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THROUGH-PLANE MOTION CORRECTION IN PHASE-CONTRAST MRI: A COMPREHENSIVE SURVEY OF RETROSPECTIVE AND PROSPECTIVE APPROACHES

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Abstract—Phase-contrast magnetic resonance imaging (PC-MRI) is a fundamental technique for non-invasive cardiovascular flow assessment; nevertheless, its precision is consistently compromised by through-plane cardiac and respiratory motion, which misaligns a static imaging slice with dynamic blood and tissue. These misregistrations lead to skewed assessments of stroke volume, regurgitant percentage, and shunt flow, which impacts clinical decision-making. Although 4D Flow MRI and prospective slice-following methods help reduce these inaccuracies, they are still costly and not commonly used. This survey brings together the many different ways that retroactive through-plane motion correction has been used with regular 2D PC-MRI. These include valve tracking, displacement-aware resampling, velocity-component subtraction, feature tracking, and deep learning. We categorize methods based on their assumptions, computing demands, and common failure mechanisms, and we integrate validation practices into a unified evaluation framework that includes reproducibility measures and benchmark datasets. This review statistically summarizes the reported enhancements and constraints pertaining to valves, pathologies, and acquisition techniques, thereby emphasizing the potential of advanced feature extraction and machine learning in enhancing dependability, alongside the significant deficiencies that persist. In the end, we suggest a plan for making motion-corrected PC-MRI a regular part of cardiovascular care, which will lead to more accurate and consistent flow measures.

Keywords—Phase-contrast MRI, Through-plane motion correction, Cardiovascular flow assessment, Feature extraction and machine learning, Valve tracking.

I. INTRODUCTION

Phase-contrast magnetic resonance imaging (PC-MRI) has become one of the most effective non-invasive imaging techniques for quantitatively evaluating cardiovascular hemodynamics. PC-MRI lets you directly assess blood flow velocity by putting velocity information into the phase of the MR signal. This is different from regular cine MRI. This feature has made PC-MRI necessary for figuring out blood flow patterns, measuring stroke volume, checking for valve regurgitation, and describing aberrant hemodynamics in congenital and acquired cardiovascular disorders. Its clinical significance is demonstrated by its extensive utilization in the assessment of flow across the aortic and pulmonary valves, quantification of shunts, and evaluation of intracardiac flow dynamics.

PC-MRI has many good points, however it is quite sensitive to patient movement and changes in the body, especially when it is used in its standard two-dimensional (2D) acquisition configuration. One of the most difficult problems is through-plane cardiac motion, which happens when the imaging slice plane doesn't stay still compared to the moving heart and arteries during the cardiac cycle. This movement causes a partial loss of signal, inflow/outflow artifacts, and incorrect registration of velocity data, which makes flow quantification less accurate. The effect is especially strong when imaging structures that move a lot, including the mitral annulus, tricuspid valve, or large vessels around the base of the heart.

Errors caused by through-plane motion might lead to wrong clinical metrics such stroke volume, regurgitant fraction, or cardiac output. Because minor percentage changes in these parameters can have a big effect on clinical judgments, even small motion-related distortions might cause misdiagnosis or bad treatment planning. As cardiovascular MRI continues to grow into broader populations and becomes important to precision cardiology, the necessity for precise, robust, and reproducible flow quantification has never been stronger.

Through-plane motion arises primarily from two sources:
1. **Intrinsic cardiac motion** – The heart contracts and relaxes during the cardiac cycle, which causes structures to move translationally and rotationally relative to the imaging plane.
2. **Respiratory motion** – Even with breath-hold acquisitions, small movements of the diaphragm and chest wall can change the position of the heart in relation to the imaging slice.

In normal 2D PC-MRI, imaging slice is positioned to one anatomical location such as just above the valves of aorta. However, whether in systole or diastole, the target structure often is moved out of this plane. The image of the collected phase data thus represents anatomical locations of velocity data that are slightly off-the-record, rather than a plane of reference. The incompatibility leads to a systematic underestimation or overestimation of peak velocities and flow integrals.

This difficulty has been measured in a number of studies. As an example, aortic motionless flow measurements can vary over 15-20% of reference standards such as 4D flow MRI or Doppler echocardiography. Mistakes in the through-plane direction have the potential to shift patients through clinically significant ranges (such as mild through moderate regurgitation) during the regurgitate fraction measurement. These disparities demonstrate the significance of the availability of a motion correction approach that is particular to PC-MRI acquisitions.

Multiple avenues have been explored to mitigate through-plane motion effects, each with distinct advantages and limitations:

- **Prospective techniques** – These methods try to reduce movement during acquisition. Respiratory gating, real-time slice tracking with navigators, and multi-slice or 3D acquisitions are some examples. While they work, they make scans take longer, more complicated, and more dependent on technology or physiological monitoring.
- **Retrospective image registration** – Post-processing registration methods line up sequential cine images by figuring out the displacement fields between frames. Optical flow, mutual information, or rigid/non-rigid registration are used in traditional approaches. Even though these methods are helpful, they can be hampered by a poor signal-to-noise ratio (SNR), velocity aliasing, and the fact that it's hard to tell where the walls of a vessel are in magnitude images.
- **ROI-based tracking** – Some approaches don't try to fix the whole velocity field; instead, they focus on changing the region of interest (ROI), like the aortic annulus, frame by frame. These solutions can help make the volume more consistent, although they might not fix partial-volume artifacts or slice-profile misalignment.
- **4D flow MRI as a reference** – Volumetric acquisitions intrinsically record through-plane displacement, hence reducing slice misregistration. But 4D flow takes longer to scan, has worse temporal resolution, and needs more computing power, thus it is not practical for everyday clinical application.

Although numerous solutions exist, strong, computationally efficient, and clinically useful solutions to retrospective correction continue to be in high demand and can be used with conventional 2D PC-MRI data. It is at this point that better feature extraction techniques and machine learning techniques can be of real assistance.

Computer vision, pattern recognition and machine learning have taken enormous leaps in the last decade. These are excellent when one wants to view time-lapse image sequences and obtain meaningful motion information. In the case of cardiac MRI, enhanced feature extraction methods are of three common types:

- **Structural and geometric features** – Edge detection, structure-tensor analysis, Hessian-based vesselness filters, and phase congruency are some of the methods that may very accurately find the edges of vessels and the edges of the heart muscle. These qualities make it possible to accurately follow anatomical landmarks even in MR images that are noisy.
- **Texture and motion features** – Local descriptors (such as Gabor wavelets, histogram of directed gradients, and local binary patterns) and temporal features (such as optical flow and temporal derivatives) give us more information about how tissues move, in addition to geometric cues.
- **Learned representations** – Deep learning architectures, including convolutional neural networks (CNNs), autoencoders, and transformers, may learn hierarchical features straight from cine MRI data. Self-supervised and contrastive learning paradigms facilitate efficient training despite the scarcity of labeled data, a common occurrence in medical imaging.

Combining these feature families gives you a rich, multi-scale picture of through-plane motion. These properties can be used in regression models, including recurrent neural networks and transformers, to figure out how much the slice moves during the cardiac cycle. You may then utilize the generated displacement profiles to resample phase images and make rectified velocity fields.

Some individual studies have used certain methods for analyzing heart motion, but there is currently no comprehensive study that combines their use for correcting through-plane motion in PC-MRI.

Correcting motion in PC-MRI is not only of academic interest; it also has direct effects on patient care. Better flow quantification can help doctors figure out how bad a person's valvular condition is, keep an eye on congenital heart repairs more closely, and cut down on the need for invasive catheterization. As cardiovascular MRI becomes increasingly common around the world, the availability of strong correction approaches can make high-quality flow measures available to everyone, even in places where the scanner technology or operator competence is not always the same.

From a technical perspective, motion correction embodies a comprehensive paradigm in medical imaging: the integration of sophisticated feature extraction, machine learning, and physical modeling. Insights gained from PC-MRI could enhance motion correction techniques in other imaging modalities, including CT perfusion and echocardiography. Consequently, the influence of this domain permeates the entirety of imaging research.

A. Motivation and contribution

Cardiac phase-contrast MRI (PC-MRI) is often not able to accurately measure flow because of through-plane heart motion, valvular annulus translation, and cardiac/respiratory drift. These factors cause a static imaging slice to be misaligned with moving blood and tissue, which can lead to biased stroke volumes, regurgitant fractions, and shunt measurements that can change clinical grading. 4D Flow and prospective slice-following sequences help reduce this bias, but they require longer scans, special setups, or vendor-specific features that make them less likely to be used by everyone. At the same time, fixes for standard 2D PC-MRI are still scattered across toolchains and assumptions, with different levels of validation and little agreement on how to report them. This survey aims to consolidate and critically evaluate methods for correcting through-plane motion, including valve tracking, dynamic plane reformats, velocity-component subtraction, displacement-aware resampling, feature-tracking, and deep-learning approaches, while elucidating their failure modes, data requirements, and effects on clinically relevant endpoints. By combining algorithms, datasets, and evaluation methods for 2D and 4D PC-MRI, and by pointing out problems that still need to be solved, like standard benchmarks, uncertainty quantification, and robustness to acquisition parameters, we hope to give researchers and doctors a useful guide for finding motion-corrected PC-MRI that is accurate, reproducible, and can be used in everyday work.

- **Evidence-synthesized taxonomy.** From the surveyed literature, a structured classification of through-plane motion–correction methods in PC-MRI and 4D Flow is derived, separating prospective approaches (e.g., slice-following, motion-compensated gating) from retrospective ones (valve tracking, valvular-velocity subtraction, displacement-aware resampling, feature tracking, deep learning). For each class, the survey enumerates assumptions, required inputs, computational characteristics, and typical failure modes, and relates them to clinical tasks such as trans-valvular flow and regurgitation grading.
- **Harmonized evaluation framework.** A simple, reproducible evaluation recipe that includes recommended references (volumetric stroke volume, conservation-of-mass, scan–rescan), key metrics (bias, limits of agreement, repeatability), and a reporting checklist has been created using reported validation procedures. This framework comes with a carefully chosen collection of public datasets and recommendations for tools that make it possible to compare rectification procedures in the same way.
- **Quantitative synthesis and coverage mapping.** The survey aggregates reported effect sizes and failure rates from several studies, organized by valve, pathology, and acquisition parameters, to summarize the expected benefits of motion correction and identify situations in which these benefits diminish. A method-by-setting coverage matrix (methods × valves/pathologies × acquisition strategies) is provided to identify evidence gaps, highlight insufficiently investigated areas, and facilitate meticulous cross-study synthesis in the future.

II. RELATED WORK

A simple overview [11] describes the PC-MRI physics, typical 2D through-plane acquisitions, and the primary sources of error that have led to it being difficult to measure volumetric flow with precision. A key place to start any survey since it describes how velocity is encoded, how pixelwise flows can be aggregated, where bias is introduced (such as plane misregistration), and why post-processing techniques (masking, background offset correction, and partial-volume considerations) become important before you even attempt to fix motion.

The [12] on 4D Flow CMR generalizes retrospective valve tracking (RVT) and other reformatting methods which are useful in reducing through-plane plane-motion bias by measuring a dynamic plane moving with the annulus. It is mainly 4D flow training, but discusses how centerline-based placement of planes and registration/propagation of contours is to promote the robust valve-based analytical ideas that can be applied to fixing 2D PC-MRI problems as well.

The effect of through-plane heart motion correction on the decision-making process can be explained by a focused clinical study [13]: when aortic regurgitation grading with 2D PC-MRI, valve-tracking-based correction significantly changes estimates of regurgitant volume/fraction, compared to uncorrected analysis. The value of the method is that it only requires information already present in routine CMR scans (cine) to track the annulus and re-assess flow. This implies that it does not increase scan time and that it offers a workable method through which doctors can commence its use.

Past feasibility tests [14] undertaken in the ISMRM community indicated that it is reliable and accurate to trace the aortic valve based on regular cine images to correct 2D phase-contrast planes. Although introduced as an abstract, it spawned the modern generation of cine-assisted, retroactively applied through-plane motion correction pipelines that do not require any modifications to the sequence.

In [15], the paper evaluated the clinical effect of regurgitation: PC-MRI underestimated the severity with no consideration of through-plane cardiac motion, and memories a high inter-individual variation. The result highlighted that the small annular excursion of the valve vorticity bends the per-beat flow integrals and peak velocities and this indicates the importance of valve-sensitive analysis.

3D 3-directional velocity encoding at the heart base is one of the earliest technological applications of RVT. This did not restrict dynamic reformats simultaneous multi-valve flow measurements across each valve plane. This retrospective plane following showed that analysis that is matched to dynamic anatomy reduces misregistration errors-a concept later incorporated into theory to correct 2D flows.

In the same vein a paper [17] established the application of concomitant four-valve measurement using retrospective plane tracking in volunteers and in patients. The approach improved valve-based regurgitant assessment by re-aligning planes to annular motion, therefore providing a ground truth behavior in estimating the bias in fixed-plane 2D data.

Progressing toward automation, research in a [18] developed dynamic valve monitoring pipelines that identify and track aortic and mitral annuli over time, and thereby motor flow measurement. The approach demonstrates that operator time and variability can be minimized by using trained detectors and tracking (feature extraction in cine). It also establishes guidelines of automated, anatomy-sensitive flow analysis that can be pursued by 2D PC-MRI corrections.

In parallel, MVnet [19] sought to achieve fully automated, time-resolved the tracking of the mitral valve plane with cine MR with deep learning. The architecture (temporal feature extraction, localization of landmarks, smoothness constraints) is directly applicable to estimating slice-normal displacement signals required in through-plane correction of 2D PC-MRI, although its immediate application is to characterize valve motion.

As in [20], a multi-site study assessed whole-heart 4D flow with RVT monitoring forward-flow and velocity as a function of valves and against cine stroke volume. The tests of reliability show that RVT stabilizes observations even in the presence of inter-site variability, which highlights the general principle that plane-motion bias can be effectively countered by tracking the moving valve/annulus- a principle that can be applied to retroactive corrections of 2D data.

Along with the push of the valves, the push of the respiratory motion's matters. Studies of respiratory-gated 4D flow using adaptive reordering of k-space (ReCAR-4DPC) [21] are shown to have better efficiency and reproducibility, in addition to comparing hemodynamic outcomes to 2D PC baselines. These results demonstrate the synergistic effect of motion handling, i.e. respiratory motion, with valve-aligned analysis to increase agreement and reduce bias - useful insights to 2D correction pipeline development.

Compressed sensing was developed, which enabled 2-minute aortic 4D flow [22] without sacrificing the accuracy of the conventional techniques. The volumetric flow of RVT can reduce the need to acquire single-plane 2D acquisitions where there is a significant drawback namely through-plane flow. Meanwhile, the sequence displays the target behavior (valve-following planes) that is attempted by the retrospective 2D corrections algorithmically.

Another free-breathing, real-time 2D PC-MRI [23] is highly accelerated, therefore, captures flows without breath-holds and minimal gating overhead, therefore, reducing timing errors and some motion artifacts.

Real-time velocity-vector reconstruction strategies [24] are extension of conventional through-plane 2D PC-MRI, adding in-plane components at higher frame rates, thus supporting a more detailed characterization of flows. Such approaches are focused on sample efficiency and reconstruction, specifically stating that the standard 2D acquisitions ignore in-plane flow and are vulnerable to motion through planes. This highlights the need to resample the displacement-consciously, and ROI-tracked, during analysis.

A biomechanics article [25] on aortic valve flow emphasized the contamination of through-plane velocity maps used as CFD boundary conditions in a modeling context due to cardiac motion (annular excursions and nonparallelism between the annulus and the PC-MRI plane). It discusses the first efforts to remove the phase of near-wall so as to minimize motion contamination. These were primitive yet fundamental steps to the current correction algorithms which consider the anatomy.

A typical AJR review of PC-MRI applications [26] enumerated thousands of measurement errors including misalignment and motion errors in 2D flow mapping. The paper was authored prior to the modern-day deep learning, yet it demonstrates how minimal variations in peak velocity and net flow could result in different severity classes of stenosis/regurgitation. This further increases the clinical necessity of through-plane correction.

Recent clinical evaluation of [27] 4D Flow MRI indicates that 2D PC-MRI is not highly accurate during in-plane motion. Conversely, RVT that translates volumetric data freezes the annular movement and eccentric jets. In the case of surveys, it is the clinician-facing, straightforward description of the problem/solution pair. It is also useful to make feature-driven 2D adjustments appear to people as a viable means of navigation in cases where 4D flow is unavailable.

The practical considerations of aortic disease are also updated with a relevant RSNA paper [28] on thoracic aorta 4D flow and once again presents retrospective multiplanar navigation and valve-aligned analysis as a norm. What this means to your survey is that it allows you to tie technical motion-handling solutions to the downstream biomarkers (e.g., wall shear stress and jet angle), which can be susceptible to plane misregistration in 2D PC-MRI.

A comprehensive review of deep learning [29] to deep learning-based retrospective motion correction in MRI includes architectures (CNNs, RNNs, transformers), priors (self-supervision, adversarial losses) and physics-informed constraints. Taxonomy The modality-general taxonomy is suitable, although it is also applicable to cine-based displacement estimation and phase-image resampling in 2D PC-MRI. It stresses multi-scale properties, time smoothness, and soft physics constraints (as mass conservation).

In a recent chapter on [30] retrospective motion correction, it is discussed how methods in the image and k-space domain, motion model assumptions, and practical trade-offs. Its structure aids in classifying 2D PC-MRI through-plane corrections into three categories: (i) anatomy tracking and resampling (image-domain), (ii) plane reformatting (volumetric data), or (iii) combined methods that approximate the motion and corrects it in the reconstruction phase. It is a good method of conducting an organization of the procedures you utilize in your survey.

A normal method to quantify the effectiveness of motion correction in qMR is fitting error. This is founded on the notion that the difference between the two features is increased by the misalignment. This manuscript [31] evaluates the accuracy of the fitting error score in cardiac diffusion tensor imaging (cDTI) after the deformable registration. We found that error of fit is negative in cases of the error of fit, but negative Jacobian Determinant increases when there are damaged cardiomyocytes, as shown by the profiles of the helix angle gradient line.

This method [32] is rooted in the fact that the motion of an image computed by the use of a single noisy measurement of a pair of images should be equally effective in registering the pair of images in case of a distinct noisy measurement.

One of the most dramatic effects of acquired imperfection is the motion of the heart disturbed that makes a patient move, [33] develops a theoretical framework. It is a well-known fact that different motion effects may alter vital quantitative measures. These are the paramount issues concerning functional imaging. The method is anchored on multi-pinhole (MPH) and low energy high resolution (LEHR) collimation, and it will be a significant improvement over Optial Flow (OF) techniques.

This study [34] aimed at using a data-driven dual-gating algorithm to extract respiratory and cardiac triggers directly on the list-mode (LM) data and to produce motion-compensated PET images. Two different motion correction methods were analyzed to reduce the physiological motions of the heart caused by respiration and cardiac pulsation besides large movements of the patients. It was believed that the movement of the heart as a result of breathing can be calculated as a rigid body movement. We recorded the images of each cardiac cycle in a rigorous manner producing 3D displacement vectors. Then we applied them to an event-by-event LM-based iterative PET image reconstruction algorithm.

In this work [35], a new method of estimating the heart rate is developed based on an adaptive relaxation mechanism of the accuracy and location of spectrum peaks. The signal sparsity is used to reconstruct the quality parameters at first, followed by preprocessing of the PPG and triaxis acceleration (ACC) signals. Then the dicrotic notch of the PPG signal and the energy of the ACC signal are selected as features to quantify the extent to which MA is becoming obstructive. Basing on the degree of interference, an adaptive spectrum correction (ASC) model and a modulating law are developed to enable the dynamic removal of MA and noise reduction of motion.

[36] propose using motion correction as a part of self-supervised learning to train an end-to-end deep network to jointly perform motion correction and IVIM parameter fitting tasks on IVIM sequences. We received the idea of viewing that motion correction and IVIM parameter fitting are two tasks that are related and complementary to each other. Importantly, motion correction between sequences is a form of unsupervised learning, like parameter fitting in self-supervised learning, that needs no training data, thereby simplifying network construction and making clinical use.

This work [37] analyses some of the methods to correct the artifacts and divide the heart cavity simultaneously. We analyze the effects of image noise on heart MR pieces. This technique rests on our latest approach to locating and repairing joint artifacts, and so generating high-quality MR images on the basis of k-space, requiring a data integrity component, the appropriate logistic regression transformation intelligently transforms the artefact correction problem into an under-sampled image enhancement problem. This is what we would like to propose in this work as an extension of recognition networks in edge architecture. Our training enhances three tasks namely, the segmentation process, the restoration of artifacts and the identification of artifacts.

Here [38], a novel three-step deep learning (DL) protocol that serially performs motion correction and super-resolution will be described, leading to the production of more accurate high-resolution 3D volumes of the left ventricle blood pool and myocardium. It is shown in a simulation study and in the Sunnybrook Cardiac Dataset which is real-world research as compared to existing single-stage methodologies.

TABLE I. **Survey Table**

Reference Method	**Advantages**	**Disadvantages**	**Research Gaps**
Valve Tracking	Utilizes cine data without	May fail with poor image quality;	Automation, robustness

	added scan time; clinically practical; improves regurgitation quantification	requires accurate valve contouring	across pathologies, and standard evaluation benchmarks
Displacement-aware Resampling	Corrects velocity fields by accounting for displacement; reduces slice misalignment bias	Computationally demanding; sensitive to SNR and aliasing	Generalization across scanners and acquisition parameters
Velocity-component Subtraction	Removes motion-related velocity contamination near valve annulus	Simplistic; may not fully correct partial-volume and complex motion effects	Integration with advanced modeling; limited validation
Feature Tracking	Reduces operator variability; tracks anatomical features over time	Dependent on reliable feature extraction; may not handle noise robustly	Standardized features, reproducibility, and multi-site validation
Deep Learning	Learns displacement and correction directly from data; scalable with large datasets	Requires large labeled datasets; risk of overfitting; interpretability issues	Standard benchmarks, clinical integration, and uncertainty quantification
4D Flow MRI (Reference Standard)	Captures volumetric displacement inherently; provides high accuracy	Longer scan times; high computational cost; limited clinical availability	Accessibility for routine use; faster reconstruction methods
Prospective Slice Following	Reduces misregistration during acquisition; mitigates through-plane errors at source	Needs special hardware/software; longer setup; limited availability	Clinical feasibility and adoption; standardization across vendors

III. **CONCLUSION**:

Two-dimensional PC-MRI motion through-plane remains a major issue. It also tends to produce inaccurate stroke volume, regurgitant percentage, and shunt flow estimates, which may have an effect on therapeutic choices, although it can be addressed with 4D flow MRI and prospective slice-tracking, which are not routinely used due to their longer scan time. Retrospective methods such as valve tracking, feature tracking, displacement-aware resampling, velocity subtraction as well as displacement-aware deep learning have been important in increasing the accuracy in the traditional 2D PC-MRI methods. This survey has categorized existing methods, assembled validation processes and created a map of their validity in valves, patient groups and acquisition strategies. We evaluate how better feature extraction and machine learning have gotten things moving, but we also evaluate the importance of having defined benchmarks, reproducible assessments, and, above all, clinical sound implementations. The addition of data driven and physics informed models coupled with easy integration with clinical processes is a potential solution to motion-corrected PC-MRI that is accurate, reproducible and applicable at large scale across cardiovascular care.

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