Detection of Quiescent Cardiac Phases in Echocardiography Data Using Nonlinear Filtering and Boundary Detection Techniques

Lakshminarayan Ravichandran · Carson A. Wick ·
James H. McClellan · Tian Liu · Srinidhi Tridandapani

Published online: 24 May 2014
© Society for Imaging Informatics in Medicine 2014

Abstract We describe an algorithm to detect cardiac quiescence within a heartbeat using nonlinear filtering and boundary detection techniques in echocardiography images. The motivation for detection of these quiescent phases is to provide improved cardiac gating to obtain motion-artifact-free images of the heart at cardiac computed tomography (CT). Currently, cardiac gating is provided through electrocardiography (ECG), which does not provide information about the instantaneous mechanical state of the heart. Our goal is to test if information about the actual mechanical motion of the heart obtained from B-mode echocardiographic data could

potentially be used for gating purposes. The nonlinear filtering algorithm presented involves anisotropic diffusion to smooth the homogeneous regions of the B-mode images while preserving image edges that represent myocardial boundaries. Following this, we detect the boundary of a particular region of interest (ROI) using a thresholding step. The positional changes of this ROI are then observed for quiescent phases over multiple cardiac cycles using the ECG's R-R interval. In a pilot study, seven subjects were imaged in the apical, four-chamber view, and quiescence of the interventricular septum was primarily observed in the diastolic region of the ECG signal. However, the position and length of quiescence vary across multiple heartbeats for the same individual and for different individuals as well. The center of quiescence for the seven patients ranged from 51 to 84 % and did not show a trend with heart rates, which ranged from 54 to 83 beats per minute. The gating intervals based on such analysis of echocardiographic signals could potentially optimize cardiac CT gating.

A preliminary version of this paper was presented at IEEE EMBC 2012.

L. Ravichandran · S. Tridandapani
Department of Radiology and Imaging Sciences, Emory University
School of Medicine, Atlanta, GA 30322, USA

L. Ravichandran
e-mail: lakshminarayan.r@gmail.com

C. A. Wick · J. H. McClellan · S. Tridandapani
School of Electrical and Computer Engineering, Georgia Institute of
Technology, Atlanta, GA 30332, USA

C. A. Wick
e-mail: carson@gatech.edu

J. H. McClellan
e-mail: jim.mcclellan@gatech.edu

T. Liu
Department of Radiation Oncology, Emory University School of
Medicine, Atlanta, GA 30322, USA
e-mail: tliu34@emory.edu

S. Tridandapani (✉)
Department of Radiology and Imaging Sciences, Winship Cancer
Institute, Emory University, 1701 Uppergate Drive NE, Atlanta,
GA 30322, USA
e-mail: stridan@emory.edu

Keywords Cardiac gating · Cardiac quiescence · ECG ·
Echocardiography

Background

We are developing a technique for the identification of relatively stationary, or quiescent, phases of the heart within a cardiac cycle. This information will eventually be used to provide cardiac gating and obtain motion-free images of the heart with cardiac computed tomography (CT). The current electrocardiograph (ECG)-based gating signal may be suboptimal because it does not represent the true mechanical state of the heart. We believe that the true mechanical motion derived from echocardiography data may provide a more consistent and reliable gating tool to obtain motion-free images.

From the American Heart Association 2013 statistics [1], one in every six deaths in the USA in 2009 was due to coronary heart disease. CT coronary angiography (CTCA) [2, 3] is at the cusp of revolutionizing diagnosis of heart disease. CT evaluation is fast, inexpensive, and minimally invasive and has relatively rare complications—mostly limited to contrast reactions, compared with the more invasive and expensive catheter-based coronary angiography [4]. However, CT evaluation of the heart has a fundamental drawback in the form of temporal resolution. CT gantry rotation times are of the order of 330 ms, and slice acquisition times are about 170 ms for current single-source CT scanners. Moreover, the heart is a moving target, which makes acquisition of motion-free images challenging. There are, however, portions of the cardiac cycle when the heart is relatively quiescent, and scanning during these periods may reduce motion artifacts. For example, if the heart rate is below 70 beats per minute (bpm), then CT slice acquisition in the diastolic portion of the cardiac cycle may provide relatively motion-free images of the coronary arteries, and if the heart rate is greater than 70 bpm, then scanning in the systolic portion of the cycle may yield better CT images [5]. Currently, prediction of cardiac quiescence is based almost entirely on electrocardiography (ECG), and CT slice acquisition is based on a gating signal that is derived from real-time ECG [3, 6, 7]. ECG is an excellent marker of the instantaneous electrical state of the heart; however, it is not a reliable indicator of the instantaneous mechanical motion of the heart.

Our hypothesis is that cardiac CT gating can be improved if the gating signal is based on the true mechanical motion of the heart rather than the surrogate electrical marker. It has previously been shown that ultrasound (US), which similar to ECG can provide real-time evaluation of the heart, may potentially provide a better signal for gating since it directly interrogates cardiac mechanical motion [8]. It was shown in [8] that quiescent periods within the cardiac cycle can vary between individuals even if their heart rates are similar. Thus, ECG gating at a fixed percent interval within the cardiac cycle that is based on population-derived averages may not be optimal. A limitation of the work in [8] was that it was based on beat-to-beat cross-correlation of one-dimensional (M-mode) US signals from the left ventricular wall. M-mode can only resolve motion in one direction at a time, and motion in the orthogonal direction is not resolved. The cardiac motion in the orthogonal direction was shown to be significant in [9], indicating that a two-dimensional sensing modality provides a more accurate indication of cardiac velocity.

In this paper, estimation of cardiac quiescence is performed by observing the motion of the interventricular septum (IVS) in a series of two-dimensional, B-mode US images from the apical four-chamber view. The B-mode US image is a two-dimensional depiction of the echoes plotted as a function of depth. However, speckle noise is usually associated with this imaging modality, which can hamper edge detection and

image segmentation. The cardiac quiescence estimation algorithm in this paper performs despeckling of the ultrasound image using a nonlinear filtering technique called anisotropic diffusion (AD), which also performs contrast enhancement and edge detection. Using this filtered image, the boundary around the region of interest (ROI), also referred to as object contour, and drawn around the IVS, is obtained, and the centroid of the ROI is calculated to represent the position of the ROI. This process is repeated for the entire series of US frames, and an estimate of the position of the ROI, i.e., the IVS, over multiple frames is thus obtained. We then compare the periods of quiescence estimated by this approach with a simultaneously acquired ECG signal.

Methods

In this section, we describe the steps involved in the detection of cardiac quiescence from B-mode US data, as outlined in Fig. 1.

Anisotropic Diffusion

To segment the image into a pre-specified ROI and perform tracking, we initially use a filtering algorithm to remove the speckle noise. Speckle noise is a form of locally correlated noise, which is a result of the interference of ultrasound waves while gathering backscattered data [10]. While speckle has proved to be useful in tracking applications [11], the speckle in the B-mode echocardiograph data used in this study can cause distortions in the image, which can substantially hamper the detection of the ROI. To detect the motion of the ROI from this ultrasound image, we need to suppress the speckle noise. This suppression can both enhance the contrast of the image and enable better edge and boundary detection of the ROI. However, in a few cases, the features of the ROI and the speckle may have the same magnitude, thus making the suppression of speckle noise a challenging task. The key requirements of a filtering technique for medical images are to minimize information loss by preserving object boundaries and detailed structures and to sharpen discontinuities, thus providing an image with better morphological definition [12].

There are many linear and nonlinear filtering techniques including averaging filters, Wiener filters, Lee filter [13–15], Frost filter [16], and Kuan filter [17] that have been used to remove speckle noise primarily in the synthetic aperture radar (SAR) community. While the Wiener, Lee, and Frost filters remove speckle noise, the despeckled images tend to lose important edge details due to smoothing, and these edge details are important in the detection of ROI. This primarily occurs due to the sensitivity of the filters to the size and shape of the filter window. A large window over a smaller ROI usually leads to over-smoothing and blurring of edges, while

Fig. 1 Algorithm overview: detection of cardiac quiescence from B-mode echocardiography data using anisotropic diffusion and boundary detection

a smaller window reduces the smoothing and leaves behind speckle noise.

In this algorithm, we use the anisotropic diffusion (AD) filter originally proposed in [18] which was modified for medical images in [10, 12]. We use the AD filter since it performs smoothing adaptively based on the gradient of the image intensity and provides an edge- and contrast-enhanced image while minimizing the speckle noise. As opposed to the other previously mentioned filtering techniques, there is no restriction on the filtering due to filter window size or shape. The following mathematical framework for the AD algorithm follows the approach presented by Gerig et al. in [12].

For a vector $\bar{x}$ which represents the spatial coordinates and t , the process ordering parameter, the process of AD smoothing is given by the following:

$$\frac{\partial}{\partial t} u(\bar{x}, t) = \text{div} \left(c(\bar{x}, t) \nabla u(\bar{x}, t) \right)$$

where $c(\bar{x}, t)$ is the diffusion function that depends on the magnitude of the gradient of the image intensity $I(\bar{x}, t) = u(\bar{x}, t)$, and this controls the diffusion strength.

The diffusion functions are obtained as a function of the image intensity:

$$c_1(\bar{x}, t) = \exp \left(- \frac{|\nabla I(\bar{x}, t)|^2}{\kappa} \right)$$

$$c_2(\bar{x}, t) = \left[1 + \left(\frac{|\nabla I(\bar{x}, t)|}{\kappa} \right)^{1+\alpha} \right]^{-1}, \alpha > 0$$

We use the diffusion function $c_2(\bar{x}, t)$ with $\alpha=1$, i.e.,

$$c(\bar{x}, t) = \left[1 + \left(\frac{|\nabla I(\bar{x}, t)|}{\kappa} \right)^2 \right]^{-1}.$$

This diffusion function is a monotonically decreasing function, which diffuses within the regions, leaving the boundaries (high-gradient regions) unaffected. The diffusion process continues until the gradient reaches a large value, i.e., discontinuity occurs. The parameter κ depends on the noise level and the edge strength. The choice of the diffusion function is critical in not only preserving the edges but also in enhancing them while being numerically stable. In addition, over multiple

iterations, the slope of the edge increases, thus providing enhanced edges. Thus, anisotropic diffusion performs piecewise smoothing of the original signal and propagates information between discontinuities within regions of constant intensity or regions with low variations in intensity.

The two-dimensional implementation of the AD filtering $\bar{x} = [x \ y]$ for an image sequence with intensity $I(\bar{x}, t)$ is given by:

$$\begin{aligned} \frac{\partial}{\partial t} I(\bar{x}, t) &= \text{div} \left(c(\bar{x}, t) \times \nabla I(\bar{x}, t) \right) \\ &= \nabla^T \left(c(\bar{x}, t) \times \nabla I(\bar{x}, t) \right) \\ &= \frac{\partial}{\partial x} \left[c(\bar{x}, t) \times \frac{\partial}{\partial x} I(\bar{x}, t) \right] + \frac{\partial}{\partial y} \left[c(\bar{x}, t) \times \frac{\partial}{\partial y} I(\bar{x}, t) \right] \\ &= \frac{1}{\Delta x^2} \left[c \left(x + \frac{\Delta x}{2}, y, t \right) \times \{ I(x + \Delta x, y, t) - I(x, y, t) \} \right. \\ &\quad \left. - c \left(x - \frac{\Delta x}{2}, y, t \right) \times \{ I(x, y, t) - I(x - \Delta x, y, t) \} \right] \\ &\quad + \frac{1}{\Delta y^2} \left[c \left(x, y + \frac{\Delta y}{2}, t \right) \times \{ I(x, y + \Delta y, t) - I(x, y, t) \} \right. \\ &\quad \left. - c \left(x, y - \frac{\Delta y}{2}, t \right) \times \{ I(x, y, t) - I(x, y - \Delta y, t) \} \right] \\ &= \Phi_{\text{east}} - \Phi_{\text{west}} + \Phi_{\text{north}} - \Phi_{\text{south}} \end{aligned}$$

The signal flow is calculated between neighboring nodes as shown in the equation above and the updated pixel intensity is given by the following:

$$\begin{aligned} I(\bar{x}, t + \Delta t) &= I(\bar{x}, t) + \Delta t \times \frac{\partial}{\partial t} I(t) \\ &= I(\bar{x}, t) + \Delta t \times (\Phi_{\text{east}} - \Phi_{\text{west}} + \Phi_{\text{north}} - \Phi_{\text{south}}), \end{aligned}$$

where Δt is the integration constant and is used to approximate the stability. To obtain better isotropy, the flow along the diagonal pixels may also be calculated.

Since this algorithm does not have a specific convergence, that is, the smoothing continues to occur up to infinite time, a constraint on the number of iterations is imposed. The number of iterations depends on the application and the amount of smoothing desired. This process of AD blurs smaller discontinuities and sharpens the edges, which is useful in this despeckling process while retaining the discontinuities and not affecting their positions. We refer to this anisotropic diffused image as $I_{AD}(\bar{x}, t)$ or simply I_{AD} .

Boundary Detection Using Thresholding

Following the removal of the speckle noise to enhance the image contrast and enable edge detection, we perform a hard thresholding on the image I_{AD} to better identify the contour of the ROI. This is a binary thresholding process with the value for the threshold obtained by the separation between the hyperechoic (higher pixel intensity) and the hypoechoic region (lower pixel intensity) of the despeckled image, particularly in the area surrounding the region of interest. Due to AD filtering, there is enhancement of contrast, thus widening the separation between the hypoechoic and the hyperechoic regions. The threshold is chosen manually based on the image intensity on the boundary of the ROI. Manual selection is necessary due to variation of the pixel intensities of the hyperechoic and hypoechoic regions. If necessary, the selection could be automated from the pixel intensity histogram for each B-mode sequence [19]. The pixel values greater than the threshold are set to one (white), while the pixel values less than the threshold are set to zero (black).

On the binary image obtained after thresholding, we perform the boundary detection using the Moore neighbor algorithm modified by Jacob's stopping criteria [20]. This boundary detection algorithm delineates the contour of the ROI and the points within the contour. Using these points, we find the centroid (c_{x_i}, c_{y_i}) of the ROI for frame i . The above process of finding the ROI, corresponding to the part of the heart whose motion we are tracking, and the center of mass for this ROI is repeated over the entire set of frames. This results in the vector C that provides the position of the ROI for each of the frames from which cardiac quiescence can be computed.

Detection of Quiescence

The position vector $C = [C_1, C_2, \dots, C_N]^T$, where $C_i = (c_{x_i}, c_{y_i})$ and N is the number of frames, is used to compute the motion of the ROI over the entire set of frames. To observe quiescence, i.e., the periods of minimal or no motion, the position of the ROI in two consecutive frames needs to be compared. For this, we consider the first difference between the x and the y positions of consecutive frames, i.e., $\Delta C_i = C_i - C_{i-1}$. This first difference ΔC_i of the spatial coordinates provides a measure of the velocity in the x and y directions. The magnitude of the velocity is then obtained from these two velocities with time intervals of minimal velocity (as defined later) corresponding to phases of cardiac quiescence. An ancillary benefit of using the first difference to calculate velocity is that the effect of ultrasound operator hand motion is mitigated because the extent of any hand motion will be minimal over a period of one sampling interval.

Experimental Setup

This study was conducted under the approval of the Institutional Review Board (IRB) at Emory University. Three male and four female subjects in the age range 23–45 with no known cardiac conditions were recruited between March 2012 and December 2012 and provided full, informed consent. The experimental data, consisting of B-mode echocardiographic images and synchronously recorded ECG data, were obtained from each subject using a SonixTOUCH Research ultrasound machine (Ultrasonix, Vancouver, BC, Canada). The data were acquired over a period of 10 to 30 s. The data acquisition rate of the B-mode echocardiography data was either 30 or 50 frames/s and that of the ECG data was 200 samples/s. The differing echocardiography rates were due to a vendor software update to the ultrasound scanner that enabled 50 frames/s acquisition. The size of a single echocardiography data frame was 640×480 . The algorithm was implemented using Matlab v7.10 (MathWorks Inc., Natick, MA).

To evaluate the cardiac quiescence detection algorithm, synchronously acquired ECG data and B-mode echocardiography data were acquired from the apical four chamber by a single ultrasound operator. The interventricular septum (IVS) of the heart visible in this view was chosen for tracking purposes, as this feature has been shown to be a reliable indicator of coronary vessel motion [21].

Results

A raw B-mode echocardiography frame of the four-chamber apical view with the IVS indicated is shown in Fig. 2. For AD

Fig. 2 Raw B-mode echocardiography frame of the apical four-chamber view showing the interventricular septum (IVS)

filtering, the values for κ and the number of iterations were set by observing the gradient image and speckle characteristics of the US frame. The output of the AD filter applied to a raw US image shown in Fig. 2 for diffusion functions of $\kappa=1, 2$, and 5 for 100, 200, 500, and 1,000 iterations is shown in Fig. 3.

Note that for a κ value of 5, over-smoothing takes place, and the outer contour of the ROI diffuses into the rest of the image when the number of iterations increases. It was observed that 500 iterations with $\kappa=2$ adequately removed the speckle noise and enhanced the contrast for six of the seven subjects. The image sequence from one subject had predominant speckle noise over the ROI and required 1,000 iterations.

For the hard-thresholding process following the AD filtering, the threshold was manually determined from the

pixel value along the edges of the ROI in the speckled image. Note that this threshold can vary with the brightness and contrast of the image acquired following the AD filtering process.

In Fig. 4, the algorithm steps to detect the centroid of the IVS are illustrated for the US image shown in Fig. 2. Note that for this work, AD filtering was performed over the entire image. However, it is sufficient to perform filtering over a roughly estimated area containing the ROI rather than the entire image as long as the area contains the ROI in all frames. Figure 4a–c demonstrates an AD-filtered US image, the binary thresholded image after AD filtering upon which the boundary detection is performed, and the detected boundary and centroid of the IVS, respectively.

Fig. 3 a–i Effect of anisotropic diffusion on the raw B-mode echocardiography frame in Fig. 2 for diffusion function $\kappa=1, 2$, and 5 for iterations $N=100, 500, 1,000$

Fig. 4 **a** Despeckled US image after performing AD. **b** Binary thresholded US image. **c** Raw US image with the boundary along the ROI, i.e., IVS; the center of mass for the IVS is shown by the *plus sign*

Upon obtaining the centroids C of the IVS for the complete sequence of frames, we find the first difference ΔC of the centroids and obtain the magnitude of the two-dimensional velocity. We then observe the regions of minimal (near zero) velocity, which imply that there has been little to no motion between consecutive frames of B-mode data. The regions of quiescence are then indicated on the synchronously acquired ECG signal.

The results of this process are shown in Fig. 5 for one subject with an average heart rate of 57 bpm. The displacement in the x and y directions, the velocity obtained from the first difference of the displacement in the two directions obtained from the B-mode data, and the ECG signal for a segment of the data (two cardiac cycles) are shown. The region of quiescence is determined by a velocity threshold of 2 cm/s, i.e., the phases of the cardiac cycle below this velocity threshold are said to be quiescent. Given an acquisition time of 83 ms, this choice of velocity threshold corresponds to a feature displacement of 1.66 mm. Assuredly, any greater displacement would result in motion artifacts. Fortunately, the velocity magnitude is generally much less than this threshold during periods of cardiac quiescence as shown in Fig. 5. Note that the longest quiescent phase for each cycle is indicated by a gray-shaded region, and the start and stop times are indicated by the vertical bars.

For the seven subjects for whom the IVS was tracked, the average heart rate, the duration of longest quiescent phase in milliseconds, and the center of quiescence as a percentage of the cardiac cycle are shown in Table 1, with the variance shown in parenthesis.

Discussion

Our goal in this study was to obtain information about cardiac quiescence by observing the motion of the IVS. We have demonstrated the combined use of anisotropic diffusion,

binary thresholding, and boundary detection to segment and track the IVS from B-mode echocardiographic data to identify cardiac quiescent phases for gating purposes. Cardiac motion was tracked in two dimensions, as opposed to the conventional approach of motion tracking using tissue Doppler, which provides the velocity estimate solely in the direction of ultrasonic interrogation.

The results of this study, consisting of data from seven subjects with various heart rates, showcased the following findings. The longest duration of quiescence is observed to occur primarily in the diastolic portion of the cardiac cycle for six of the seven cases, with a shorter quiescence occurring in the systolic portion of the cardiac cycle. However, for one subject with an average heart rate of 66, the longest quiescent phase was observed to occur much earlier than the ECG-predicted diastolic portion of the cardiac cycle. On average, the longest quiescent phase for this subject was centered at 50.77 % (± 12.34 %) of the cardiac cycle during systole.

For the two subjects with higher heart rates (77 and 83 bpm), the duration of quiescence in the diastolic region is observed to be significantly lower, almost half that of subjects with lower heart rates. This is not unexpected because the duration of the diastolic quiescent phase has been shown to decrease as the heart rate increases [3, 5]. In addition, a quiescent phase with an average duration 136.66 ms centered at 45.2 % of the cardiac cycle was observed in systole for one subject with a heart rate of 77 bpm. With further increases in heart rate, the duration of diastolic quiescence may get shortened even more: therefore, the systolic quiescent phase may provide a better gating window.

In prospective ECG gating, in general, the same absolute percentage interval (40 % in systole and 70 % in diastole) is used as the center of the gating interval within a cardiac cycle. From the above analysis, we observe that this is suboptimal and could lead to motion-blurred images during cardiac CTCA examinations. Using a gating signal approach, where

Fig. 5 Displacement in **a** x and **b** y directions (in cm), **c** velocity (in cm/s), and **d** ECG signal. The *gray* regions in the velocity plot indicate that the velocity is below the threshold (2 cm/s), and the *vertical lines* associated with these gray regions indicate the start and stop of quiescence

the true mechanical motion is used to assist in predicting quiescence, may result in images of higher diagnostic quality. Our results suggest that the timing of cardiac quiescent phases is nondeterministic, i.e., the exact position and duration of cardiac quiescent phases on a beat-to-beat basis cannot be determined given just the cardiac cycle duration or the heart rate. This can also be observed from the results shown in Table 1 where the variance of the center of quiescence and the duration of quiescence is fairly significant. Though not indicated by Table 1, the timing of cardiac quiescent phases was found to vary even during individual acquisitions from the same subject.

Table 1 Cardiac quiescence statistics

Subject ID ^a	Average heart rate	Quiescence duration in milliseconds ^b	Center of quiescence (%) ^{b,c}	Number of cardiac cycles observed
1	54	405.00±15.0	75.58 %±2.59	27
2	55	493.00±6.00	77.51 %±4.13	33
3	57	307.60±2.10	75.85 %±1.89	9
4	62	319.40±2.90	74.82 %±4.13	10
5	66	362.85±5.40	50.77 %±12.34	10
6	77	161.66±0.30	84.10 %±0.84	12
7	83	195.00±3.00	71.38 %±6.93	10

^a Subjects sorted by average heart rate

^b Data presented as mean±standard deviation

^c Data presented as percentage of the R-R interval (i.e., % of cardiac cycle length). Longest quiescent durations were in diastole

A limitation of this study is that it is not executable in real-time due to the significantly higher computational intensity of the anisotropic diffusion step. The large number of iterations carried out in the despeckling process is a bottleneck in this algorithm. As a result, the algorithm cannot be used for real-time CTCA gating or the prediction of the quiescent phases in subsequent cycles. However, performing AD on a smaller region enclosing the ROI as opposed to the entire image can significantly reduce the computational time. Alternatively, AD could be performed offline to determine optimal gating parameters, i.e., start and stop of quiescent period, for an individual patient, and these parameters could be used to tailor prospective ECG gating for CTCA. This approach would add additional time and expense to patient care. Therefore, the relative improvement in CTCA image quality resulting from such an offline individualization of gating parameters is an important topic for further study.

A second limitation of this technique is that we perform two-dimensional US, and thus the motion in the z -direction, i.e., orthogonal to the imaging plane, is not captured. Two-dimensional US is superior to one-dimensional methods of imaging, such as tissue Doppler imaging as shown in [9], but is less accurate than three-dimensional imaging. However, the drawback with three-dimensional US is that the frame rate drops substantially, thus reducing temporal resolution of the observed quiescence.

Future work in this area concerns testing the proposed method on a larger subject population and formulating and testing gating techniques from the observed quiescence. For a larger number of subjects, it would be necessary to automate the selection of the binary image-intensity threshold. This could be accomplished by calculating the threshold from a histogram of the pixel intensities observed for each B-mode sequence [19].

Conclusions

We demonstrated that the gating intervals obtained from positional information of the IVS in the B-mode echocardiography data differ significantly from the current ECG gating intervals. Since B-mode echocardiography looks directly at cardiac motion, we submit that it may potentially provide a more consistent gating signal than ECG for cardiac CT applications. Future work will focus on observing the quiescence over a larger range of heart rates for the same subject and particularly determining if there is any quiescence detected by this algorithm in the diastolic region of the cardiac cycle for higher heart rates. In addition, we would like to observe the correlation between the motion from different ROIs for the same set of frames, to study if quiescence occurs simultaneously or with a delay, on all parts of the left ventricle and eventually the other regions of the heart. Additionally, we would like to retain the speckle noise and observe if tracking this speckle noise enables better motion analysis and quiescence prediction. Ultimately, we would like to develop algorithms using a nonlinear filtering approach to develop models for cardiac motion and prediction of quiescence. This will lead to optimal gating for CTCA.

Acknowledgments This work was supported by the Award Number K23EB013221 from the National Institute of Biomedical Imaging and Bioengineering. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institute of Biomedical Imaging and Bioengineering or the National Institutes of Health.

References

- Go AS, Mozaffarian D, Roger VL, Benjamin EJ, Berry JD, Borden WB, Bravata DM, Dai S, Ford ES, Fox CS, Franco S, Fullerton HJ, Gillespie C, Hailpern SM, Heit JA, Howard VJ, Huffman MD, Kissela BM, Kittner SJ, Lackland DT, Lichtman JH, Lisabeth LD, Magid D, Marcus GM, Marelli A, Matchar DB, McGuire DK, Mohler ER, Moy CS, Mussolino ME, Nichol G, Paynter NP, Schreiner PJ, Sorlie PD, Stein J, Turan TN, Virani SS, Wong ND, Woo D, Turner MB, American Heart Association Statistics Committee and Stroke Statistics Subcommittee: Heart disease and stroke statistics—2013 update: a report from the American Heart Association. *Circulation* 127:e6–e245, 2013
- Budoff MJ, Achenbach S, Blumenthal RS, Carr JJ, Goldin JG, Greenland P, Guerci AD, Lima JAC, Rader DJ, Rubin GD, Shaw LJ, Wiegers SE, American Heart Association Committee on Cardiovascular Imaging and Intervention, American Heart Association Council on Cardiovascular Radiology and Intervention, American Heart Association Committee on Cardiac Imaging, Council on Clinical Cardiology: Assessment of coronary artery disease by cardiac computed tomography: a scientific statement from the American Heart Association Committee on Cardiovascular Imaging and Intervention, Council on Cardiovascular Radiology and Intervention, and Committee on Cardiac Imaging, Council on Clinical Cardiology. *Circulation* 114:1761–1791, 2006
- Desjardins B, Kazerooni EA: ECG-gated cardiac CT. *AJR Am J Roentgenol* 182:993–1010, 2004
- Bruschke AVG, Sheldon WC, Shirey EK, Proudfit WL: A half century of selective coronary arteriography. *Journal of the American College of Cardiology* 54:2139–2144, 2009
- Earls JP, Berman EL, Urban BA, Curry CA, Lane JL, Jennings RS, McCulloch CC, Hsieh J, Londt JH: Prospectively gated transverse coronary CT angiography versus retrospectively gated helical technique: improved image quality and reduced radiation dose. *Radiology* 246:742–753, 2008
- Achenbach S, Ulzheimer S, Baum U, Kachelriess M, Ropers D, Giesler T, Bautz W, Daniel WG, Kalender WA, Moshage W: Noninvasive coronary angiography by retrospectively ECG-gated multislice spiral CT. *Circulation* 102:2823–2828, 2000
- Mao S, Budoff MJ, Bin L, Liu SC: Optimal ECG trigger point in electron-beam CT studies: three methods for minimizing motion artifacts. *Acad Radiol* 8:1107–1115, 2001
- Tridandapani S, Fowlkes JB, Rubin JM: Echocardiography-based selection of quiescent heart phases: implications for cardiac imaging. *Journal of Ultrasound in Medicine* 24(11):1519–1526, 2005
- Wick CA, McClellan JH, Ravichandran L, Tridandapani S: Detection of cardiac quiescence from b-mode echocardiography using a correlation-based frame-to-frame deviation measure. *Translational Engineering in Health and Medicine, IEEE Journal of* 1:1900211, 2013
- Yu Y, Acton ST: Speckle reducing anisotropic diffusion. *IEEE Trans on Image Process* 11:1260–1270, 2002
- Rubin JM, Feng M, Hadley SW, Fowlkes JB, Hamilton JD: Potential use of ultrasound speckle tracking for motion management during radiotherapy: preliminary report. *J Ultrasound Med* 31: 469–481, 2012
- Geric G, Kubler O, Kikinis R, Jolesz FA: Nonlinear anisotropic filtering of MRI data. *IEEE Trans Med Imaging* 11:221–232, 1992
- Lee J-S: Digital image enhancement and noise filtering by use of local statistics. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 2:165–168, 1980
- Lee J-S: Refined filtering of image noise using local statistics. *Computer Graphics and Image Processing* 15:380–389, 1981
- Lee J-S: Speckle suppression and analysis for synthetic aperture radar images. *Opt Eng* 25:255636, 1986
- Frost VS, Stiles JA, Shanmugan KS, Holtzman JC: A model for radar images and its application to adaptive digital filtering of multiplicative noise. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 4:157–166, 1982
- Kuan DT, Sawchuk AA, Strand TC, Chavel P: Adaptive restoration of images with speckle. *Acoustics, Speech and Signal Processing, IEEE Transactions on* 35:373–383, 1987
- Perona P, Malik J: Scale-space and edge detection using anisotropic diffusion. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 12:629–639, 1990
- Otsu N: A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics* 9:62–66, 1979
- González RC, Woods RE: *Digital Image Processing*. Pearson Prentice Hall, Upper Saddle River, 2008
- Liu G, Qi X-L, Robert N, Dick AJ, Wright GA: Ultrasound-guided identification of cardiac imaging windows. *Med Phys* 39:3009–3018, 2012