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Arbitrary Point Tracking with Machine Learning to Measure Cardiac Strains in Tagged MRI

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Abstract

Cardiac tagged MR images allow for deformation fields to be measured in the heart by tracking the motion of tag lines throughout the cardiac cycle. Machine learning (ML) algorithms enable accurate and robust tracking of tag lines. Herein, the use of a massive synthetic physics-driven training dataset with known ground truth was used to train an ML network to enable tracking any number of points at arbitrary positions rather than anchored to the tag lines themselves. The tag tracking and strain calculation methods were investigated in a computational deforming cardiac phantom with known (ground truth) strain values. This enabled both tag tracking and strain accuracy to be characterized for a range of image acquisition and tag tracking parameters. The methods were also tested on *in vivo* volunteer data. Median tracking error was <0.26mm in the computational phantom, and strain measurements were improved *in vivo* when using the arbitrary point tracking for a standard clinical protocol.

Keywords

Cardiac Strains; Machine Learning; MRI Tagging

1 Introduction

Measuring the regional function of the heart is a useful tool to aid in the diagnosis and treatment planning for several forms of heart disease. One tool to measure the function of the heart is cine tagged MRI, which places tag lines or grid patterns throughout the myocardium that are subsequently imaged as they deform during the cardiac cycle. Tracking the tag lines enables computing the myocardial deformation mapping, which can be used to calculate derived parameters such as cardiac strains, or twist and torsion [4].

While the acquisition of tagged MRI images is widely available and straight-forward, obtaining the deformation mapping from the images remains a difficult process with a variety of proposed methods. Tracking methods utilizing active contours, B-splines, or optical flow techniques have all been proposed to solve the problem [6]. Spectral methods such as HARP have also been proposed to produce displacement maps at the expense of image filtering [8]. Recently, machine learning (ML) has emerged as a promising method for measuring displacements from tagged images [3], wherein neural networks were used to

process the tagged data. In our previous work, we demonstrated the achievable accuracy and precision when using physics-driven synthetic data to train a tag tracking neural network. This approach allowed training with known ground truth motion and did not require a large manually annotated *in vivo* datasets [7].

After obtaining the deformation mapping the myocardial strains can be calculated by looking at the changes in “lengths” along different directions with respect to the reference configuration [11]. When the tracked points are distant from one another, then radial basis function (RBF) interpolation can be combined with arbitrary point tracking. RBFs provide robustness with respect to different measurement positions and densities. Indeed, RBF has been used effectively in ultrasound [2] and tagged MRI studies [1]. Therefore, we incorporated RBF interpolation after tag tracking to investigate the impact of tag tracking point density on the strain measurements.

In this work, we have developed and trained a physics driven ML-based tag tracking method that allows selecting arbitrary tracking points. These points do not need to be anchored to the tag lines. This method increases the number of locations in the myocardium to be tracked compared to conventional methods. Subsequently, we investigated the effect of the arbitrary tracking point density and tag line spacing on the strain calculations to test if this enhanced tracking method can improve strain measurements.

2 Methods

2.1 Tag Tracking

In brief, our ML-based tag tracking approach used a Resnet-18 neural network [5]. Similar to previous work, this network was trained on a physics-driven synthetically generated dataset of tagged deforming objects. We’ve shown this approach leads to accurate tracking of tag intersections when used on *in vivo* data (positional error < 1.0mm *in vivo*) [7]. Herein, we generalize the method to track arbitrary points. The points to track were selected from the initial time-frame of a cine tagged MR image series, and fed into the neural network for patching. The output of the network was a vector of Lagrangian displacements of the tracked points for each time point.

The synthetic training dataset affords access to the ground truth motion needed for training the network to track arbitrary points in the image, rather than just along tag lines or at tag lines intersections. To explore this capability, the network was trained to track random points in the training images. After training the network, tag tracking was evaluated using both a computational deforming cardiac phantom embedded in an anatomical image and *in vivo* data with three different tag tracking point density selections: tag intersections only, and tracking on a 2mm and 1mm rectilinear grid (Fig. 1).

2.2 Strain Calculation

RBFs were used to interpolate the deformation at a point $\mathbf{R}$ (defined in the reference configuration) from the tracked point locations according to:

$$s(\mathbf{R}) = \sum_{k=0}^N w_k \varphi(\mathbf{R} - \mathbf{P}_k), \quad (1)$$

where N is the number of tracked points $\mathbf{P}_k$ defined in the reference configuration, w_k are the interpolation coefficients, and φ is the RBF function, which for our work is Gaussian:

$$\varphi(\mathbf{r}) = \exp\left(-\frac{\|\mathbf{r}\|^2}{\alpha^2}\right), \quad (2)$$

where α is the shape parameter that defines the size of the Gaussian RBF. The deformation gradient tensor is calculated by taking the analytical derivative of $s(\mathbf{R})$ and it is then used to compute the Green-Lagrange strain tensor.

A first order polynomial fit was added to $s(\mathbf{R})$ to better account for translations, and Tikhonov regularization was used when solving for w_k to account for the presence of noise. Optimal values for RBF size (α) and regularization amount (λ) were determined using the computational phantom and searching for the parameters that produced the least discrepancy between computed and ground truth strain values.

2.3 Computational Deforming Cardiac Phantom

As a reference standard to test tracking accuracy, we used a computational deforming cardiac phantom generated to have prescribed strains [12, 10]. The phantom was constructed with an axially symmetric heart-like geometry with initial ($t = 0$) inner radius equal to 25mm and wall thickness equal to 12mm. The radial, circumferential, and longitudinal displacement fields for the phantom were computed by solving an optimization problem to best match target peak systolic strains in the myofiber ($E_{ff} = -0.13$) [9], radial ($E_{rr} = 0.45$ to 0.30, endocardium to epicardium), circumferential ($E_{cc} = -0.20$ to -0.15 , endocardium to epicardium), and longitudinal ($E_{ll} = -0.15$) directions.

The computational deforming cardiac phantom was then combined with a static body MR image and used to simulate a tagged MR image acquisition with a full Bloch simulation. To test the effects of tag line spacing on tracking and strain accuracy, the image simulation was performed with tag line spacing of 10 mm, 8 mm, 6 mm, and 4 mm. The tag line spacing in pixels was held constant by increasing the resolution (image resolutions = 1.75 mm, 1.40 mm, 1.05 mm, and 0.70 mm respectively). An example of the simulated images for 6 mm and 10 mm tag spacing are shown in Fig. 1, and the computational phantom strains at the peak systolic time-frame are shown in Fig. 2.

2.4 In vivo Data

In vivo images were acquired from healthy pediatric volunteers ($N = 9$, median age = 15Y, with IRB approval and informed consent). Cine grid-tagged images were acquired with 110° total tagging flip angle for the tagging pulse and 8 mm grid spacing, 8mm slice thickness, TE/TR = 2.5ms/4.9ms, flip angle = 10° , field of view = 260 mm $\times$ 320 mm,

spatial resolution = $1.4\text{mm} \times 1.4\text{ mm}$, 25 temporal time frames, 8 – 12 s breath hold. Three short axis slices at basal, middle, and apical locations were acquired for each subject for 27 total slices. The LV was manually segmented on each slice, and tag tracking and strain calculations were performed as above with intersection tracking, and 2mm and 1mm rectilinear grid tracking. Strain maps and values were compared across the subjects.

3 Results

Fig. 3 shows the results of testing a range of RBF interpolation parameters for estimating strains. With ideal tracking locations, the lowest error was seen with an RBF window size of 10 – 14 mm, and the lowest error corresponded to the lowest regularization value of $1\text{e-}4$. Using the neural net tracked locations, a similar range was observed for the optimal RBF size, while a regularization parameter equal to $1\text{e-}3$ produced the lowest overall error. In general, 1 mm point density led to the lowest errors in all comparisons, particularly with small RBF sizes. For the rest of this study, the RBF size was set to 14 mm and regularization was chosen equal to $1\text{e-}3$.

Fig. 4 shows the results of comparing the tracked displacements with the known ground truth motion from the computational deforming cardiac phantom. Linear regression shows very good agreement for all combinations of tag line spacing and tracking point density, with slopes between 0.99 and 1.05, and $r^2 \geq 0.99$. Violin plots show the displacement error for each of the tag line spacing and point densities at peak systole, where the median error was [0.26, 0.26, 0.25] mm, [0.22, 0.22, 0.22] mm, [0.13, 0.14, 0.13] mm, and [0.10, 0.10, 0.11] mm for [1 mm, 2 mm, and intersection] tracking densities with 10 mm, 8 mm, 6 mm, and 4mm tag line spacing, respectively. The median error and interquartile range did not change noticeably when tracking arbitrary points versus intersections, but there were slightly more outliers with 10 mm line spacing when tracking arbitrary points.

Strains were computed from the tracked points and the results are shown in Fig. 5. Strain maps demonstrated better qualitative agreement with the reference strain values (Fig. 2), particularly with 10mm tag line spacing and for E_{Tr} . Line plots show the E_{Cc} and E_{Tr} curves over time, as well as the error over time relative to the known true strain in the phantom. The strain error decreased with smaller tag line spacing. Tracking more points with arbitrary point tracking improved strain quantification with 10 mm and 8 mm tag line spacing. For example, with 10 mm line spacing peak E_{Cc} error reduced from 0.018 to 0.012, and peak E_{Tr} error reduced from 0.12 to 0.07. Little difference was seen between strain calculated with 2mm and 1mm point tracking density.

Results from the *in vivo* analysis are shown in Fig. 6. Strain maps show qualitatively better spatial localization, similar to the phantom experiment. Global E_{Cc} measurements were minimally different between the 1mm and 2mm tracking point densities ($< .01$), while E_{Tr} increased with the 1mm and 2mm arbitrary point tracking with respect to intersection tracking (Mean value = 0.208 ± 0.077 with intersection tracking, 0.230 ± 0.087 , 0.231 ± 0.080 with 2mm and 1mm tracking point density). Line plots in Fig. 6 show similar global E_{Cc} values with both methods, but increased E_{Tr} with 2mm tracking.

4 Discussion

This study utilized a neural network in conjunction with synthetic data training to track arbitrary points in cine MRI tagged images of the heart. This allowed for tracking a large number of arbitrary points that are not necessarily tied to the tag lines intersections. In turn, this enabled the calculation of a more complete deformation map for analysis. When tested in a computational phantom, the tracking algorithm was shown to be very accurate, with no decrease in median error for tracking arbitrary points as compared to tracking tag line intersections. When strains were computed, the extra points enabled by arbitrary tracking improved measurements qualitatively and quantitatively for standard clinical protocol parameters. The strain improvement is reduced and eventually negligible as tag line spacing and resolution are improved beyond clinically realizable protocols.

Tracking point density was investigated by tracking points on a 2mm and 1mm rectilinear grid within a left ventricular mask. No improvement was seen when moving from 2mm to 1mm point density, showing that the spatial information at that level may be beyond the capabilities of the imaging and tracking method, or may be unnecessary given the measured deformation. RBF interpolation with a fixed shape parameter α was used for all point tracking densities as it was seen to give the best strain results. However the use of a higher tracking point density allows for smaller shape parameters to be used and may provide better spatial resolution of strain maps at the expense of accuracy.

One limitation of this work is that no regional pathologies were investigated to better understand spatial characteristics of the tracking method. Future work will aim to address this, with a non-symmetric computational deforming phantom and patients with grossly abnormal contraction patterns. However, computed transmural gradients of displacements and strains were better represented, demonstrating the potential for similar spatial representation improvements in these advanced cases. The synthetic data used to train the network contains a wide range of motions, with more variation and irregularities than seen in the computational phantom data presented here. It is therefore expected that the presented model will perform similarly well when applied to complex and abnormal cardiac motions.

Additionally, both the computational phantom and the synthetic data could be further improved. For instance, the computational phantom's cylindrical wall geometry can be modified to account for more realistic trabeculations. Through plane motion is also not simulated in either the training data or test data. While through plane motion cannot be reliably tracked with any 2D tagging technique, it is still important to understand the in-plane tracking performance of the method in the presence of through plane effects.

In vivo results showed differences consistent with the improvements seen in the computational phantom, suggesting that these results may also be more accurate. However, no ground truth strain measurement exists for comparison in these patients. Future work aims to compare to other tracking methods *in vivo*, as well as with other pulse sequence techniques for measuring strain with MRI.

In conclusion, a machine learning algorithm trained with synthetic data to track tags can track any point in a cardiac image, thereby enabling higher spatial resolution deformation mapping and more accurate strain measurements from tagged cardiac MRI.

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Fig. 1.

A) Computational deforming phantom images with two different tag line spacings (10mm and 6 mm). B) Cropped images (from red bounding box in panel A) showing the point tracking density in the reference configuration (time point 1) and at peak systole (time point 12). Green 'X' markers represent the tracking locations for 2mm rectilinear grid tracking and tag intersection tracking.

Fig. 2. Circumferential (E_{cc}) and radial (E_{rr}) strain maps from the computational phantom at peak systole used for reference validation.

Ideal Tracking (Truth)

Neural Net Tracking

Fig. 3.

A) Plot of mean E_{tr} error vs RBF size for ideal tracking locations (true displacements from computational phantom). B) Mean E_{tr} error vs RBF regularization for ideal tracking locations C) and D) show similar plots but for strain calculated with neural net tracked deformations rather than the true deformation. Error is the global mean difference in strain values across the LV area.

Fig. 4.

A) Linear regressions of displacements for all tracked points with different line spacing and tracking point densities. x- and y-displacements are combined into an aggregate comparison of displacements for this analysis, and all time points are used. Best fit linear regressions and their equations are also displayed, where very good agreement is seen for all comparisons.

B) Displacement error is also calculated for all points during peak systole and displayed as violin plots. The box and circle within the violin plots show IQR and median values. Good agreement is seen between tracked and true locations, with little difference in error between intersection tracking and arbitrary point tracking.

Fig. 5.

A) E_{cc} and B) E_{tr} strain maps at peak systole for all combinations of tag line spacing and tracking point densities. C) Global E_{cc} and D) E_{tr} time curves and corresponding strain errors E), F) relative to the ground truth phantom values.

Fig. 6.

A) E_{cc} and B) E_{rr} strain maps at peak systole for a representative *in vivo* dataset for intersection tracking and 2mm tracking. Line plots show the difference in C) E_{cc} and D) E_{rr} between the two methods for all time points. Shaded errors in the line plots represent standard deviation across all slices measured.