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Feature Detection from Echocardiography Images Using Local Phase Information

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Abstract. Ultrasound images are characterized by their special speckle appearance, low contrast, and low signal-to-noise ratio. It is always challenging to extract important clinical information from these images. An important step before formal analysis is to transform the image to significant features of interest. Intensity based methods do not perform particularly well on ultrasound images. However, it has been previously shown that these images respond well to local phase-based methods which are theoretically intensity-invariant and thus suitable for ultrasound images. We extend the previous local phase-based method to detect features using the local phase computed from monogenic signal which is an isotropic extension of the analytic signal. We apply our method of multiscale feature-asymmetry measurement and local phase-gradient computation to cardiac ultrasound (echocardiography) images for the detection of endocardial, epicardial and myocardial centerline.

1 Introduction

Cardiovascular disease (CVD) is the main cause of human deaths in the developed world. Nearly half of all deaths in Europe [1] and more than one third of all deaths in the UK [2] are caused by CVD. Cardiac functional imaging is a non-invasive way to acquire dynamic images of the heart through which functional assessment and disease diagnosis can be made. In cardiac imaging, echocardiography (cardiac ultrasound) is the simplest, low-cost, and highly effective choice of image acquisition. However, these images are known to have low signal-to-noise ratio, low contrast, and high amounts of speckle. Further analysis (e.g., registration or segmentation) on these images is bound to be badly influenced from these artifacts.

We approach the problem of feature detection from echocardiography images in an attempt to extract the important features – namely: endocardial and epicardial boundaries, and the myocardial centerline – which are potentially helpful in any subsequent processing. The method is developed using an approach that is not much affected by the speckle or low contrast nature of the ultrasound images. Phase-based processing has attracted a lot of attention in echocardiography image analysis, notably by our lab. In [3], the authors presented a local phase-based method of endocardial and epicardial boundary feature detection from feature asymmetry (FA) measure which also took notice of the spatio-temporal characteristics of the images. They assumed that endocardial or epicardial boundaries have step edge characteristics (thus asymmetry). In [4, 5], the authors used the local phase representation of echocardiography images for the registration of multi-view real-time 3-dimensional (RT3D) echocardiography. Zhang et al. [6] used the local phase representation of cardiac ultrasound and cardiac magnetic resonance (MR) images for multi-modality registration.

Our work is influenced by the approach of Mulet-Parada and Noble [3] for endocardial and epicardial boundary feature detection which showed that a local phase-based method outperforms the conventional intensity-based methods. The algorithm in [3] used the quadrature filters for the computation of local phase by employing a filter bank of oriented log-Gabor band-pass filters. In contrast, we adapt the monogenic signal [7, 8] which makes use of isotropic Riesz filters (thus no specific orientation restriction) for the computation of local phase and extend the idea of feature asymmetry measure computation to multiscale. This greatly simplifies the feature asymmetry measure computation and gets rid of any potential problems that can possibly be introduced due to the use of oriented band-pass filters. Moreover, the computational complexity of the technique is reduced and the feature detection is improved. The obtained features are important edge indicator and thus potentially useful either for feature-based registration or for segmentation using active contour algorithm [9] attempting to segment the endocardial and/or epicardial boundary. We also show how to detect the myocardial centerline using the local phase-gradient. The myocardial muscle is the most important structure in the echocardiography images and detection of its centre with high degree of localization can certainly help in the tracking, segmentation and registration applications.

The next section describes the relevant background about the analytic signal, its extension to 2D using the oriented quadrature filters, and the feature asymmetry (FA) measure. Section 3 gives a detailed explanation of the proposed method for feature detection using modified single-scale and multi-scale feature-asymmetry measure and local

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phase-gradient. Section 4 shows example results on echocardiography images. The paper concludes in the final section with an indication of the future directions.

2 Background

It is well known that local phase contains the local structural information (e.g., transitions or discontinuities) whereas the local amplitude depicts the local energy of the signal. Usually, one needs to construct a complex analytic signal from a given 1D signal to perform local analysis (e.g., local phase computation). The complex analytic signal is formed by considering the original signal $f(x)$ as the real part and its Hilbert transform $H[f]$ as the imaginary part.

$$f_A(x) = f(x) + iH[f(x)] \tag{1}$$

The local phase is then computed from this complex analytic signal:

$$\varphi(x) = arctan\big(H[f(x)]/f(x)\big) \tag{2}$$

In practice, the analytic signal and the local phase are computed from a quadrature pair of band-pass filters (i.e., filters which are $\pi/2$ phase shift version of each other.) One such example is the log-Gabor filter:

$$G(\omega) = exp - \frac{\left(log\,(\omega/\omega_0)\right)^2}{2\left(log\,(k/\omega_0)\right)^2} \tag{3}$$

where ω_0 is the centre frequency and k is related to the band-width of the band-pass filter. Using the quadrature filter pair, the local phase is practically computed from the filter responses:

$$even(x) = f(x) * Re\left(F^{-1}\big(G(\omega)\big)\right) \quad \text{and} \quad odd(x) = f(x) * Im\left(F^{-1}\big(G(\omega)\big)\right)$$

$$\varphi(x) = arctan(odd(x)/even(x)) \tag{4}$$

where $*$ denotes the convolution operator, $F^{-1}(..)$ represents the inverse Fourier transform, and $Re(..)$ and $Im(..)$ extract the real and imaginary part from the complex function, respectively.

The local phase $\varphi(x)$ denotes the measure of the local symmetry ($\pm\pi/2$) or asymmetry (0 or π) of the signal. The local symmetry of the signal is often termed as even symmetry (ridges or valleys) while the local asymmetry is termed as the local odd symmetry (step edges). Thus, the concept of symmetry is naturally a 1D concept and the above description of analytic signal and local phase computation holds only for 1D signals. Mathematically, the Hilbert transform is restricted for a 1D function. Therefore, a straightforward extension of the above concept to 2D and higher dimensions is generally invalid.

Usually, the extension to 2D local analysis is performed using the construction of an oriented filter bank which holds the 1D local symmetry or asymmetry concepts. The 2D extension of the 1D log-Gabor filter (3) is:

$$G(\omega,\varphi) = exp - \left(\frac{\left(log\,(\omega/\omega_0)\right)^2}{2\left(log\,(k/\omega_0)\right)^2} + \frac{(\varphi-\varphi_0)^2}{2\sigma_\varphi^2}\right) \tag{5}$$

where φ_0 is the filter orientation and σ_φ^2 is the filter spread. The local analysis of 2D images performed using the log-Gabor filter is computed as:

$$even(x,y) = f(x,y) * Re\left(F^{-1}\big(G(\omega,\varphi)\big)\right) \quad \text{and} \quad odd(x,y) = f(x,y) * Im\left(F^{-1}\big(G(\omega,\varphi)\big)\right)$$

$$\varphi(x,y) = arctan(odd(x,y)/even(x,y)) \tag{6}$$

In local analysis, Kovesi [10] and Morrone & Owens [11] have shown that the significant features (step edges, ridges, valleys, etc.) in the image have their unique phase response and that the phase is congruent for these features. In the current work, we are only interested in the computation of endocardial or epicardial features which behave like step edges [3] and have a phase response of nearly 0 or π. It has been shown, originally in Kovesi's work [10], and later in Mulet-Parada's adaptation [3] for echocardiography images that the FA measure is actually the phase-congruency measure computed only for the step edges. Mulet-Parada [3] employed the FA measure of Kovesi [10] that can be computed directly from the quadrature pair filter responses:

$$FA_{2D}^{MP}(x,y) = \sum_m \frac{\lfloor |odd_m(x,y)| - |even_m(x,y)| - T_m \rfloor}{\sqrt{odd_m^2(x,y) + even_m^2(x,y)} + \varepsilon} \tag{7}$$

where m is the filter orientation, ε is a small constant to avoid division by zero, T_m is the orientation specific threshold and the $\lfloor..\rfloor$ operator zeros the negative values. The role of T_m and the zeroing operator is to respond only to features within the orientation range of the filter. The orientation specific threshold is computed by,

$$T_m = exp^{log\left(mean\left(\sqrt{odd_m^2(x,y) + even_m^2(x,y)}\right)\right)} \tag{8}$$

3 Method

Due to the nature of extension using oriented filters, as described above, of the local analysis theory to 2D, we face the complexity of dealing with an oriented filter bank and an additional parameter about the selection of the number of appropriate orientations. In this section, we present our modification to the FA measure for the detection of endocardial and epicardial features. We make use of the recently introduced isotropic extension of the analytic signal concept to 2D in the monogenic signal framework of Felsberg [7, 8]. The monogenic signal framework extends the analytic signal concept to 2D by the introduction of a vector valued odd filter (Riesz filter) whose Fourier domain representation is:

$$\left(H_1(u,v), H_2(u,v)\right) = \left(i\frac{u}{\sqrt{u^2+v^2}}, i\frac{v}{\sqrt{u^2+v^2}}\right)$$

The monogenic signal is then formed by combining the original 2D signal with the Riesz filtered components:

$$f_M(x,y) = [f(x,y), f(x,y) * h_1(x,y), f(x,y) * h_2(x,y)]$$

where $h_1(x,y)$and $h_2(x,y)$ are the spatial domain representation of $H_1(u,v)$ and $H_2(u,v)$, respectively. Similar to the oriented filter case described in last section, the 2D image is first filtered using a band-pass filter, for example: log-Gabor filter,

$$G(u,v) = exp - \left(\frac{\left(log\left(\sqrt{u^2+v^2}/\omega_0\right)\right)^2}{2\left(log\left(k/\omega_0\right)\right)^2}\right) \tag{9}$$

It must be noted that the above log-Gabor filter is an isotropic band-pass filter, unlike the oriented band-pass filters (5) used in the last section. Therefore, in practice, the monogenic signal is often constructed as:

$$f_M(x,y) = [g(x,y) * f(x,y), f(x,y) * g(x,y) * h_1(x,y), f(x,y) * g(x,y) * h_2(x,y)]$$

where $g(x,y)$ is the spatial domain representation of the log-Gabor filter $G(u,v)$. We have found that the monogenic signal components can be represented by scalar valued even and odd filtered responses with the following simple trick:

$$even_{MG}(x,y) = f_{M,1}(x,y) \qquad \text{and} \qquad odd_{MG}(x,y) = \sqrt{f_{M,2}^2(x,y) + f_{M,3}^2(x,y)}$$

and thus the new representation of monogenic signal can be of the same form as the 1D analytic signal (1).

$$F_{MG} = even_{MG}(x,y) + i * odd_{MG}(x,y) \tag{10}$$

It is worth mentioning that the $even_{MG}(x,y)$ and $odd_{MG}(x,y)$ filter responses contain the even-symmetry and odd-symmetry filter responses, respectively. However, interestingly in this case, $odd_{MG}(x,y)$ denotes the odd symmetry response as a scalar value in all orientations. However, the simplified monogenic signal representation (10) loses the local orientation information (see [7, 8] for details on local orientation) from the original representation but we are only interested in the local phase information for our current work which remains unaffected by the trick.

We can now define the modified FA measure to compute the phase congruency for asymmetric features (i.e., step edges) in the image. We recall that endocardial and epicardial features correspond to step edges. The modified FA measure is formulated as:

$$FA_{2D}^{KR}(x,y) = \frac{\lfloor |odd_{MG}(x,y)| - |even_{MG}(x,y)| - T \rfloor}{\sqrt{even_{MG}^2(x,y) + odd_{MG}^2(x,y)} + \varepsilon} \tag{11}$$

In contrast to the conventional FA (7), there is no need of summation operator (since there is no oriented filter bank). The threshold T is computed in a way similar to (8) but with no orientation selectivity. Thus, the filtering and the FA measure are simplified in comparison to the method of Mulet-Parada [3]. Note that the FA in (7) and the modified FA of (11) compute the asymmetric feature strength at a single scale. We propose a multiscale FA measure based on monogenic signal and the above modified FA measure (11),

$$FA_{2D}^{KR-ms}(x,y) = \sum_{sc} \frac{\lfloor |odd_{sc\,MG}(x,y)| - |even_{sc\,MG}(x,y)| - T_{sc} \rfloor}{\sqrt{even_{sc\,MG}^2(x,y) + odd_{sc\,MG}^2(x,y)} + \varepsilon} \tag{12}$$

where sc represents the scale variable and T_{sc} is a scale-specific threshold value calculated similar to (8) but with scale selectivity rather than orientation selectivity. Due to the similarity between (7) and (12), it must be clarified that the FA of (7) is summed upon different orientations (and not scales) whereas the summation in (12) is computed from multiple scales of the band-pass filter (9) used in the computation of monogenic signal.

In addition to the endocardial and epicardial features, the myocardial muscle centerline is also a very important feature in the echocardiography images which can be useful for registration and segmentation. It can be assumed that

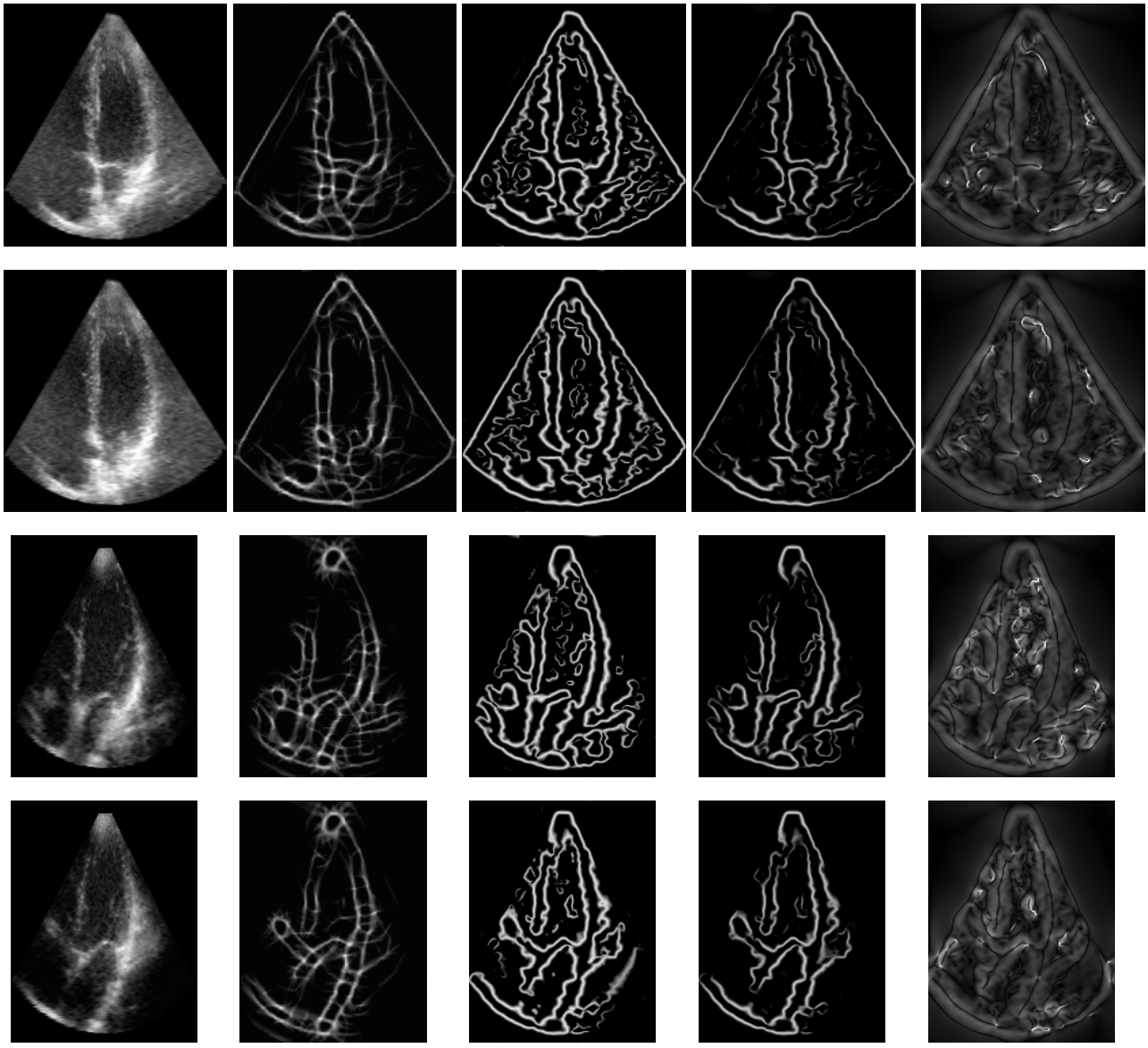
the whole myocardial muscle is a symmetrical feature (a ridge). We have noticed in our experiments that the phase-gradient computed from the filter response components of the monogenic signal (10) provides a unique and well-localized response (local minima) to the symmetrical features (i.e., myocardial muscle in this case). The phase-gradient can be directly computed from the filter responses instead of explicit derivation from the local phase. From the polar representation of the complex signal F_{MG}, one can derive that the phase-gradient is:

$$\varphi'_{MG}(x,y) = Im\left(\frac{F'_{MG}(x,y)}{F_{MG}(x,y)}\right) = \frac{even_{MG}(x,y).Im(F'_{MG}) - odd_{MG}(x,y).Re(F'_{MG})}{even^2_{MG}(x,y) + odd^2_{MG}(x,y)} \quad (13)$$

where F' denotes the derivative of F. Therefore, the phase-gradient computation is considered to be unaffected from typical problems associated with the computation of local phase (e.g., phase wrapping).

4 Results and Discussion

We present exemplar results of modified single-scale and multi-scale FA and phase-gradient computation for echocardiography images. These measures allow the localized detection of endocardial, epicardial, and myocardial centerline features. For the computation of the modified FA (11), (12) and local phase-gradient (13), the simplified monogenic signal (10) was constructed where an isotropic log-Gabor filter (9) was used for the band-pass filtering of the original image. For the feature detection using original FA measure (7), we used the same parameters as in [3].



(a) (b) (c) (d) (e)

Figure 1: Results on two frames each of two different echocardiographic sequences. (a) original image frames; (b) FA measure (7) using oriented filters technique of Mulet-Parada [3], (c) modified single-scale FA measure (11) from monogenic signal, (d) proposed multi-scale FA measure (12) from monogenic signal, and (e) phase-gradient measure computed using (13).

For the single-scale modified FA computation using (11), we used the log-Gabor filter with bandwidth $k/\omega_0 = 0.55$ (i.e., 2-octaves) and the wavelength set to 36-pixels. In the case of the multi-scale FA (12), three log-Gabor filters were used with wavelengths of $[30, 36, 42]$-pixels and the bandwidth of $k/\omega_0 = 0.55$. For phase-gradient computation (13), the parameters were the same as for single-scale FA computation.

The results of feature detection on two frames each of two echocardiographic sequences are shown in Figure 1. The FA measure shows a strong value at the step edge location. It is clearly evident that the proposed multi-scale FA measure (12) offers refined feature detection results compared to either the previous FA measure (7) or the modified single-scale FA measure (11). In the case of phase-gradient measure, the myocardial centerline response is apparent as the local regional valley (or minima). We observe that the response of both these operators is excellent and highly localized for the myocardium muscle covering the left ventricle chamber. The proposed method finds important features efficiently and with high effectiveness. A limitation of the current approach is that it performs only spatial filtering which can introduce artificial responses for weaker structures. Mulet-Parada [3] found that spatio-temporal filtering reduces any such responses. We are currently working on the extension of our method to spatio-temporal echocardiography sequences. It must be mentioned that the monogenic signal extension to higher dimensions (2D+t, 3D or 3D+t) is straightforward (for example: see [4, 5] for its 3D use). This implies that the extension of our work to higher dimension is simple unlike the technique proposed in [3] where extension of band-pass oriented filters to higher dimensions is subject to a significantly increased computational burden and design complications.

5 Conclusions

We proposed local phase-based methods for the detection of significant features in ultrasound images and showed the results of our techniques applied to echocardiography images. The proposed method has simple formulation, multiscale extension, and reduced computational complexity compared to previous related implementations [3]. We have shown that the proposed approach is capable of detecting important feature points from echocardiography images which include the endocardial, epicardial and myocardial centerline boundaries. The features detected using this method may be further useful for subsequent processing in feature-based registration and contour-based segmentation. We are currently working on the spatio-temporal feature detection to capture temporal consistency from echocardiography images with the hope of further reducing any spurious responses of the current spatial approach. We are also working on the utilization of these features in an echocardiography segmentation framework.

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