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The use of artificial intelligence in cardiac magnetic resonance imaging

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Abbreviations:
Cardiovascular magnetic resonance – CMR; artificial intelligence – AI; magnetic resonance imaging – MRI; NN – neural network

Some of the artificial intelligence features discussed in this article are not available for clinical use in the U.S. and may not be available for such use in other countries.

1. Introduction

Cardiovascular magnetic resonance (CMR) imaging is considered the gold standard imaging modality for the assessment of cardiac structure and function [1,2] and the primary imaging modality of myocardial tissue characterization. However, CMR is riddled with intrinsic difficulties as its implementation is complex and requires specialized technologist training and expertise. Varying levels of operator expertise introduce non-uniformity between scans within a center and particularly serial studies in a specific patient. In addition, generating accurate and thorough myocardial characterization results can require long periods of limited physical motion as well as repeated breath holds. Consequently, patient throughput decreases and scanner productivity declines. Furthermore, image data post-processing techniques that take advantage of the modality's potential require image processing resources unavailable in most nonacademic institutions.

Artificial intelligence (AI) is increasingly used in healthcare. A recent literature review of AI identified five main health care areas where AI is expected to have significant impact [3]: health care systems management, diagnostics, clinical decision-making, patient data and predictive medicine. For CMR, AI will shorten and simplify workflows, preserve image quality, improve uniformity between scans, and enhance data interpretation for any MR center, regardless of its size or location.

The aim of this review article is to outline and describe some of the implementations of intelligent features for CMR imaging using a 1.5T United Imaging MRI (uMR 570) scanner in collaboration with Washington University School of Medicine in St Louis. The ongoing improvements strive not only for optimal image quality and study workflow but also overall for a simpler modality more accessible for the care of a broader patient population, for example individuals receiving cardiotoxic therapies for survival.

2. EasyScan

Obtaining scout scan acquisitions for CMR in the different orientation requires a skilled technologist. However, longitudinal studies for the image-guided management of patients are inherently subject to data inaccuracy, and variability exists when different technologists are involved. With the advent of automated or semi-automated slice adjustment methods, CMR studies have incorporated new geometric prescription processes [4-11]. For example, Lelieveldt et al [4,5] matched scout images to thoracic

[1] Washington University School of Medicine receives research support from United Imaging through a sponsored research agreement. Dr. Gregory Lanza is a principal investigator for the research.

anatomy models and estimated the left ventricular orientation for automatic view planning. The technique was limited to short-axis slice alignments and computational time was 3–5 min. While the concept was good, the methods were sensitive to the errors in landmarks.

In practice, the optimal position of the reference planes differ among individuals and they do not always pass through predefined landmarks.

Alternatively, United Imaging Healthcare implemented a slice alignment method (EasyScan) based on a deep learning regression network. Rather than relying on a few anatomical points, the image plane calculation utilizes all voxels in the region, reducing landmark detection errors and adding clarity to landmark annotation. The EasyScan AI planning algorithm[2] consists of three steps: (1) cardiac region segmentation using the Otsu method (Ref); (2) distance map calculation using the trained regression network; and (3) plane fitting using a least-squares method.

In our studies, EasyScan accelerated CMR imaging 13% (2.57 min, p<0.001, 95% CI [2.31, 2.83]) versus the traditional scout scan approach. Moreover, in contradistinction to the four-breath holds needed for typical plane prescriptions, EasyScan achieved the result with a single breath-hold scan and minimal operator dependence. EasyScan simplified cardiac image planning in all subjects and also achieved better scan accuracy with less plane angulation error, compared to previous reports for all four cardiac views (Fig. 1).

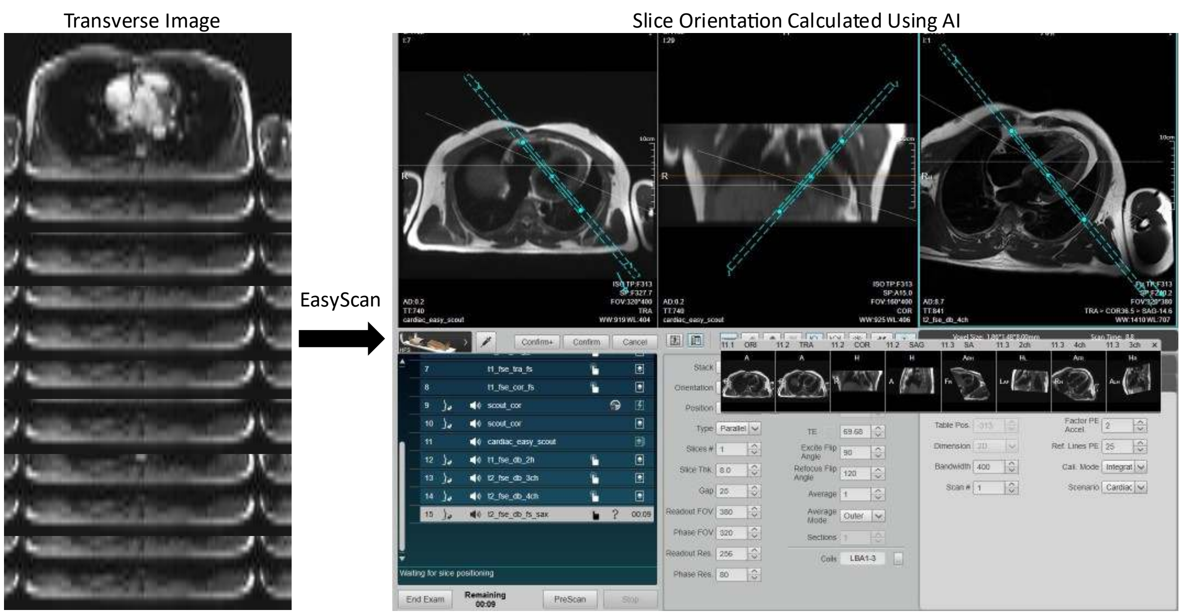

Figure 1. shows the Easy scan utilizing multiple 2D transverse slices to generate the standard views in a single breath hold, which results in faster imaging and greater reproducibility between scans.

3. AI Shim™

In CMR imaging, subject-induced magnetic field inhomogeneities can become pronounced due to susceptibility changes within the field of view [12]. Tissue-air boundaries compromise the B0 field, and careful shimming is required to establish a homogeneous and on-resonance B0 field around the heart. This is particularly true when a balanced steady state free precession (bSSFP) sequence is used for acquisition, which is sensitive to the off-resonance effect [13]. In general, a “frequency-scout” scan is involved in the workflow.

[2]The EasyScan algorithm currently is not available for clinical use in the U.S. and also may not be available for such use in other countries.

Here, a series of images with different off-resonance frequencies are acquired that help the operator choose the best scanner frequency. Unfortunately, this process is time-consuming and operator dependent.

To address these issues, a generalized shimming tool using a mask-based AI segmentation technique (AI shim™) [3] was developed [14]. AI shim™ uses a dual echo 3D gradient sequence with breath-hold to collect the 3D anatomical structure and B0 field map of the cardiac regions. A stack of transverse slices acquired at the beginning of the study is used to establish the shimming currents that automatically adjust the field for subsequent scans.

Compared with typical volume shimming, AI shim increased signal-to-noise ratio (SNR) in images obtained for all RV and LV myocardium cine planes. For instance, the mean SNR of LV myocardium SAX cine improved 17.75% with AI shim ($p<0.001$) among healthy volunteers and 10.40% ($p=0.006$) in referred patients. Similar findings were noted for contrast-to-noise (CNR) measurements. The improved SNR and CNR obtained through AI shim afforded better delineation of epicardial and endocardial borders, and the crisper AI shim images beneficially increased the efficiency and accuracy of automated contour detection algorithms utilized by the advanced CMR analysis software. Image sharpness over all four cardiac planes increased (2%) by AI shim and the relatively small improvement was notable along the thin RV free wall four-chamber and short-axis views (Fig. 2).

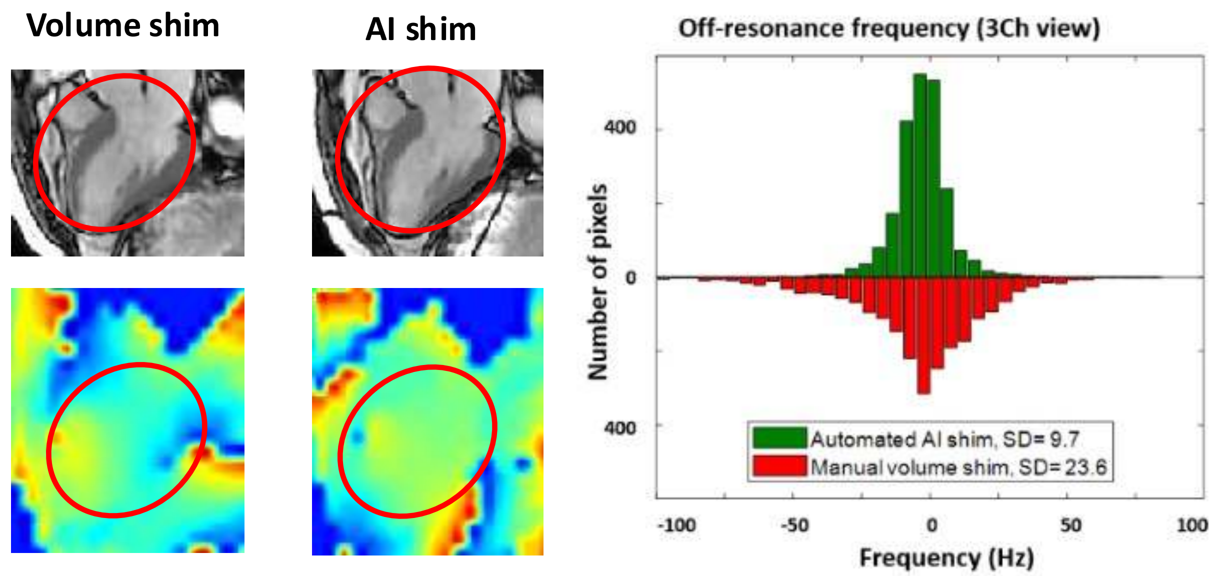

Figure 2. shows a three-chamber view example that highlights the superior image quality produced independent of the technologist with AI shim as compared to volume shim. The histograms also show the off-resonance distributions of the whole heart in the B0 field obtained with scans from 10 volunteers using two shimming methods: manual volume shim vs. AI shim. Histograms were separately generated for each cardiac plane with the standard deviation within the mask region, representing an improved field homogeneity with automated AI shim.

4. Fast-SENC

Fast-SENC Cardiac MR software operates efficiently on the United Imaging MRI scanner enabled by accelerated spiral k-space data acquisition. Fast-SENC technology is a rapid MRI scanning diagnostic feature that measures myocardium deformation from an unwound to a tense or contracted condition in one heartbeat per image plane. Breath-holds are not required, and a complete view of the ventricle is acquired in 6 seconds. This specialized pulse sequence reflects changes in the material properties cardiac muscle that can be harbingers of impending decreased contractility (Ejection Fraction, EF) [15-17]. The Fast-SENC pulse sequence quantifies circumferential (GCS) and longitudinal

[3]Not commercially available in the U.S. and some other countries for clinical use; sequence is still a work in progress.

(GLS) strain, varying with the plane of measurement, the latter being most utilized by cardiologists today (Fig. 3). The Fast-SENC has advantages of greater signal to noise ratio and more accurate strain calculation.

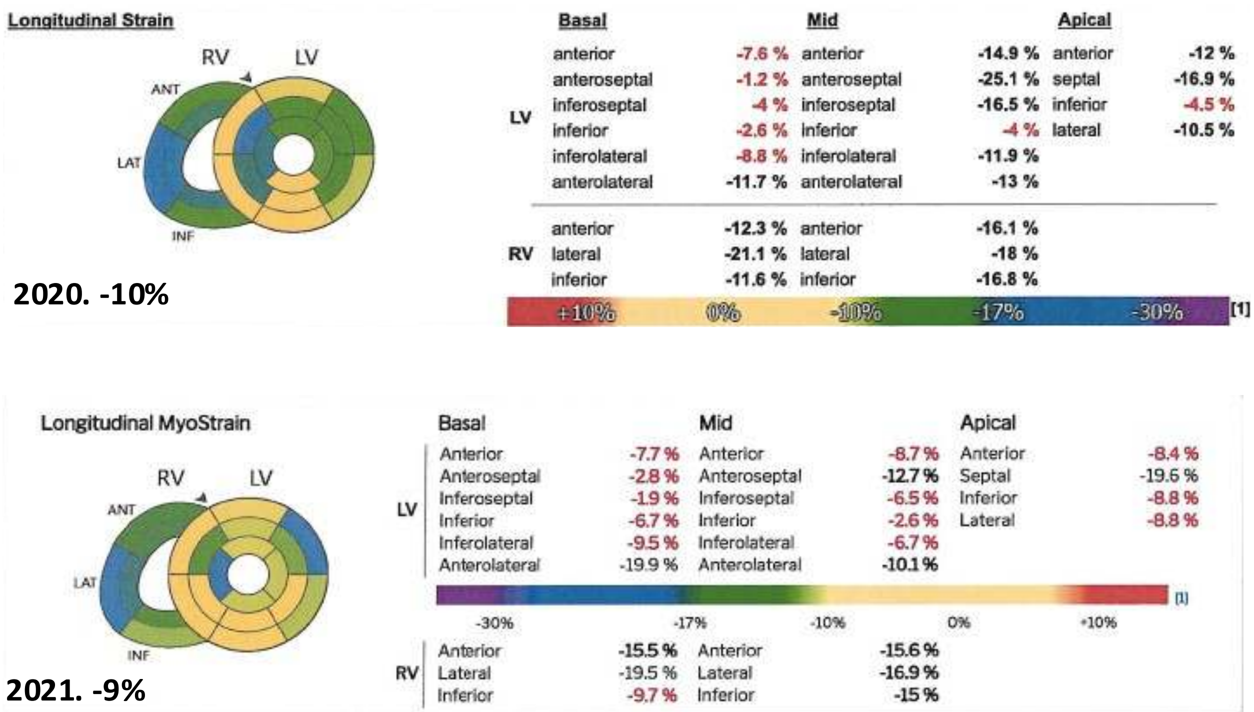

Figure 3. shows CMR results in a 84 year old patient with history of transthyretin amyloidosis in the spine. Ejection fraction was noted to be 63% in 2020 and had dropped slightly to 56% in 2021. The LV global longitudinal strain was noted to be 10% and 9% in 2021. The mapping shown below also helps to highlight the progression of myocardial involvement from the anterior, septal and posterior basal walls in 2020 to include more widespread left ventricular myocardial involvement in 2021.

5. Strain

Feature Feature-tracking (FT) [18] has been described as an alternative means of measuring myocardial strain using clinically routine cine CMR images, which require no special sequences such as tagging with DENSE or Fast-SENC [19-21]. Considerable effort has been focused on increasing the accuracy and reproducibility of FT strain assessment, but the process still requires human intervention. Moreover, performance and reproducibility of FT is directly related to observer's experience.

United Imaging Intelligence has created a deep-learning-based fully automated myocardium strain assessment system[4] (autoFT™, Fig. 4) that provides global and segmental strain estimates directly from cine CMR images without any human intervention, thereby removing observer variation or bias. The system was validated on patient data and compared to fast-strain-encoded (fast-SENC) imaging [22].

A neural network was established and trained to classify and group standard DICOM MRI images into short axis stacks, 2-chamber, 3-chamber and 4-chamber long axis images for assessment of cardiac anatomy and function. No additional MRI images are required. A convolutional neural network (UNet-like NN) detects anatomical landmarks on images to define and segment the myocardium according to the American Heart Association 17-segment model. A motion-pyramid NN is implemented to predict the dense motion field between two consecutive images. The motion tracking network is also equipped with anatomy-awareness such that the dense motion field from the network can maintain the heart anatomy through tracking [23]. Manual editing of the tracking is allowed at any frame to adjust the estimated motion and update the strain correspondingly. The myocardium, defined by the segmentation mask on the end-diastolic frame, is densely tracked through the entire cardiac cycle. Pixel-wise strains are calculated from the

[4]This product is a work in progress; the information in this article represents ongoing research and development. No 510k application has been filed with the FDA. This product is not available for sale in the U.S. for clinical uses and also may not be available for such sales in other countries.

dense motion field. Strain values along different directions (circumferential, radial and longitudinal) and at multiple spatial resolutions (global, segmental and pixel-wise) are provided in various formats, such as table, curves and bullseye.

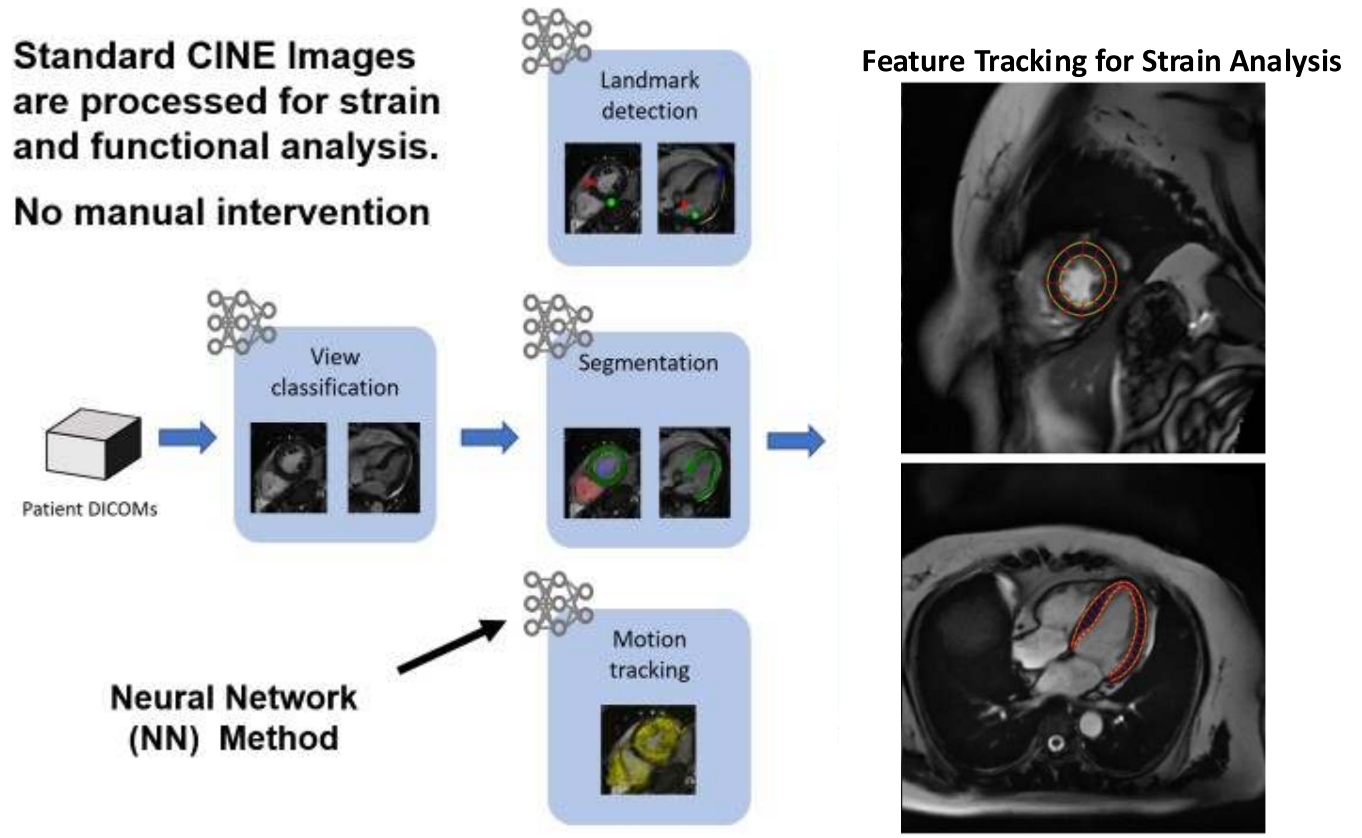

Figure 4. describes the workflow of the fully automated cardiac strain and function analyses.

The main components of this FT method include segmentation and motion tracking, which leverage the recent progress in computer vision and deep learning to achieve high accuracy, robustness, and computation speed. Repeatable preliminary results in serial studies have been obtained, in part because the short acquisition times minimize patient motion variability.

6. T1/T2 Mapping

MRI myocardial texture characterization using native T1 and T2 relaxation times can provide insight into changes in cardiac tissue. The normal practice of quantifying early changes in T1 and T2 parameters compares a subsampled region-of-interest (ROI) from the colorized T1 and T2 relaxation time maps with a ROI from chest wall muscle; the ratio of the magnetic parameter relaxation times determines the clinical significance. However, the technique is fraught with clinical variability and can be time-consuming to perform [24-25]. In the next edition of uINNOVATION-GLOBAL, a novel T1/T2 mapping feature re-envisions T1 and T2 relaxation data (Fig. 5) maps as automatic and intuitive quantitative reports.

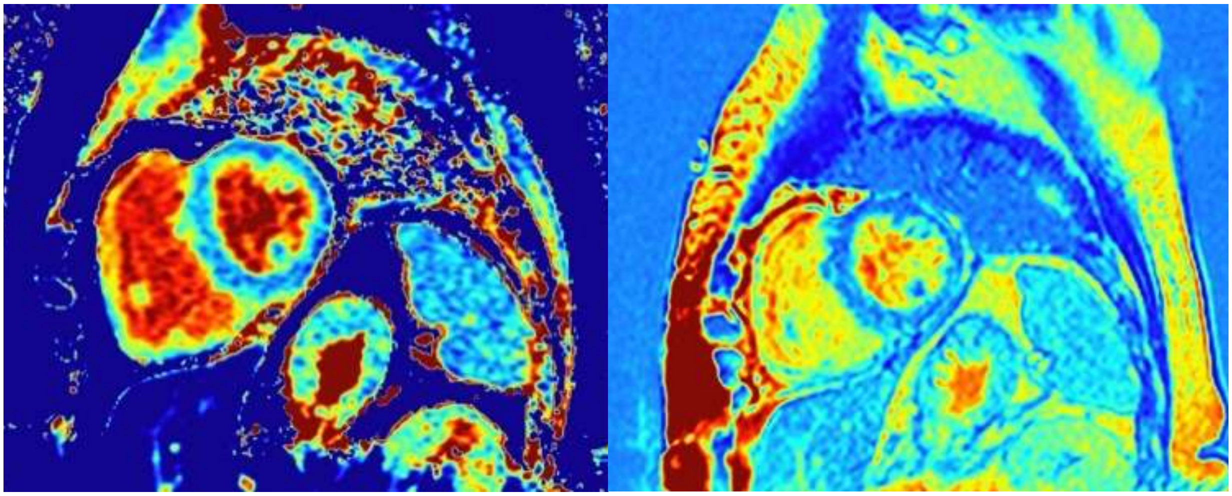

Figure 5. illustrates T1/T2 mapping of the cardiac myocardium.

7. Conclusion

CMR scans performed using the above-mentioned intelligent features are simplifying cardiac planning and image quality, decreasing the time for data processing and enhancing data interpretation. Collectively, the use of AI to achieve simpler and faster workflows will expand institutional availability, minimize technical complexity, and provide the best information for optimal patient care regardless of center location or size.

8. Image/Figure Courtesy

All images are the courtesy of Washington University School of Medicine in St Louis, USA.

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