature, ultrasound (US) imaging is usually used to assess blood flow velocity estimation. Classically, this goal is achieved using Doppler-based methods [1, 2] or some extensions [3-7]. However, the methods based on the Doppler technique have several limitations such as: bad estimation of low velocities, limited spatial resolution and dependence on the flow direction relatively to the ultrasound probe. In order to estimate the 2D velocity vector with explicit estimation of the Doppler angle, different approaches have been proposed. The most classical one is to use the well known speckle tracking method in order to estimate the displacement (and therefore the velocity) between consecutive frames. Moreover, Jensen and Oddershede [8] proposed a method to jointly estimate the magnitude and the direction of the flow using directional beamforming. Recently, in [9], Marion *et al.* related the velocity to the texture orientation in the spatiotemporal (ST) US volume. This orientation is further estimated using a bank of oriented Gabor filters. Compared to three other methods, this approach has been shown in [10] to be a good compromise between accuracy, spatial resolution and computational cost. However, the computational complexity is still an issue for this method (referred to as STF in this paper), as the accuracy of the estimates is directly linked to the angular step between two consecutive filters.

In this paper, we propose a novel velocity estimation method, based on the same assumption that a moving target leaves a trace in the ST plane, generating an orientation of the texture related to its velocity. However, the main difference compared to STF method is the way this texture orientation is estimated. Instead of using a bank of oriented filters, we use herein the monogenic signal to compute the local texture orientation. Introduced in [11] by Felsberg *et al.*, the monogenic signal extends the well known analytic signal to multiple dimensions. For images, the monogenic signal has a hypercomplex representation: the real part is represented by the original band-passed image, and the two imaginary parts are the Riesz transforms. In the same way as the analytic signal, the monogenic signal provides local amplitude and phase information. In addition, it also contains information about the local orientation of the texture in the images. Note that the monogenic signal is adapted to locally one dimensional images (i1D) and is thus adapted to the spatio-temporal planes used for flow estimation in [9] and herein.

The paper is organized as follows. In section II, we briefly summarize the main concepts of the monogenic signal. In section III, our flow estimation method is introduced. In section IV simulation results are presented, showing the contribution of our approach compared to STF method. Finally, section V concludes the paper.

II. MONOGENIC SIGNAL

The monogenic signal associated to a grey-level image is calculated as its response to three 2D spherical quadrature filters (SQF): one even rotation invariant bandpass filter (denoted by $b(\boldsymbol{x})$) and two odd bandpass filters (denoted by $h_1(\boldsymbol{x})$ and $h_2(\boldsymbol{x})$). Herein, the vector $\boldsymbol{x}=[x_1\ x_2]^T$ denotes the pixel spatial location. $h_1(\boldsymbol{x})$ and $h_2(\boldsymbol{x})$ represent the Riesz transform of $b(\boldsymbol{x})$, given in the frequency domain by:

$$H_1(\boldsymbol{u}) = -j\frac{u_1}{\sqrt{u_1^2+u_2^2}}B(\boldsymbol{u})$$
$$H_2(\boldsymbol{u}) = -j\frac{u_2}{\sqrt{u_1^2+u_2^2}}B(\boldsymbol{u}) \quad (1)$$

where $\boldsymbol{u}=[u_1\ u_2]^T$ stands for the 2D frequency variable and by capital letters we denote the 2D Fourier transforms. For computer vision applications, authors mainly used Difference of Poisson or logGabor filters for $b(\boldsymbol{x})$, but other filters may be used.

Thus, for an image denoted by $i(\boldsymbol{x})$, the three components of the associated monogenic signal ($i_b(\boldsymbol{x})$, $q_1(\boldsymbol{x})$, $q_2(\boldsymbol{x})$) are calculated as follows:

$$i_b(\boldsymbol{x}) = i(\boldsymbol{x}) * b(\boldsymbol{x})$$
$$q_1(\boldsymbol{x}) = i(\boldsymbol{x}) * h_1(\boldsymbol{x}) \quad (2)$$
$$q_2(\boldsymbol{x}) = i(\boldsymbol{x}) * h_2(\boldsymbol{x})$$

where * stands for the 2D convolution product.

From the monogenic signal, features such as local amplitude, phase and orientation can be calculated as shown in [11]. As it is the only one to be used in this paper, we only remind herein the definition of the local orientation, which is calculated pixelwise as follows:

$$\theta(\boldsymbol{x}) = a\tan\left(\frac{q_2(\boldsymbol{x})}{q_1(\boldsymbol{x})}\right) \quad (3)$$

III. Proposed Flow Estimation Method

As suggested in [9], a sequence of 2D US images is considered herein as a 3D (2D+t) volume, where the first two dimensions represent the spatial positions and the third one the time. In this preliminary work, only the case of a horizontal vessel is considered (i.e. the typical case where Doppler technique does not work).

Thus, estimating the flow is equivalent to estimate the local orientation of the texture in spatio-temporal planes extracted at different depths from the 3D volumes as shown in Figure 1. The derivation of the relationship between the velocity v and the texture orientation is given hereafter:

$$v = \frac{f_t}{f_s}\tan(\theta) \quad (4)$$

where f_t is the frame rate and f_s the lateral spatial sampling frequency of the US images.

The main contribution of this paper is to estimate the orientation θ using the monogenic signal. For this, the pixelwise formula given in (2) could be used. However, due to US speckle, this way of estimating θ in each pixel gives too noisy results. To improve the accuracy of the estimation, we propose to use two additional steps.

First, the extraction of orientation maps using the monogenic signal is not done in a pixelwise way. Instead, a more robust approach based on the maximization of the directional Hilbert transform response averaged over a local neighborhood is used [12,13]. In [12] it is shown that the solution of this optimization is equivalent to the pixelwise result if the local neighborhood considered reduces to one pixel.

Second a non linear filter is locally used in order to eliminate possible outliers. For this, an initial guess is locally calculated and only the values of the monogenic orientation map close to this guess (see the threshold S in the algorithm hereafter) are used to get the local final estimation. The initial guess of the local orientation is calculated by classical principle component analysis (PCA) applied to the Fourier domain of the spatio-temporal plane. The magnitude of the 2D Fourier transform is first binarized before applying the PCA (see Figure 2). We show in Figure 3 an example of orientation vector map, obtained before and after the elimination of outliers using the result given by the PCA.

The main steps of the proposed method are given below.

Input: A sequence of N US images: $i(x_1, x_2, t)$
Output: Velocity: $v(x_1, x_2, t)$
Parameters: Size of extracted spatio-temporal planes: (X,T)
Threshold for non linear filter of θ: S
Frame rate: f_t
Lateral spatial frequency: f_s

For each depth x_{20}
Extract the ST plane $i(x_1,x_{20},t)$
Compute the corresponding monogenic signal
Extract the orientation map $\theta(x_1,x_{20},t)$

For each lateral position x_{10} and time t_0
Extract the local ST plane $i_l(1{:}X,1{:}T)=i(x_1,x_{20},t)$ and the local orientation map $\theta_l(1{:}X,1{:}T)=\theta(x_1,x_{20},t)$ with
$x_1 \in \left[x_{10}-\frac{X}{2}, x_{10}+\frac{X}{2}-1\right]$ and
$t \in \left[t_0-\frac{T}{2}, t_0+\frac{T}{2}-1\right]$

Compute the 2D Fourier transform of i_l: I_l
Binarize the magnitude of I_l: I_{lb}
Calculate by PCA applied on I_{lb}: θ_{PCA}

Estimate the local orientation: $\hat{\theta}(x_{10}, x_{20}, t_0)$
$$\hat{\theta}(x_{10}, x_{20}, t_0) = mean\left(find\left((\theta_l(x,t) - \theta_{PCA}) < S \cdot \theta_{PCA}\right)\right)$$

Estimate the local velocity:
$$v(x_{10}, x_{20}, t_0) = \frac{f_t}{f_s} tan\left(\hat{\theta}(x_{10}, x_{20}, t_0)\right)$$

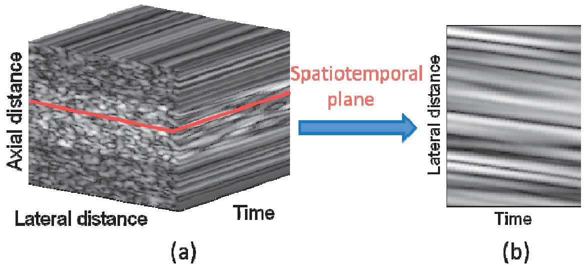

Figure 1. (a) Spatio-temporal US volume corresponding to a horizontal vessel, (b) Spatio-temporal plane used for local texture orientation estimation.

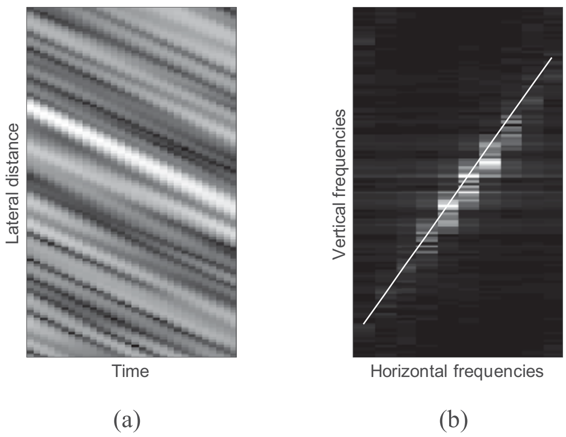

Figure 2. Example of PCA orientation estimation. (a) Spatio-temporal plane, (b) Orientation estimated by PCA (white line) superimposed to the binarized magnitude of the 2D Fourier transform of the image in (a).

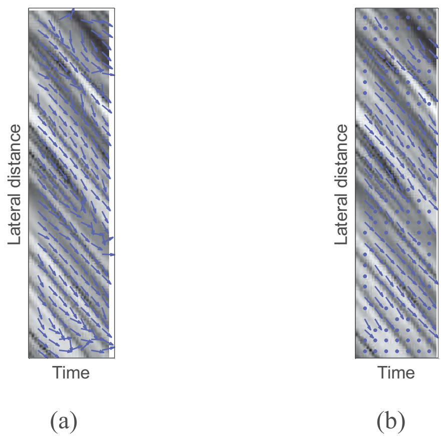

Figure 3. (a) Orientation vectors superimposed to the spatio-temporal plane, before the non-local filtering, (b) Orientation vectors superimposed to the spatio-temporal plane after the non-local filtering using the PCA result. The eliminated outliers appears equal to zero on figure (b).

IV. SIMULATION RESULTS

In this section, the results obtained on a simulated US sequence are given, in order to provide quantitative accuracy results of the proposed method. The simulated sequence was obtained using the framework described in [14]. It consisted of a horizontal vessel (i.e. corresponding to an angle of 90° between the flow direction and the US propagation) of 0.8 mm of diameter. Inside the vessel, a parabolic velocity profile was simulated, with the mean velocity equal to 0.4 mm/s. The central frequency was set at 40 MHz and the axial and lateral resolutions were equal to 40 µm and 80 µm, respectively. An out-of-plane angle equal to 5° was imposed to simulate the out-of-plane motion that occurs in real situations. The 30 simulated 2D RF images at 30 frames per second were finally demodulated and log-compressed to obtain B-mode images. Note that in this paper the difficult case of a high-frequency US sequence is considered. However, our method is not restricted to such specific application.

The theoretical velocity profile and the ones estimated with our method (blue line) and the STF method (red line) are shown in Figure 4. For the estimated profiles, the mean and standard deviation values are shown, obtained by using moving windows of 10 frames. Keeping in mind that 30 images were simulated, 21 values were estimated by each method.

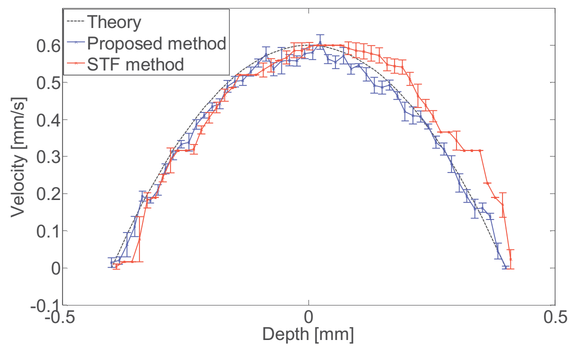

Figure 4. Imposed and estimated velocity profiles.

From the previous estimations, several quantitative performance criteria were calculated. Their expressions are given hereafter:

Mean estimated velocity:

$$\bar{v} = \frac{1}{N} \sum_{i=1}^{N} \hat{v}_i \tag{5}$$

Mean error:

$$\bar{E} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\hat{v}_i - v_i}{v_{max}} \right| \tag{6}$$

Mean standard deviation:

$$\bar{s} = \frac{1}{N} \sum_{i=1}^{N} std_i \quad (7)$$

Where $\hat{v}_i$ represents the mean estimated velocity at depth i, v_{max} the theoretical maximum velocity (0.6 mm/s) and std_i the standard deviation value of the 21 estimates at depth i. In our case, taken into account the diameter of the vessel and the axial sampling frequency, N (the number of depths) was equal to 52. The table hereafter resumes the results obtained with both methods. In the fourth column of the table, an insight about the computational cost of each method is given, in terms of number of 2D convolutions. Thus, we can observe that the proposed method is far less expensive in terms of computing time, while it provides at least similar results (in this precise case they are even better).

	$\bar{v}$ (mm/s)	$\bar{E}$ (%)	$\bar{s}$ (%)	Number of 2D convolutions
STF	0.42	4.3	1.9	39
Proposed	0.38	3.5	1.6	3

V. Conclusion

In this paper, we proposed a novel velocity estimation based on the texture orientation obtained using the framework of monogenic signal.

The proposed method was shown to provide competitive results compared to a previous similar method. Moreover, the proposed approach is far less expensive in terms of computational cost, shown by the smaller number of 2D convolution required.

In future work, our method will be modified so that the estimation be possible for vessels with different (and unknown) space orientation.

References

[1] C. Kasai, N. Namekawa, A. Koyano and R. Omoto, "Real-time two-dimensional blood flow imaging using an autocorrelation technique," *IEEE Trans. Son. Ultras.*, vol. 32, pp. 458-463, 1985

[2] O. Bonnefous, "Statistical analysis and time correlation processes applied to velocity measurement," *Proc. of IEEE Ultras. Symp.*, vol. 2, pp. 887-892, 1989.

[3] Newhouse, V. L., Dickerson, K. S., Cathignol, D., et al., "Three-dimensional vector flow estimation using two transducers and spectral width," *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, volume 41, no. 1, (1994), pp. 90–95.

[4] P. Tortoli, G. Bambi and S. Ricci, "A novel dual-beam Doppler approach for removing Doppler angle ambiguity," *Proc. of IEEE Ultras. Symp.*, vol. 1, pp. 150-153, 2005.

[5] D. Kouamé, J.M. Girault and F. Patat, "High resolution processing techniques for ultrasound Doppler velocimetry in presence of colored noise Part I: non stationary methods," *IEEE Trans. Ultras., Ferro., Freq. Contr.*, vol. 50, pp. 257-266, 2003.

[6] D. Kouamé, J.M. Girault, J.P. Remenieras, J.P. Chemla and M. Lethiecq, "High resolution processing techniques for ultrasound Doppler velocimetry in presence of colored noise Part II: multiple phase pipe flow velocity measurement," IEEE *Trans. Ultras., Ferro., Freq. Contr.*, vol. 50, pp. 267-276, 2003.

[7] K.W. Ferrara and V.R. Algazi, "A new wideband spread target maximum likelihood estimator for blood velocity estimation-Part 1: Theory," *IEEE Trans. Ultras., Ferro., Freq. Contr.*, vol. 38, pp. 1-16, 1991.

[8] A. Jensen, N. Oddershede, "Estimation of velocity vectors in synthetic aperture ultrasound imaging, " IEEE Trans. Med. Ima., vol 25, pp 1637-1644, 2006.

[9] A. Marion and D. Vray, "Spatiotemporal filtering of sequences of ultrasound images to estimate a dense field of velocities," *Elsevier Pattern Recognition*, vol. 42, pp. 2989-2997, 2009.

[10] A. Marion, W. Aoudi, A. Basarab, P. Delachartre and D. Vray, “Blood flow evaluation in high-frequency, 40 MHz imaging: A comparative study of four vector velocity estimation methods”, *Ultrasonics*, Vol. 50, pp 683-690, 2010.

[11] Felsberg, M., G. Sommer, The monogenic Signal, *IEEE Trans. Signal Proc.*, 2001, 49:3136.

[12] M. Unser, D. Sage, and D. Van De Ville, “Multiresolution monogenic signal analysis using the riesz laplace wavelet transform,” *Image Processing, IEEE Transactions on*, vol. 18, no. 11, pp. 2402 –2418, nov. 2009.

[13] M. Alessandrini, A. Basarab, H. Liebgott, O. Bernard, “Multiscale Optical Flow Computation from the Monogenic Signal”, *IEEE Transactions on Image Processing*, under revision.

[14] A. Marion, D. Vray, Toward a real-time simulation of ultrasound image sequences based on a 3D set of moving scatterers, *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control,* 56 (2009) 2167–2179.

Acknowledgements

The authors thank Adrien Marion for useful discussions and for providing the simulated US data.