Deep learning for automated insertion point annotation of CMR late gadolinium enhancement and virtual native enhancement images

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Background

Late gadolinium enhancement (LGE) on cardiovascular magnetic resonance (CMR) imaging can reproducibly identify the location and the extent of myocardial scar[1]. Left ventricular (LV) segmental analysis that allows accurate assignment of myocardial territories (based on the AHA 16-segment model[2]) is particularly important for assessment of coronary artery disease and aiding clinical decision-making regarding revascularisation. Advances in automated LGE post-processing to-date have primarily focused on segmentation of the LV endo- and epi-cardial contours[3]; however annotation of the anterior right ventricular (RV) insertion point to determine the orientation and segment assignments is also critical to allow full segmental quantification of scar volume fraction and transmurality on LGE. We present a deep learning approach for automated anterior RV insertion point annotation for LGE, applicable to the emerging contrast-agent-free CMR modality, virtual native enhancement (VNE) imaging[4].

Methods

We adapted our CMR tracking technology[5] to determine the RV entry line, as defined by the anterior RV insertion point and LV centre point. In short, the method involved a residual neural network backbone to regress the Cartesian coordinates of both points in a given image[5]. The imaging data comprised of 1085 (n = 816/269 LGE/VNE) short-axis images from 135 patients with myocardial infarction. The datasets were manually annotated by 2 experienced observers, which served as ground truth. A randomly selected set of 140 images was used for independent testing, and the rest for training the deep neural networks. The spatial annotation accuracy was measured by: (i) the Euclidean distance (mm) between the reference and predicted points, and (ii) the absolute angular error (°) between the ground-truth and predicted RV entry lines, in all slices and stratified by the slice position. The segmental scar transmurality error was measured by comparing the metrics derived from the ground-truth and predicted annotations on available LV myocardial manual contours (n = 70), using the intra-class correlation coefficient (ICC).

Results

The proposed model accurately predicted the RV entry line in all of the testing materials (Fig. 1), taking around 60 ms per slice. The overall Euclidean distance error was 2.9 ± 2.0 mm, the angular distance error 6.2 ± 5.9°, with an increasing trend towards the apical slices (Table 1). The errors between the test LGE set (n = 105; 2.8 ± 2.0 mm, 5.9 ± 5.7°) and the test VNE set (n = 35; 3.2 ± 2.0 mm, 6.9 ± 6.4°) were not statistically significant ($p > 0.05$). There was no perceivable impact on the derivation of the segmental scar transmurality (Fig. 2; n = 70, bias = 0.14 ± 3.49%, ICC = 0.99).

Conclusion

The presented deep learning-based approach is robust and effective for annotating the anterior RV insertion point in CMR images. Together with LV segmentation and quality control, it completes the pipeline for automated segmental quantification of LGE and VNE for clinical use.

References

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(a) LGE of patient A (b) LGE of patient B (c) LGE of patient C (d) VNE of patient C

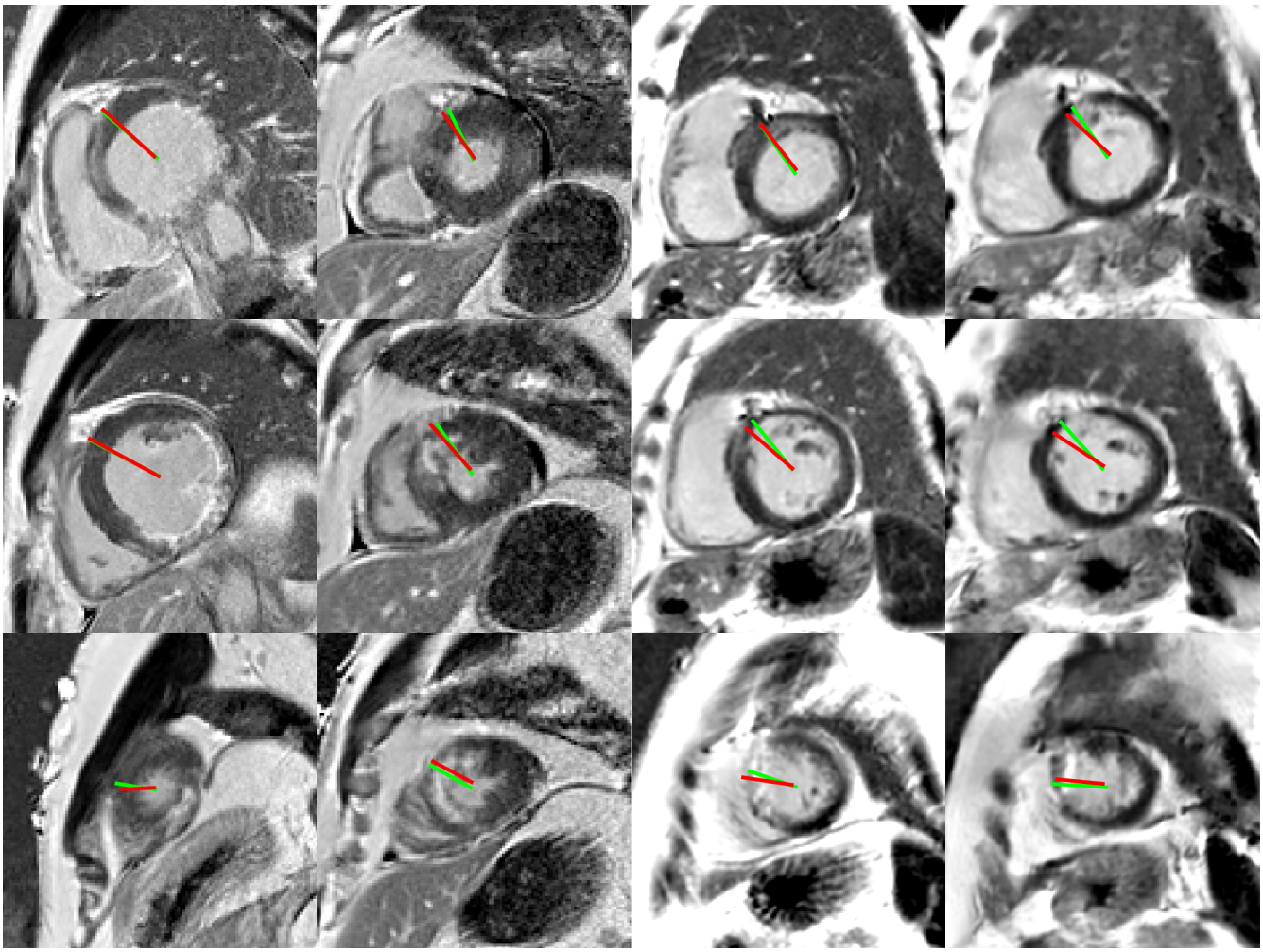

Figure 1. Four examples of manual (green) and automated (red) entry lines at the anterior right ventricular insertion point in late gadolinium enhancement (LGE) images (a-c) and virtual native enhancement (VNE) images (d), across basal, mid-ventricular and apical slices (top to bottom).

Table 1. Spatial annotation accuracy metrics evaluated in the test set and stratified by the basal, mid-ventricular and apical slices.

	All slices (n = 140)	Basal slices (n = 46)	Mid-ventricular slices (n = 57)	Apical slices (n = 37)
Euclidean distance error (mm)	2.9 ± 2.0	2.7 ± 1.9	3.0 ± 2.0	3.1 ± 2.1
Angular distance error (º)	6.2 ± 5.9	5.0 ± 3.7	6.3 ± 4.8	7.4 ± 8.8

(a) Linear regression plot

(b) Bland-Altman plot

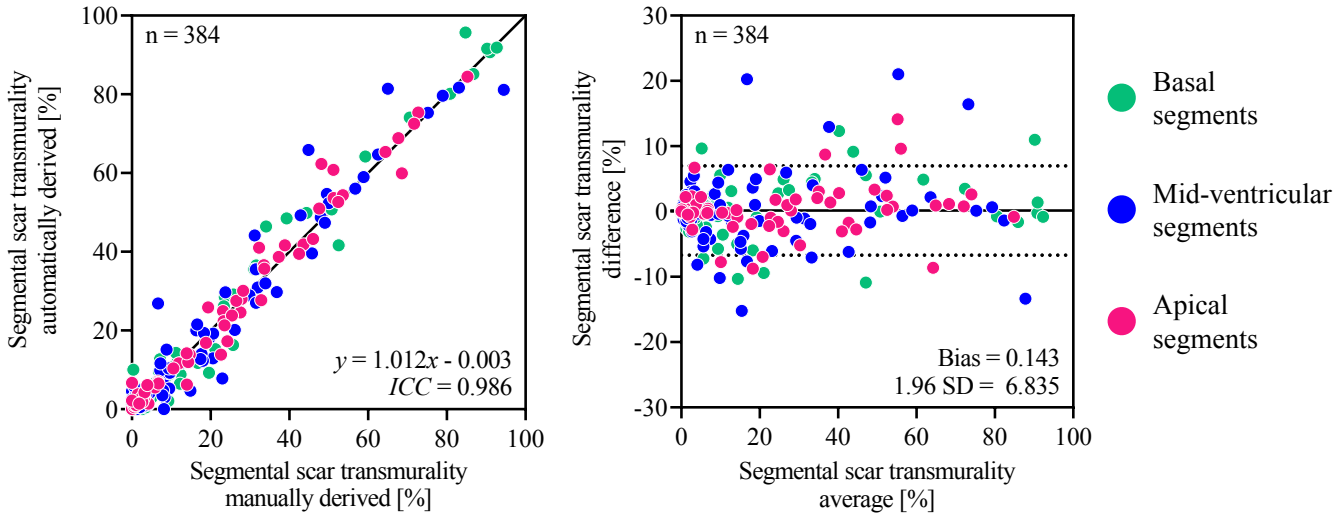

Figure 2. Clinical metric agreement of segmental scar transmurality using (a) linear regression, with the intra-class correlation coefficient (ICC), and (b) Bland-Altman plot showing the bias and the 95% limits of agreement.