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A method to correct background phase offset for phase-contrast MRI in the presence of steady flow and spatial wrap-around artifact

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Abstract

Purpose—Background phase offsets (BPO) in phase contrast (PC) MRI are often corrected using polynomial regression; however, correction performance degrades when temporally-invariant outliers such as steady flow or spatial wrap-around artifact are present. We describe and validate an iterative method, called Automatic Rejection of Temporally-invariant Outliers (ARTO), that excludes these outliers from the fitting process.

Theory and Methods—ARTO iteratively removes pixels with large polynomial regression errors analyzed by a Gaussian mixture model fitting of the residual distribution. One-hundred-fifty trials of a simulated phantom (75 with wrap-around artifact) and 125 PC-MRI cines from 22 healthy subjects (48 with wrap-around artifact) were used for validation. BPO offsets were corrected using 2nd order weighted regularized least squares (WRLS) with and without ARTO. Flow volumes after WRLS and WRLS+ARTO corrections were compared to the known truth (phantom) and stationary phantom reference (in vivo) using Bland-Altman analysis. Qp/Qs ratio was also computed in a subset of 6 subjects.

Results—In the simulated phantom, compared to WRLS and no-correction, correction with WRLS+ARTO produced superior agreement in volumetric flow quantification with the known truth. In vivo, WRLS+ARTO also produced superior agreement with stationary phantom corrected volumetric flow compared to WRLS and no-correction. In datasets with wrap-around artifact, WRLS produced significantly larger variance in Qp/Qs ratio than stationary phantom correction ($P=0.0008$).

Conclusion—The proposed method provides automatic exclusion of temporally-invariant outliers and produces flow quantification results comparable to stationary phantom correction.

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Keywords

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INTRODUCTION

Time-resolved phase-contrast magnetic resonance imaging (PC-MRI) is a valuable tool for clinical assessment of cardiovascular hemodynamics (1,2). In particular, volumetric flow quantification using PC-MRI has been shown to provide repeatable measurements of stroke volume, intracardiac shunt flow (3), and valvular regurgitation fraction (4,5). Accurate measurement of such flow indices is critical for the evaluation of cardiovascular disease (6). However, the accuracy of flow quantification is compromised by spatially-varying background phase errors. One source of these phase errors is concomitant gradient field effects. The correction for these effects can be derived directly from the gradient waveforms and is generally included as part of the standard reconstruction pipeline on modern MR systems (7). Eddy currents generated by the rapidly switching magnetic field gradients are another source of spatially-varying background phase. While eddy current pre-emphasis of the gradient waveforms may reduce some of this background phase (8), residual background phase offset (BPO) often remains.

The double integration over both space and time required to calculate net volumetric flow allows even small BPO to propagate into large errors in flow quantification. The scope of this problem was explored by Gatehouse et al. across twelve sites and three scanner models, each from different vendors. All twelve sites were found to exhibit BPO significant enough to generate > 5% error in stroke volume or > 10% error in shunt flow (9). Several techniques have been proposed to correct for BPO. For instance, repeating PC-MRI acquisitions with identical scan parameters on a stationary phantom has been used as a reference for BPO (10). The original phase image can then be corrected by direct pixelwise phase subtraction. While this method has been repeatedly shown to improve the accuracy and diagnostic quality of flow measurements (11–14), widespread clinical adoption has been hampered by the time required to setup and perform additional phantom scans after the patient has been removed from the magnet. Consequently, background phase correction methods which do not require additional data acquisition are preferred. As originally proposed by Walker et al., a polynomial surface may be fit using the time-averaged measured phase in the outlying stationary tissue, thus estimating BPO over the entire field-of-view (FOV) (15,16). Subtraction of the fitted surface from the phase image provides the correction. Discrimination between stationary and non-stationary pixels is made through binary thresholding based on the temporal standard deviation of the phase. For instance, Walker et al. found success by classifying pixels with temporal standard deviation in the bottom 15th percentile as stationary (15). Lankhaar et al. reported similar findings (16).

Despite the presence of higher-order BPO (17–19), the instability of higher-order polynomial surface fitting when stationary tissue is limited (19) – as is the case in thoracic imaging – means linear fits are typically employed in practice (16) at the cost of reduced

accuracy (18,20). Various approaches have been proposed recently which aim to improve the stability of higher-order surface fitting. These include weighted least squares (17), self-calibration by constraining the residual to reside within specified values (18), or regularization of polynomial coefficients, thereby preventing overfitting (21).

Regardless of the approach or polynomial order used, the success of image-based background phase correction via polynomial regression ultimately depends on the individual contributions of pixels included in fitting. Inclusion of pixels that belong to regions with flow or spatial wrap-around artifact can negatively impact the accuracy of BPO correction. Although temporal standard deviation of phase can effectively identify pixels with pulsatile flow, it cannot distinguish steady flow, e.g., in veins, from stationary tissue. Also, temporal standard deviation of phase alone cannot discriminate regions of spatial wrap-around artifact from the rest of the image. When wrap-around artifact is present, the spatially-varying BPO in the stationary tissue is mapped to image positions different from its physical locations, leading to phase discontinuity in the measured phase image. Such discontinuity causes large fitting errors, and depending on the extent of wrap-around, may even amplify BPO around the region of interest. Furthermore, wrap-around artifacts can be encountered on a regular basis in clinical exams. In a 2013 study by Rigsby et al. (22), 157 pediatric patients underwent PC-MRI of the ascending aorta and main pulmonary artery. Data from 29 (18.5%) of these patients were eventually excluded because their automated BPO correction algorithm failed due to wrap-around artifact.

Although oversampling along the phase encoding dimension can produce images free of wrap-around artifacts (23), such a remedy will prolong scan time and require longer breath-holds. Manual segmentation of steady flow or wrap-around artifact prior to polynomial surface fitting can also eliminate such outliers, but it can hamper the clinical workflow. In this work, we present a fully-automated method, called Automatic Rejection of Temporally-invariant Outliers (ARTO), to iteratively identify outliers. The ARTO method is coupled with a weighted regularized least squares (WRLS) polynomial fitting and validated using simulated data and PC-MRI data collected from twenty-two volunteers.

THEORY

Weighted Regularized Least Squares

Residual background phase offsets may be estimated by polynomial regression of stationary pixels in the temporally-averaged phase image. Most commonly, this is done by solving the ordinary least-squares problem:

$$\hat{\mathbf{x}} = \operatorname{argmin}_{\mathbf{x}} \|\mathbf{PM}(\mathbf{Ax} - \boldsymbol{\phi})\|_2^2 \quad [1]$$

where vector $\mathbf{x}$ represents the coefficients of a polynomial surface of arbitrary order, each column of matrix $\mathbf{A}$ has unit norm and defines the spatial distribution of one of the polynomial terms, vector $\boldsymbol{\phi} \in [-\pi, \pi]$ is the temporally-averaged, measured phase image, and computing $\mathbf{Ax}$ gives the estimate of BPO. Binary classification of an i^{th} pixel as

stationary or non-stationary is typically based on user-defined thresholding of its temporal standard deviation, σ_i , of the measured phase, wherein only pixels classified as stationary are used for the fit. Likewise, similar binary classification may be performed based on magnitude thresholding designed to further exclude low-signal pixels such as those from air. Here, row-pruning operators (i.e., identity matrices with some of the rows omitted), M and P , represent binary exclusion based on the magnitude and temporal standard deviation of phase, respectively, and may be viewed as a masking of the phase image.

An alternative and potentially more robust approach (17) to overfitting when stationary tissue is limited involves solving for the polynomial coefficients via weighted least-squares (WLS):

$$\hat{\mathbf{x}} = \operatorname{argmin}_{\mathbf{x}} \|WM(A\mathbf{x} - \boldsymbol{\phi})\|_2^2, \quad [2]$$

where diagonal matrix W replaces P as a pixelwise weighting operator. To emphasize pixels with lower temporal standard deviation of phase, the diagonal entries in W are set as $1/\sigma_i$. While suppressing contributions from pixels with pulsatile flow, inclusion of W in Eq. 2 also deemphasizes pixels with low magnitude because such pixels have larger σ_i values. However, when pixel magnitude is zero or small compared to the noise floor, the phase noise cannot be approximated by a Gaussian distribution, and σ_i for that pixel does not tend to infinity but tends to a finite value of $\pi/\sqrt{3}$. To explicitly exclude these pixels the operation M is utilized in conjunction with W .

Robustness of WLS to overfitting may be further improved through weighted regularized least squares (WRLS) (21), where an ℓ_1 - or ℓ_2 -norm penalty is enforced on the polynomial coefficients and the resulting $\ell_2 - \ell_2$ or $\ell_2 - \ell_1$ optimization problem can be solved using one of many optimization routines (24). Compared to ℓ_2 -norm penalty, ℓ_1 -norm penalty encourages the under-contributing coefficients to be set to zero and thus acts as a means to model reduction (25). This allows for estimation of higher order background phase while reducing the risk of overfitting when stationary tissue is limited. The resulting $\ell_2 - \ell_1$ optimization can be expressed as

$$\hat{\mathbf{x}} = \operatorname{argmin}_{\mathbf{x}} \|WM(A\mathbf{x} - \boldsymbol{\phi})\|_2^2 + \lambda \|\mathbf{x}\|_1. \quad [3]$$

Regularization strength, λ , is a positive constant which determines the balance between the data fidelity and regularizing terms. Optimum λ may be determined empirically and applied generally or determined automatically and applied on an individual basis using methods such as the L-curve criterion (26). Hereafter, correction via Eq. 3 will be referred to as WRLS.

Automatic Rejection of Temporally-invariant Outliers (ARTO)

The non-conformity of spatially localized outliers, such as steady flow and spatial wrap-around artifact, to polynomial fitting can be leveraged to identify and exclude them. Here,

we propose an outlier rejection scheme, ARTO, that identifies pixels with relatively large residual error, $WM(A\hat{x} - \phi)$ and iteratively removes them from the fitting process, leading to a more robust BPO correction. Mathematically, this process is captured in Eq. 4,

$$\hat{x}^k = \operatorname{argmin}_x \|S^k WM(Ax - \phi)\|_2^2 + \lambda \|x\|_1 \quad [4]$$

where S^k is a row pruning operator that enforces a binary inclusion mask. The operator, S^k , is updated iteratively for $k = 0, 1, 2, \dots, K_{max}$, and the resulting optimization problem (Eq. 4) is solved after every update of S^k . Furthermore, S^k is initialized so as to accentuate residual error in wrap-around artifact. The process of initializing and updating S^k and $\hat{x}^k$ is summarized below.

1. Initialize S^k ($k = 0$) such that only a central region in the phase-encode (PE) direction (e.g., $FOV_{PE}/2 \pm FOV_{PE}/4$) assumed free from spatial wrap-around artifact is accepted.
2. Solve Eq. 4 to obtain polynomial coefficients, $\hat{x}^k$, and compute the k^{th} estimate of the background phase correction map, $A\hat{x}^k$, over the full FOV. For $k = 0$, calculation of $A\hat{x}^k$ represents extrapolation from the central initialization region.
3. Compute weighted residual error (ϵ^k) between the measured phase (ϕ) and k^{th} estimate of the background phase correction map ($A\hat{x}^k$) using the following equation:

$$\epsilon^k = WM(A\hat{x}^k - \phi). \quad [5]$$

4. Fit the histogram of ϵ^k with a three-component Gaussian Mixture Model (GMM) using an expectation-maximization algorithm (27), yielding

$$(\mu_l^k, \gamma_l^k, \mu_c^k, \gamma_c^k, \mu_r^k, \gamma_r^k) = \mathcal{G}(\epsilon^k, \delta), \quad [6]$$

where $\mathcal{G}$ represents GMM fitting, $\delta > 0$ represents a user-defined minimum distance enforced between the means of the Gaussian components to avoid degenerate fitting, $\mu_l^k, \mu_c^k, \mu_r^k$ represent means of left, central, and right Gaussian components, respectively, and $\gamma_l^k, \gamma_c^k, \gamma_r^k$ represents standard deviations of left, central, and right Gaussian components, respectively.

5. The outlier mask, S^k , for the i^{th} pixel is updated based on the following rule:

$$S_i^{k+1} = \begin{cases} 0, & \epsilon_i^k \geq |\mu_c^k \pm \tau \gamma_c^k| \\ 1, & \epsilon_i^k < |\mu_c^k \pm \tau \gamma_c^k| \end{cases} \quad [7]$$

where τ is a user-defined constant which determines the strength of exclusion.

6. Step $k = k + 1$. Repeat Steps 2–6 while $k < K_{max}$, where K_{max} is the maximum number of iterations.
7. On the final iteration ($k = K_{max}$), solve Eq. 4 using $S^{K_{max}}$ to obtain polynomial coefficients, $\hat{x}^{K_{max}}$.
8. Finally, subtract the BPO correction map ($A\hat{x}^{K_{max}}$) from the measured phase (ϕ) to obtain the final corrected phase image, $\phi_C = \phi - A\hat{x}^{K_{max}}$.

Although the steps listed above utilize WRLS regression, ARTO can be equally applied with WLS as well. The ARTO procedure is also summarized in Figure 1. In the following analysis, two iterations ($K_{max} = 2$) of ARTO are performed. Furthermore, the initial polynomial fitting ($k = 0$) from the central PE FOV is first order; subsequent iterations utilize second order polynomials. Further parameters used for WRLS+ARTO are listed in the Methods. Description of these parameter choices can also be found in the Discussion.

METHODS

Simulated Phantom

A simulated phantom to test the impact of ARTO on BPO correction was constructed in MATLAB (MathWorks, Natick, MA) and was designed to mimic the limited stationary tissue when imaging the thoracic aorta. Each phantom trial was composed of a single magnitude image (binary mask), a single time-averaged phase image, and a temporal standard deviation map representing the underlying standard deviation across frames, which were not simulated explicitly. The initial phase in the stationary tissue set at zero. Two vessels, one with pulsatile flow and the other with steady flow, were simulated for flow quantification. The time-averaged phase in each of the two vessels was randomly selected in the range of $\pm[\pi/15 \text{ to } \pi/6]$ radians and $\pm[\pi/30 \text{ to } \pi/15]$ radians for the pulsatile and steady vessels, respectively. Randomized background phase, simulated as a 2nd order polynomial with the origin defined at the center of the image and coefficients derived from a random normal distribution, was generated and added to the phase image. Second order coefficients were weighted down by a factor of 10 relative to the intercept and first order coefficients to minimize exaggerated quadratic behavior. White Gaussian noise with standard deviation of $\pi/(300\sqrt{20})$ radians (as described in Table 1) was additionally added to the phase image. Temporal standard deviations of the two vessels were randomly selected; however, compared to the vessel with steady flow, the temporal standard deviation of the vessel with pulsatile flow was substantially higher. Temporal standard deviation within the stationary tissue was constant ($\pi/300$ radians) and was smaller than in either vessel. A summary of the parameters used to construct the phantom are listed in Table 1.

One hundred and fifty trials were conducted, each with randomized vessel phase (flow), background phase, and temporal standard deviations. In 75 of these trials, wrap-around artifact was induced prior to background phase correction through image-domain zero-

padding and k-space downsampling by a random amount uniformly distributed between 0 to 20% of the FOV in either direction. In some cases, tissue-on-tissue overlap occurred.

In Vivo PC-MRI Acquisition

Twenty-two healthy subjects (age range, 19–44) were prospectively recruited for this study. Informed written consent was obtained from each subject prior to scanning. This study was approved by the local internal review board. All subjects were imaged on a 3T clinical MR system (MAGNETOM Trio, Siemens Healthcare, Erlangen, Germany). Breath-held, segmented, 2D PC-MRI cines were acquired using a FLASH-based pulse sequence with through-plane velocity encoding and retrospectively gated into twenty cardiac phases (4–5 lines per cardiac cycle) using each subject's ECG signal. Acquisition parameters for PC-MRI were as follows: TR: (5.21 – 5.83) ms, TE: (2.14 – 3.09) ms, flip angle: 15°, FOV_{PE}: (146–425) mm, FOV_{FE}: (289–425) mm, spatial resolution (PE): (1.7 – 3.3) mm, spatial resolution (FE): (1.6 – 3.3) mm, slice thickness: 6 mm, and rate 2 GRAPPA acceleration (24 auto-calibration lines, integrated). One or more of the following imaging planes transecting the great vessels of the heart were prescribed for each subject: the aorta at the level of the main pulmonary artery and at the level of the abdomen, main pulmonary artery, right pulmonary artery, and left pulmonary artery. To limit scan times to within one hour, not all views were collected in all subjects. Exact slice orientations varied between individuals. Velocity encoding (VENC) ranged from 90 cm/s to 175 cm/s and was adjusted for each subject and vessel of interest to ensure adequate velocity-to-noise ratio and to avoid velocity aliasing. In some subjects, imaging planes were reacquired after shifting and/or reducing the FOV to introduce spatial wrap-around artifact. Out of 125 datasets in total, 48 were collected with, and 77 were collected without wrap-around artifact. To establish a reference for the background phase, all PC-MRI acquisitions were repeated with identical parameters on a stationary oil calibration phantom immediately after the subject was removed from the magnet. It was ensured that there was no wrap-around artifact covering the vessels of interest in the stationary phantom images. The parameter ranges for in vivo acquisition are provided in Table 2.

Post-processing

For the simulated phantom, flow quantification through the pulsatile vessel was performed for each trial. Volumetric flow rate was calculated by averaging the velocity, $VENC \times (\phi/\pi)$, of pixels in the pulsatile vessel and multiplying it with vessel area ($1.5 \times 1.5 \text{ mm}^2$ spatial resolution). Multiplication by the simulated cardiac period (1 s) yielded net volumetric flow. For a summary of parameters used for quantification, refer to Table 1.

All in vivo images were reconstructed on the scanner with automatic Maxwell correction. Semi-automatic segmentation of the vessels of interest was performed using the freely available software package Segment v2.0 R5201 (<http://segment.heidelberg.se>) (28). Flow quantification and background phase correction were performed using custom-built MATLAB software. Net volumetric flow through the cardiac cycle was computed for the ascending and descending aorta (AAo and DAo) at the level of the main pulmonary artery, abdominal aorta (AbAo), and the main, right, and left pulmonary arteries (MPA, RPA, and LPA) before and after background phase correction. In a subset of 6 subjects in which both

the AAo and MPA were imaged with and without wrap-around artifact, the ratio (Q_p/Q_s) between the pulmonary flow (Q_p) and systemic flow (Q_s) was also calculated.

In all datasets, residual BPO was corrected using weighted regularized least squares with and without ARTO (WRLS and WRLS+ARTO). For the initialization of WRLS+ARTO, $k = 0$, 1st order correction was applied to extrapolate beyond the central region to accommodate the potentially (very) limited stationary tissue and lower SNR in the central FOV; in subsequent iterations of WRLS and WRLS+ARTO, 2nd order correction was applied. Regularization strength, λ , was set to 50, which was manually tuned using four extra datasets not included in the results. The binary magnitude mask (M) was based on a 4% threshold, i.e., pixels with less than 4% of the maximum signal magnitude were removed by the application of M . The binary inclusion operator for ARTO, S^k , was initialized ($k = 0$) to only include pixels within the central 50% of the FOV in the PE direction ($FOV_{PE}/2 \pm FOV_{PE}/4$) to account for wrap-around artifact up to 25% of the FOV. The threshold, τ , for ARTO was set at 3, i.e., any pixel with a weighted residual beyond ± 3 standard deviations from the mean, μ_c^k , of the central Gaussian component was excluded. With perfect extrapolation to non-wrapped outlying stationary tissue, setting τ to 3 would capture 99.7% of pixels from the primary distribution. Minimum separation between Gaussian components, δ , for each iteration of Eq. 6 was set at $2\gamma_c^k$ to tolerate some overlap in the Gaussian components. Two iterations of ARTO ($K = 2$) were performed across all datasets. Typical computation time for in vivo datasets using ordinary computing resources was within 1 second.

To evaluate the performance of BPO correction methods in vivo, BPO correction was also performed by pixelwise subtraction of the reference BPO map from the corresponding PC-MRI phase images. The reference map was constructed from the stationary phantom PC-MRI cines, which were time-averaged across all twenty frames under the assumption that BPO remained stable between cardiac phases since retrospective gating was used (29). Thus, the same correction was applied for each cardiac phase.

Statistical Analysis

Bland-Altman analysis was used to assess the agreement of calculated net flow volume in the vessels before and after BPO correction in both the simulated phantom and in vivo datasets, with the true noiseless phase (flow) values and stationary phantom correction as the respective references. Mean biases and limits-of-agreement (LOA) were reported in terms of percent error.

Means and standard deviations of Q_p/Q_s ratios in the subset of six subjects before and after BPO correction were calculated. Medians, interquartile ranges, and ranges were also reported in box-and-whisker plots. Paired t -tests with respect to stationary phantom correction were performed to evaluate significant differences in mean Q_p/Q_s . F -tests with respect to stationary phantom correction were performed to assess differences in variance. Paired t -tests and F -tests were performed using the JMP Pro 12 (SAS Institute Inc, Cary, NC) software package. To account for multiple comparisons, Bonferroni correction (12

comparisons) was applied to an initial significance level of 0.05. Thus, statistical tests were reported as significant for P -values less than 0.05/12 or 0.0042.

RESULTS

Simulated Phantom

One representative trial of the simulated phantom with steady flow and wrap-around artifact exhibiting tissue-on-tissue overlap is shown in Figure 2. The BPO seen in the stationary tissue was generated with a 2nd order polynomial, however, the wrap-around artifact and overlap create spatial discontinuities in the distribution of phase (Figure 2A). Moreover, the vessel with steady flow (left) has a strong localized phase while still being weighted at a similar level as stationary tissue in the fitting (Figure 2B). Polynomial regression (WRLS) of the phase image without accounting for these two outliers (Figure 2D) unsurprisingly leads to poor correction of the BPO, as indicated by the remaining non-zero offsets seen in the stationary tissue in the corrected image (Figure 2C). WRLS+ARTO, in contrast, successfully excludes both the vessel with the steady flow and wrap-around artifact from the fitting (Figure 2F), resulting in a substantially improved correction of the background phase (Figure 2E). Figures 3A and 3B depict the weighted residual histograms and GMM components from the simulation example presented in Figure 2 after one and two iterations of ARTO, respectively. Pixels fit by WRLS+ARTO correspond to those with residuals contained within the ARTO thresholds (dashed lines). Pixelwise masks are displayed after the second iteration of ARTO for pixels with residuals less than, within, and greater than the ARTO thresholds.

Bland-Altman plots comparing net flow volumes in all 150 trials of the simulated phantom before and after background phase correction to the known truth are shown in Figure 4. In the 75 trials without wrap-around artifact (top), correction with 2nd order WRLS accounted for most of the BPO, with bias±LOA (in % error) of 0.09±2.0%, as compared to -0.19±10.06% for no-correction. Addition of ARTO to WRLS further improved agreement with -0.01±0.15%. In the 75 trials with wrap-around artifact (bottom), correction with WRLS alone performed worse than no-correction, with -0.30±11.84% for WRLS compared to 0.31±10.62%. Correction with WRLS+ARTO, however, performed best in these trials, with 0.02±0.86%, even in the presence of wrap-around artifact. Expanded Bland-Altman plots showing correction with weighted least squares (WLS) and weighted least squares with ARTO (WLS+ARTO) in the simulated phantom data is included in Supporting Information Figure S1.

In Vivo

The phase image for a typical slice transecting the thoracic aorta with wrap-around artifact is shown in Figure 5. While BPO is consistent with the tissue's physical location with respect to the gradient coils, there is a discontinuous transition due to the wrap-around artifact (Figure 5A). The wrap-around artifact is not distinguishable from ordinary stationary tissue by temporal standard deviation alone (Figure 5B). Applying WRLS polynomial regression in the stationary tissue without accounting for the wrap-around artifact thus incorrectly estimates the background phase, as clearly demonstrated by remaining non-zero offsets in

the corrected phase image (Figure 5C). After exclusion of the wrap-around artifact and slow flow by WRLS+ARTO (Figure 5F), the background phase correction is substantially improved (Figure 5E). A similar example for the main pulmonary artery view is shown in Figure 6. The evolution of the weighted residuals and GMM components for the in vivo examples in Figures 5 and 6 are shown in Supporting Information Figures S2 and S3, respectively.

Figure 7 compares the measured net flow volumes from the 125 quantified vessels before and after BPO correction with WRLS and WRLS+ARTO to the values obtained after stationary phantom correction using Bland-Altman analysis. When wrap-around artifact is not present (top), correction with 2nd order WRLS, unsurprisingly, improves agreement with stationary phantom correction with bias±LOA (in % error) from $-1.39\pm 8.16\%$ before correction to $0.44\pm 4.57\%$ after WRLS. Addition of ARTO to WRLS provides further improvement over WRLS with $0.29\pm 3.74\%$. In datasets with wrap-around artifact (bottom), indiscriminate correction with 2nd order WRLS performs worst overall with respect to stationary phantom correction, from $-1.10\pm 9.56\%$ before correction to $-1.20\pm 14.25\%$ after correction. WRLS+ARTO, in contrast, successfully excludes wrap-around artifact from the fittings, leading to the best overall agreement with $0.54\pm 3.64\%$, comparable to the levels seen in the datasets without wrap-around artifact. Expanded Bland-Altman plots showing correction with WLS and WLS+ARTO in the 22 healthy subjects is included in Supporting Information Figure S4. Although comprehensive analysis of BPO correction using higher order polynomials is beyond the scope of this work, additional expanded Bland-Altman plots showing in vivo datasets processed with 4th order BPO correction rather than 2nd order are included in Supporting Information Figure S5. As expected, advantage of WRLS over WLS is more pronounced for the 4th order fitting. The convergence profile of WRLS+ARTO over five iterations is also provided in Supporting Information Figure S6.

Qp/Qs ratios before and after BPO correction in the subset of six healthy subjects are shown in Figure 8. In datasets (N=6) without wrap-around in both the AAo or MPA, means ± standard deviations of Qp/Qs ratios were 1.10 ± 0.07 uncorrected, 1.05 ± 0.05 with stationary phantom correction, 1.06 ± 0.05 with WRLS, and 1.07 ± 0.05 with WRLS+ARTO. Neither the means nor variances of Qp/Qs ratios after no-correction, WRLS, and WRLS+ARTO were found to be significantly different from stationary phantom correction. In datasets (N=6) where wrap-around artifact was present in both the AAo and MPA images, means ± standard deviations of Qp/Qs ratios were 1.12 ± 0.05 uncorrected, 1.05 ± 0.02 with stationary phantom correction, 1.03 ± 0.14 with WRLS, and 1.07 ± 0.02 with WRLS+ARTO. The variance in Qp/Qs between WRLS and stationary phantom correction was found to be significantly different ($P=0.0008$) in these datasets.

DISCUSSION

Inadequate correction of BPO due to eddy currents may compromise the accuracy of flow quantification measurements. Although polynomial surface regression of pixels comprising stationary tissue are effective under ideal circumstances, such methods can fail in the presence of temporally-invariant outliers. In particular, presence of steady flow and spatial

wrap-around artifact can degrade the performance of WLS (Eq. 2) or WRLS (Eq. 3). In clinical application of PC-MRI, these outliers are routinely encountered. Here, we have presented an automated BPO correction procedure that is robust to such outliers. The proposed technique is based on weighted regularized least squares polynomial regression coupled with an outlier rejection method, ARTO, that iteratively eliminates outliers based on the residual.

Effects of steady flow and wrap-around artifact on polynomial regression were evaluated using a simulated phantom in which true flow volumes were known. The simulation process was repeated 150 times with different combinations of background phase, wrap-around extent, and flow parameters. For trials (N=75) without wrap-around artifact, WRLS correction improved flow quantification (top row, Figure 4), and the inclusion of ARTO to WRLS provided additional, albeit minor, improvement via exclusion of the steady vessel. For trials (N=75) with wrap-around artifact (bottom row, Figure 4), WRLS correction alone degraded flow quantification beyond no-correction. Inclusion of ARTO to WRLS in these trials provided substantial improvement over WRLS.

The in vivo results without wrap-around artifact (top row, Figure 7) also highlight the added benefit of ARTO, with WRLS+ARTO outperforming WRLS. The performance gain of WRLS+ARTO over WRLS, however, was modest due to the limited number of pixels with steady flow (outliers). In contrast, the results with wrap-around artifact (bottom row, Figure 7) highlight the limitation of WRLS, which does not account for outliers. Correction with WRLS not only failed to improve flow quantification error on average but instead resulted in greater error than no-correction. Inclusion of ARTO, brought the flow quantification errors down to the levels observed in the absence of wrap-around artifact. The impact of ARTO on WLS was similar to that on WRLS (Supporting Information Figures S1 and S4).

In the subset of 6 datasets without wrap-around artifact (Figure 8A), significant differences in Qp/Qs mean or variance were not discovered with respect to stationary phantom correction for uncorrected, WRLS, and WRLS+ARTO. Conversely, in datasets with wrap-around artifact (Figure 8B), degraded BPO correction with WRLS led to large variation in measured Qp/Qs ratios, performing significantly worse than stationary phantom correction. WRLS+ARTO was not impacted by wrap-around artifact, thus leading to similar Qp/Qs measurements as stationary phantom correction. Due to the small sample size, however, these statistical tests may have been insufficiently powered to detect additional differences, if present. The conservative Bonferroni correction, while decreasing the probability of Type 1 error from multiple tests, also increased our probability of committing a Type 2 error. Although datasets with and without wrap-around artifact in this subset came from the same subjects, and were collected using identical values of TE, TR, receiver bandwidth, VENC, spatial resolution, and temporal resolution, there was a discrepancy in the Qp/Qs standard deviation after stationary phantom correction between the two conditions. We conjecture this discrepancy could be the result of several possible factors. For one, in our acquisition workflow, there was consistently less delay between the AAo and MPA acquisitions in the datasets with wrap-around artifact. These datasets would thus be less susceptible to small variations in stroke volume over time. Breath-hold lengths were also generally longer for datasets not containing wrap-around artifact than those that did, possibly leading to small but

different perturbations in cardiac function as breath-holds are known to slightly affect flow (30), although all breath-holds in this study were conducted at full expiration.

Although the simulation study was setup to mimic in vivo acquisition, several differences were observed between the simulation and in vivo study. First, the performance of WRLS +ARTO for the simulation study was superior to that for the in vivo study. This discrepancy can be partially attributed to inherent noise in the stationary phantom reference (0.05% – 0.4% of Venc velocity noise standard deviation within vessel contours after time-averaging) (31), slightly different BPO in the stationary phantom than in vivo due to thermal drift (32), or potentially non-ideal BPO which cannot be perfectly described by a 2nd order polynomial for in vivo data. For simulation, in contrast, the reference was noiseless and the simulated BPO could be perfectly described by a 2nd order polynomial. Second, correction with WRLS in the presence of wrap-around artifact amplified BPO error both in simulation and in vivo; however, the effect was more pronounced in vivo. Along with the above explanations, this may also be attributed to the greater proportion of extensive wrap-around artifact in vivo. In the case of simulation, the wrap-around artifact was uniformly but randomly varied between 0 to 20% of FOV. In contrast, wrap-around artifact, whenever present, was typically in the 10–20% range for in vivo datasets. Also, Maxwell correction could further increase the BPO in the wrap-around region, exaggerating the impact of wrap-around artifact for the in vivo datasets. Third, the performance of WRLS+ARTO in simulation subtly degraded in the trials with wrap-around artifact compared to trials without, potentially due to decreased number, and spatial diversity of pixels available for fitting in these trials. This behavior was not observed in vivo, however it is possible such degradation still occurred only was masked by the larger LOA in vivo. Lastly, the in vivo datasets contained a diverse range of stationary tissue geometries owing to the variety of vessels imaged. In contrast, only a single geometry was evaluated in simulation.

Although some studies have shown the added benefit of using higher-order polynomials, we chose second order polynomial fitting because 1st and 2nd order fittings have been found to be adequate (16,19). Weighting (17) and regularization (21) can also help to stabilize 2nd order correction. The advantage of WRLS over WLS was subtle (Supporting Information Figures S1 and S4) for both phantom and in vivo data. Considering that the regularization in WRLS is intended to guard against overfitting when higher-order polynomials are used or when stationary tissue is scarce, the relative advantage of WRLS over WLS should grow with the polynomial order (Supporting Information Figure S5) or for imaging in pediatric patients with limited stationary tissue.

Fitting the three-component GMM does not require ideal weighted residuals (i.e. three separate, and distinct distributions) to be successful. Indeed, histograms shown in Figure 3 and Supporting Information Figures S2 and S3 all exhibit some deviation from ideality; WRLS+ARTO, nevertheless, still excluded substantial outliers from BPO correction. Because threshold criteria are based solely on statistics derived from the central component, this is the only component which needs to approximate its underlying distribution. The left, and right GMM components are designed to draw variance away from the central component to improve its estimation. Of course, this requires the underlying distribution approximated by the central GMM component to be Gaussian; however, non-Gaussian

secondary distributions or deviations from exactly three residual distributions can be tolerated.

Despite the encouraging results, this work has several limitations. First, the performance of WRLS and WRLS+ARTO is based on the λ value. We initially implemented an L-curve strategy (26) to automatically tune λ (data not shown) but found its performance to be equivalent to a manually-tuned fixed value. Although we found success using fixed λ and did not find the results to be sensitive to small changes in λ , it is possible that finding optimal λ becomes important when higher-order polynomials are used or when stationary tissue is extremely limited. For such cases, the L-curve strategy can be used to tune λ at the cost of added computational complexity. Note, however, that λ also depends on how the spatial distribution of the polynomial coefficients in matrix, A , in Eqs. 3 and 4 is defined. In this work, A was defined in terms of distance from the central pixel. Second, the performance of ARTO is dependent on the selection of τ and δ . We observed the values of 2 to 3 for τ and $2\gamma_c^k$ to $3\gamma_c^k$ for δ to generate consistent results, which is not surprising because a z-score of 2 to 4 is commonly used across many outlier rejection applications (33), although there is still considerable room for optimization. Third, we set $K_{max} = 2$, with the first iteration yielding most of the improvement (Supporting Information Figure S6). In future, we will consider automated methods based on the extent of ϕ update to terminate the iterative process. Fourth, constraining the initialization mask (S^0) to only the central 50% of pixels in the PE direction would be robust to wrap-around artifact covering up to 25% of the FOV. Extreme wrap-around artifact extending beyond this may cause ARTO to fail. It is possible to use a narrower S^0 to accommodate extreme cases, but such an initialization may require more iterations and may get stuck in bad local minima due to limited stationary tissue for $k = 0$. Indeed, successful application of ARTO is based on the assumption S^0 contains sufficient stationary tissue to reasonably extrapolate BPO to the remainder of the FOV; even an initialization of 50% has the potential to produce unsatisfactory results by further restricting what may already be extremely scarce stationary tissue in some cases. Applying 1st order regression only for $k = 0$ helps to mitigate this, as 1st order corrections tend to remain stable under limited tissue and low SNR conditions, without sacrificing the ability to estimate higher order BPO in subsequent iterations. Fifth, sample size to quantify Qp/Qs is small as previously addressed. Future studies will evaluate the impact of ARTO on Qp/Qs quantification in a larger cohort.

Although this work was focused on 2D PC-MRI, with only a few modifications, the general procedure of ARTO could be applied to correct BPO in 4D flow as well. For one, volumetric polynomial regression would have to be employed instead of the surface regression employed for 2D PC-MRI. Furthermore, corrections must be calculated separately for each velocity encoding component. Finally, the nature of volumetric k-space sampling in 4D flow gives the potential for wrap-around artifact to occur not only in the PE direction but also in the through-slab direction unless sufficient through-slab oversampling is utilized, at the cost of increased acquisition time.

Lastly, the rapid processing time (~ 1 s) of WRLS+ARTO makes it computationally feasible to be implemented during inline image reconstruction, similar to the algorithm developed by Rigsby et al. (22), Philips's "LPC filter", or automatic Maxwell correction.

CONCLUSION

Spatially varying BPO due to eddy currents can compromise the accuracy of flow quantification in PC-MRI, which may lead to clinical mischaracterization of stroke volume, intra-cardiac shunt flow, and valvular regurgitation fraction. Polynomial surface regression of outlying stationary pixels commonly utilized to correct for BPO often becomes unreliable in the presence of localized outliers such as steady venous flow or wrap-around artifact which are routinely encountered in the clinic. We have described an iterative outlier rejection procedure coupled with weighted regularized least squares regression (WRLS+ARTO) designed to automatically identify and exclude these outliers from the fit. We found that while steady flow can cause small errors in BPO correction, wrap-around artifact can substantially decrease flow quantification accuracy when not taken into account. We validated WRLS+ARTO in a simulated phantom and in 22 healthy subjects and found WRLS+ARTO produced strong agreement in flow quantification measurements with the stationary phantom reference over no-correction and WRLS, even when extensive wrap-around artifact was present.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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REFERENCES

1. Nayler GL, Firmin DN, Longmore DB. Blood flow imaging by cine magnetic resonance. *J Comput Assist Tomogr* 1986;10:715–722. [PubMed: 3528245]
2. Nayak KS, Nielsen JF, Bernstein MA, Markl M, Gatehouse PD, Botnar RM, et al. Cardiovascular magnetic resonance phase contrast imaging. *J Cardiovasc Magn Reson* 2015;17:71. [PubMed: 26254979]
3. Colletti PM. Evaluation of intracardiac shunts with cardiac magnetic resonance. *Curr Cardiol Rep* 2005;7:52–58. [PubMed: 15610649]
4. Rebergen SA, Chin JG, Ottenkamp J, van der Wall EE, de Roos A. Pulmonary regurgitation in the late postoperative follow-up of tetralogy of Fallot. Volumetric quantitation by nuclear magnetic resonance velocity mapping. *Circulation* 1993;88:2257–2266. [PubMed: 8222120]
5. Gelfand EV, Hughes S, Hauser TH, Yeon SB, Goepfert L, Kissinger KV, Rofsky NM, Manning WJ. Severity of Mitral and Aortic Regurgitation as Assessed by Cardiovascular Magnetic Resonance: Optimizing Correlation with Doppler Echocardiography. *J Cardiovasc Magn Reson* 2006;8:503–507. [PubMed: 16755839]
6. Richter Y, Edelman ER. Cardiology Is Flow. *Circulation* 2006;113:2679–2682. [PubMed: 16769924]

7. Bernstein MA, Zhou XJ, Pelc NJ, Polzin JA, King KF, Ganin A, Pelc NJ, Glover GH. Concomitant Gradient Terms in Phase Contrast MR: Analysis and Correction. *Magn Reson Med* 1998;300–308. [PubMed: 9469714]
8. Bernstein MA, King KF, Zhou XJ. *Handbook of MRI Pulse Sequences*. Burlington: Academic Press 2004;292–362.
9. Gatehouse P, Rolf MP, Graves MJ, et al. Flow measurement by cardiovascular magnetic resonance: a multi-centre multi-vendor study of background phase offset errors that can compromise the accuracy of derived regurgitant or shunt flow measurements. *J Cardiovasc Magn Reson* 2010;12:5 [PubMed: 20074359]
10. Caprihan A, Altobelli SA, Benitez-Read E. Flow-velocity imaging from linear regression of phase images with techniques for reducing eddy-current effects. *J Magn Reson* 1990;90:71–89.
11. Chernobelsky A, Shubayev O, Comeau CR, Wolff SD. Baseline correction of phase contrast images improves quantification of blood flow in the great vessels. *J Cardiovasc Magn Reson* 2007;9:681–685. [PubMed: 17578724]
12. Miller TA, Landes AB, Moran AM. Improved accuracy in flow mapping of congenital heart disease using stationary phantom technique. *J Cardiovasc Magn Reson* 2009;11:52. [PubMed: 20003318]
13. Holland B, Printz B, Lai W. Baseline correction of phase-contrast images in congenital cardiovascular magnetic resonance. *J Cardiovasc Magn Reson* 2010;12:11. [PubMed: 20205725]
14. Nelson EA, Hsu L-Y, Noreuil A, Berger, SE, et al. The Magnitude of Static Phantom Corrections for Velocity Encoded Phase Contrast Cine MRI and Clinical Importance. In *Proceedings of the 25th Annual International Society of Magnetic Resonance in Medicine*, Honolulu, HI, 2017 p. 2850.
15. Walker PG, Cranney GB, Scheidegger MB, Waseleski G, Pohost GM, Yoganathan AP. Semiautomated method for noise reduction and background phase error correction in MR phase velocity data. *J Magn Reson Imaging* 1993;3:521–530. [PubMed: 8324312]
16. Lankhaar JW, Hofman MBM, Marcus JT, Zwanenburg JJM, Faes TJC, Vonk-Noordegraaf A. Correction of phase offset errors in main pulmonary artery flow quantification. *J Magn Reson Imaging* 2005;22:73–79. [PubMed: 15971181]
17. Ebbers T, Haraldsson H, Dyverfeldt P. Higher order weighted least-squares phase offset correction for improved accuracy in phase-contrast MRI. In *Proceedings of the 16th Annual International Society of Magnetic Resonance in Medicine*, Toronto, Canada, 2008 p. 1367.
18. Tan ET, Glockner JF, Solana AB, Stanley DW, Hardy CJ. Self-calibrated phase-contrast correction of nonlinear background phase in quantitative cardiac imaging. In *Proceeding of the 22nd International Society of Magnetic Resonance in Medicine*, Milan, Italy 2014; p. 3849.
19. Busch J, Giese D, Kozerke S. Image-based background phase error correction in 4D flow MRI revisited. *J Magn Reson Imaging* 2017;46:1516–1525. [PubMed: 28225577]
20. Nilsson A, Bloch KM, Toger J, Heiberg E, Stahlberg F. Accuracy of four-dimensional phase-contrast velocity mapping for blood flow visualizations: a phantom study. *Acta Radiol* 2013;54:663–671. [PubMed: 23486562]
21. Ahmad R, Jin N, Simonetti OP. Background Phase Correction for Quantitative Phase-Contrast MRI. In *Proceedings of the 24th International Society of Magnetic Resonance in Medicine*, Singapore 2016 p. 2584.
22. Rigsby CK, Hilpiper N, McNeal GR, Zhang G, Boylan EE, Popescu AR, et al. Analysis of an automated background correction method for cardiovascular MR phase contrast imaging in children and young adults. *Pediatr Radiol* 2014;44:265–273. [PubMed: 24306733]
23. Winkelmann R, Bornert P, Nehrke K, Dossel O. Efficient foldover suppression using SENSE. *Magn Reson Mater Phy* 2005;18:63–68.
24. Beck A, Teboulle M. A Fast Iterative Shrinkage-Thresholding Algorithm for Linear Inverse Problems. *Soc Ind Appl Math J Imaging Sci* 2009;2:183–202.
25. Tibshirani R Regression Shrinkage and Selection via the Lasso. *J R Stat Soc Ser B* 1996;58:267–288.
26. Hansen PC. The L-Curve and its Use in the Numerical Treatment of Inverse Problems. *Comput Inverse Prob Electromagnetics* ed P Johnston *Adv Comput Bioeng* 2000;4:119–142.

27. Dempster AP, Laird NM, Rubin DB. Maximum Likelihood from Incomplete Data via the EM Algorithm. *J R Stat Soc Ser B* 1977;39:1–38.
28. Heiberg E, Sjögren J, Ugander M, Carlsson M, Engblom H, Arheden H. Design and validation of Segment - freely available software for cardiovascular image analysis. *BMC Med Imaging* 2010;10
29. Sondergaard L, Stahlberg F, Thomsen C, Spraggins TA, Gyomai E, Malmgren L, et al. Comparison Between Retrospective Gating and ECG Triggering in Magnetic Resonance Velocity Mapping. *Magn Reson Imaging* 1993;11:533–537. [PubMed: 8316066]
30. Sakuma H, Kawada N, Kubo H, Nishide Y, Takano K, Kato N, et al. Effect of Breath Holding on Blood Flow Measurement Using Fast Velocity Encoded Cine MRI. *Magn Reson Med* 2001;45:346–348. [PubMed: 11180443]
31. Conturo TE, Smith GD. Signal-to-noise in phase angle reconstruction: Dynamic range extension using phase reference offsets. *Magn. Reson. Med* 1990;15:420–437. [PubMed: 2233221]
32. Gatehouse PD, Rolf MP, Bloch KM, Graves MJ, Kilner PJ, Firmin DN, et al. A multi-center inter-manufacturer study of the temporal stability of phase-contrast velocity mapping background offset errors. *J Cardiovasc Magn Reson* 2012;14:72. [PubMed: 23083397]
33. Iglewicz B, Hoaglin D. How to detect and handle outliers. ASQC Quality Press; 1993.

Figure 1.

Flow chart summarizing BPO correction with the ARTO process. Images shown are from one trial of the simulated phantom with wrap-around artifact (see Methods). For the binary masks displayed (S^0 , $S^k M$, and S^{k+1}), white indicates pixels included in the fitting while black indicates pixels excluded from the fitting.

Figure 2.

(A) Representative phase image from simulated phantom experiment with wrap-around artifact and tissue-on-tissue overlap and spatial discontinuities in the BPO (black arrow). Outlier regions are indicated as steady flow (*), wrap-around artifact (†), and tissue-on-tissue overlap (▲). (B) Pixelwise temporal standard deviation (σ_j) displayed on a logarithmic scale. (C) BPO corrected using WRLS alone and (D) corresponding temporal standard deviation map masked by M . (E) BPO corrected using WRLS+ARTO and (F) corresponding temporal standard deviation masked by $S^{K_{max}}M$. In D and F, gray regions

indicate exclusion from the fitting. ARTO completely excludes both the steady vessel (dashed red line) and wrap-around artifact (solid red line).

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Figure 3.

Weighted residual (ϵ) histograms and GMM components after the (A) 1st and (B) 2nd iterations of WRLS+ARTO for the simulation example presented in Figure 2. Secondary residual distributions from pixels derived from the steady vessel (*), wrap-around artifact (†), and tissue-on-tissue overlap (▲) are indicated as such. ARTO cutoff points are indicated by the vertical dashed lines. Pixelwise masks from pixels with residuals less than, within, and greater than the ARTO cutoff points are also displayed for the 2nd iteration of ARTO, where white indicates pixels which are included in each group. Note that the pulsatile vessel is not explicitly excluded by ARTO because its influence on the fitting is sufficiently down-weighted by its high temporal standard deviation as observed in Figure 2.

Figure 4.

Comparison of simulated phantom volumetric flow before and after BPO correction with WRLS and WRLS+ARTO using Bland-Altman analysis. Here, the ground truth was known and used as the reference. The top row contains trials without wrap-around artifact while the bottom row contains trials with wrap-around artifact. The y-axis and LOA are reported in terms of percent error.

Figure 5.

(A) Temporally-averaged phase image of the thoracic aorta from a healthy subject with wrap-around artifact displayed from -3% to $+3\%$ VENC to highlight BPO. (B) Corresponding temporal standard deviation (σ_j) displayed on a logarithmic scale. (C) BPO corrected using WRLS alone and (D) corresponding temporal standard deviation masked by M . (E) BPO corrected using WRLS+ARTO and (F) corresponding temporal standard deviation masked by $S^{K_{max}}M$. Gray regions in D and F indicate exclusion from the fitting. ARTO successfully excludes the wrap-around artifact (solid red line) as well some slowly varying flow (black arrow).

Figure 6.

(A) Temporally-averaged phase image of the main pulmonary artery from a healthy subject with wrap-around artifact displayed from -5% to $+5\%$ VENC (B) Temporal standard deviation (σ_j) displayed on a logarithmic scale. (C) BPO corrected using WRLS alone and (D) corresponding temporal standard deviation masked by M . (E) BPO corrected using WRLS+ARTO and (F) corresponding temporal standard deviation masked by $S^{K_{max}}M$. Gray regions in D and F indicate exclusion from the fitting. ARTO successfully excludes the wrap-around artifact (solid red line) as well some slowly varying flow (black arrow). A third region of localized phase was also removed (black arrowhead).

Figure 7.

Comparison of volumetric flow in healthy subjects before and after BPO correction with WRLS and WRLS+ARTO using Bland-Altman analysis. Here, correction with a stationary phantom was used as the reference. The top row contains datasets without wrap-around artifact while the bottom row contains datasets with wrap-around artifact. The y-axis and LOA are reported in terms of percent error.

Figure 8.

Qp/Qs ratios in 6 healthy subjects before and after BPO correction with the stationary phantom, WRLS, and WRLS+ARTO. (A) Datasets without wrap-around artifact. (B) Datasets from the same subjects containing wrap-around artifact. Boxes represent interquartile ranges. Medians are given by solid horizontal lines. Means are given by “x’s”. Extents indicate data range. †Statistically significant difference between the variances ($P < 0.0042$). Significance level was determined by Bonferroni correction (12 comparisons) to an initial level of 0.05. Both paired t -tests and F -tests were performed with respect to the stationary phantom correction.

Table 1.

Parameters used to construct the simulated phantom

	Stationary Tissue	Vessel 1 (pulsatile)	Vessel 2 (steady)
# Trials (wrap-around)		150 (75)	
Abs. Temporal Mean Phase Before Noise	0 rad	$(\frac{\pi}{15} - \frac{\pi}{6})$ rad	$(\frac{\pi}{30} - \frac{\pi}{15})$ rad
Temporal Standard Deviation	$\frac{\pi}{300}$ rad	$(\frac{\pi}{10} - \frac{\pi}{3})$ rad	$(\frac{\pi}{220} - \frac{\pi}{50})$ rad
Added Phase Noise Standard Deviation *		$\frac{\pi}{300\sqrt{20}}$ rad	
Wrap-around extent		(-20% – +20%) of FOV	
Background phase		2 nd order	
Spatial Resolution		1.5 mm ²	

For quantification purposes, velocity was scaled by assuming a VENC of 150 cm/s. A cardiac interval of 1 s and 1.5mm² resolution were assumed to calculate net flow volumetric flow rate.

* The standard deviation of the added Gaussian noise was scaled by a factor of $1/\sqrt{20}$ relative to the temporal standard deviation to mimic SNR gain resulting from temporally averaging over 20 frames, which is a typical number used for cardiac PC-MRI.

Table 2.

Acquisitions parameters for PC-MRI

	Thoracic Ao [*]	Abdominal Ao	MPA	RPA	LPA
# Total (wrap)	19 (7)	18 (8)	29 (12)	17 (6)	23 (8)
Acq. Time [s]	9.03 – 24.5	9.03 – 19.04	11.06 – 22.17	10.22 – 17.29	13.31 – 22.3
TE [ms]	2.14 – 2.87	2.15 – 2.87	2.14 – 3.09	2.28 – 3.09	2.28 – 3.09
TR [ms]	5.21 – 5.76	5.21 – 5.61	5.46 – 5.83	5.60 – 5.83	5.60 – 5.83
Temporal Resolution [ms]	41.68 – 54.7	41.68 – 54.4	43.7 – 58.3	44.85 – 58.3	45.5 – 58.3
FOV [mm]	PE 158 [†] – 284	146 [†] – 262	223 – 380	174 [†] – 380	207 – 425
	FE 300 – 399	300 – 399	325 – 399	340 – 380	289 – 425
Spatial Resolution [mm]	PE 2.2 – 2.8	1.7 – 2.9	2.0 – 3.1	1.8 – 3.1	2.0 – 3.3
	FE 1.6 – 2.7	1.6 – 2.9	1.7 – 3.0	1.8 – 3.0	1.5 – 3.3
VENC [cm/s]	100 – 170	100 – 175	90 – 150	90 – 130	90 – 130
Slice Thickness [mm]			6		
Flip Angle [°]			15		

^{*} Both the ascending aorta (AAo) and descending aorta (DAo) were quantified in this imaging plane.

[†] These narrow dimensions were obtained by decreasing the FOV to induce wrap-around artifact.