StyleReg - Style Transfer as a Preprocess Step for Myocardial T1 Mapping

Eyal Hanania[1*] **Lilach Barkat**[2*] **Israel Cohen**[1] **Haim Azhari**[2] **Moti Freiman**[2]

[1]Faculty of Electrical Engineering
[2] Faculty of Biomedical Engineering
Technion – Israel Institute of Technology
Haifa, Israel

Abstract

Diffuse myocardial diseases can be diagnosed using T_1 mapping technique based on T_1 relaxation times from MRI data. The T_1 relaxation parameter is acquired through pixel-wise fitting of the MRI signal. Hence, pixels misalignment resulted by cardiac motion leads to an inaccurate T_1-mapping. Therefore, registration is needed. However, due to the intensity differences between the different time-points, recent unsupervised deep-learning approaches based on minimizing the mean-squared-error (MSE) between the images cannot be utilized directly. To overcome this challenge, we propose a new double-stage method, in which a style-transfer is used to harmonize the signal intensities over time, followed by an unsupervised deep-learning based minimization of the MSE between the images. We evaluated our approach on a publicly available cardiac T1 mapping database of 210 subjects. Our approach achieved the best median model-fitting R^2 compared to baseline methods (0.9794, vs. 0.9651/0.9744/0.9756) and T_1 values which are much closer to the the expected myocardial T_1 value. Furthermore, both metrics have less variability compared to the other methods.

1 Introduction

T_1 relaxation time is a key source of soft tissue contrast in MRI. Mapping of each pixel T_1 relaxation time, can depict relatively small variations within the cardiac muscle, highlight tissue pathology such as acute myocardial infarction, chronic scar tissue, or detect fatty infiltration. (14)

Creating T_1 mapping (Fig.1) requires a time series of aligned images in which each pixel describes the same tissue across time. Nonetheless, during image acquisition there are inevitable cardiac motion, respiratory motion and involuntary patient motion (15). Therefore there is a great need of image registration before curve fitting (4). In recent years, additional to traditional and to machine learning methods, deep learning-based methods have emerged (2). Usually, the standard metric for deep learning registration, where the images for alignment differ in their appearance, is Mutual Information (MI) (1; 5; 13; 16). Unfortunately, this metric is far behind within-contrast metrics such as Normal Cross Correlation (NCC) and Mean Square Error (MSE) in terms of accuracy (6; 7).

To tackle the motion-related challenges involved in cardiac T1 mapping, we propose changing the style of all the time series images to the same style using a style transformer approach (11). Then, we

36th Conference on Neural Information Processing Systems (NeurIPS 2022).

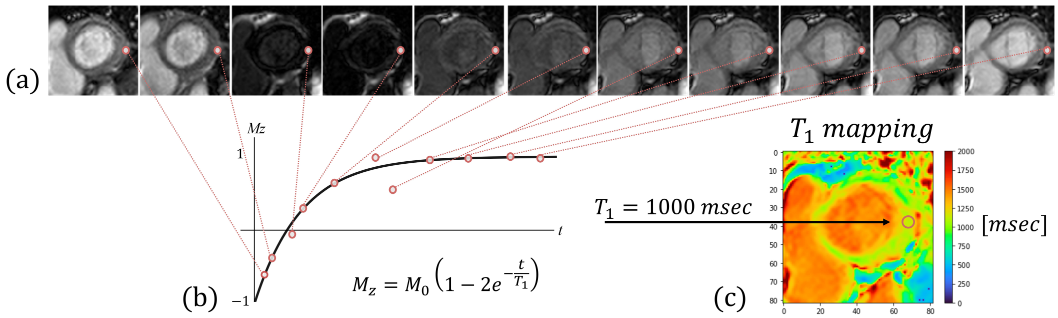

Figure 1: Schematic description of T_1 mapping for a single pixel. (a) myocardial images at 11 sequential time points (displayed at their absolute value). (b) Fitting an inversion recovery curve of the magnetization M_z over different time points t and extracting the corresponding T_1 and M_0 parameters. (c) Displaying T_1 mapping for all the pixels in the image.

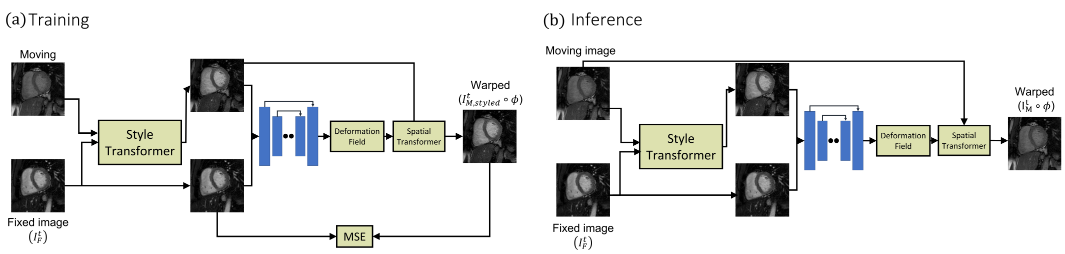

Figure 2: (a) Illustration of the training process. First, harmonization of the fixed and moving images using the style network, and afterward, registration of the harmonized images using voxelmorph. (b) Illustration of the inference time - First, harmonization of the fixed and moving images using the style network, calculating the the deformation field for the harmonized pair images and applying it to the original moving image.

propose using the harmonized images as input to the within-contrast registration network based on MSE loss (2) that fits cases of images with similar contrast and intensity distributions.

2 Methods

Our proposed method consists of two sequential stages. The first stage is a preparation stage, adjusting the color style of each image in the MRI sequence according to the first image color style using StyleGAN architecture (9; 11). Once all the images consist of the same color style, the registration can be learned using voxelmorph (2) based on the mean square error indices as the loss function. The voxelmorph architecture is used for pairwise registration. Aligning a moving image I_M to a fixed image I_F by yielding an optimized deformation field ϕ and a warped image $I_M \circ \phi$.(2; 8).

During the network training, firstly, for each patient, every image in the N length sequence images $I_M^t, \{t \in 1, \cdots, N\}$ harmonized to the first time point image I_F^0 as a reference style, using StyleGAN as the style transfer network. Following, the voxelmorph network was trained on the harmonized images, while for each patient, the moving image is one of $I_{M,stayled}^t, \{t \in 1, \cdots, N\}$ and the fixed image is I_F^0. The above training process is demonstrated in Fig.2(a). In inference time as demonstrated in Fig.2(b), the deformation field is calculated according to the harmonized moving image, but the yielded deformation field is applied on the original moving images.

In order to evaluate the proposed metric, a publicly available myocardial T_1 mapping dataset was used. (3) The dataset includes 210 patients with known or suspected cardiovascular diseases. For each patient, 5 slices at 11 time points were available with their corresponding myocardial segmentation map.

[*]Equal contribution

2.1 Implementation details

The implementation was based on PyTorch and ran on NVIDIA Tesla V100 GPU with 32G RAM. The style transfer network was trained for 100k iterations with $\lambda_{cycle} = 100$, $\lambda_{style} = 20$, $\lambda_{divergence} = 1$, style dimension and batch size of 4. The registration network was trained for 50k iterations with $\lambda_{smooth} = 0.003$ and a batch size of 64. For both network, ADAM optimizer was used with a learning rate of $1 \cdot 10^{-4}$.

3 Results

In order to evaluate the effectiveness of our two-staged method, the results were compared with the state of the art deep learning algorithms for medical image registration: pairwise VoxelMorph with mutual information loss (2) and pairwise SynthMorph (6), as well as with non-registered images. The four methods were evaluated comparing the pixels R^2 and T_1 value. The mean and median values are presented in Table.1 and their values distribution is presented in Fig.3.

T_1 value is vary according to the magnetic field, the imaging protocol, gender and the specific cardiovascular disease. (10; 12). Moreover, according to the imaging protocol, the images are relatively aligned with no significant movements during time. Therefore, it is reasonable to deduce that the original images estimated median T_1 value is closer to the actual median value. For the VoxelMorph algorithm, although the mean R^2 was higher than the non-registered images, the median R^2 was lower, indicates an higher variation in the estimated T_1 results. The proposed method and the SynthMorph, both, have reasonably close T_1 value and high R^2 value with less variability. Nonetheless, for both criteria, our proposed method is slightly better.

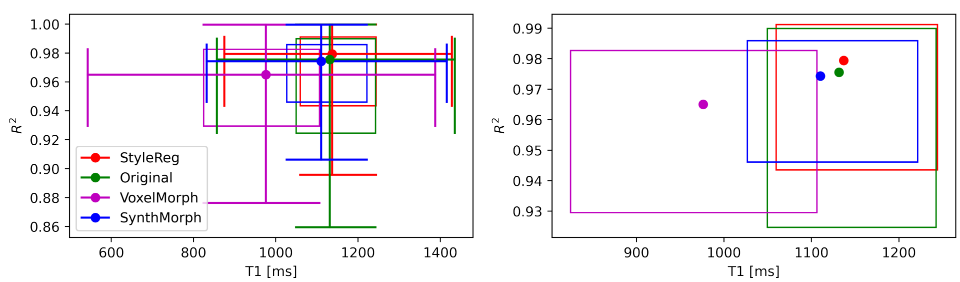

Figure 3: 2D boxplot comparing R^2 and T_1 value for different registration methods. (left) zoom out, (right) zoom in to the interquartile interval. Our StyleReg method achieves the highest median R^2 value while keeping the T_1 around the median of the original T_1 values. The full circles are the intersection between T_1 and R_2 medians.

Table 1: Evaluation of the four algorithms according to R^2 and T_1 mean and median results.

	$mean R^2 \pm std$	$median R^2$	$mean T_1 \pm std[ms]$	$median T_1[ms]$
Original	0.9267 ± 0.1136	0.9756	1155.6256 ± 244.6994	1131.5202
SynthMorph	0.9416 ± 0.0932	0.9744	1130.248 ± 223.1061	1110.2073
VoxelMorph	0.9443 ± 0.0722	0.9651	964.8632 ± 195.3005	976.1892
StyleReg	0.9436 ± 0.0919	0.9794	1154.3392 ± 210.2422	1136.8539

4 Conclusion

Varying appearance over the different time points, impose challenging registration task. In this work We propose a two-step method based on style transfer as preprocessing harmonization step before registration. Our approach benefits the within-contrast registration while we solve a cross-contrast problem. Our experimental results on a publicly available cardiac T1 mapping of 210 patients show that our process improves regressions R^2 and the accuracy of the T_1 values, which are much closer to the myocardial expected T_1 values compared to state-of-the-art methods. Our method was trained on myocardial T_1w images but can extend to other quantitative MRI tasks, which includes different contrasts images registration.

References

[1] Arava, D., Masarwy, M., Khawaled, S., Freiman, M.: Deep-learning based motion correction for myocardial t 1 mapping. In: 2021 IEEE International Conference on Microwaves, Antennas, Communications and Electronic Systems (COMCAS). pp. 55–59. IEEE (2021)

[2] Balakrishnan, G., Zhao, A., Sabuncu, M.R., Guttag, J., Dalca, A.V.: Voxelmorph: a learning framework for deformable medical image registration. IEEE transactions on medical imaging **38**(8), 1788–1800 (2019)

[3] El-Rewaidy, H., Nezafat, M., Jang, J., Nakamori, S., Fahmy, A.S., Nezafat, R.: Nonrigid active shape model–based registration framework for motion correction of cardiac t1 mapping. Magnetic resonance in medicine **80**(2), 780–791 (2018)

[4] Fu, Y., Lei, Y., Wang, T., Curran, W.J., Liu, T., Yang, X.: Deep learning in medical image registration: a review. Physics in Medicine & Biology **65**(20), 20TR01 (2020)

[5] Gong, L., Wang, H., Peng, C., Dai, Y., Ding, M., Sun, Y., Yang, X., Zheng, J.: Non-rigid mr-trus image registration for image-guided prostate biopsy using correlation ratio-based mutual information. Biomedical engineering online **16**(1), 1–21 (2017)

[6] Hoffmann, M., Billot, B., Greve, D.N., Iglesias, J.E., Fischl, B., Dalca, A.V.: Synthmorph: learning contrast-invariant registration without acquired images. IEEE transactions on medical imaging **41**(3), 543–558 (2021)

[7] Iglesias, J.E., Konukoglu, E., Zikic, D., Glocker, B., Leemput, K.V., Fischl, B.: Is synthesizing mri contrast useful for inter-modality analysis? In: International Conference on Medical Image Computing and Computer-Assisted Intervention. pp. 631–638. Springer (2013)

[8] Jaderberg, M., Simonyan, K., Zisserman, A., et al.: Spatial transformer networks. Advances in neural information processing systems **28** (2015)

[9] Karras, T., Laine, S., Aila, T.: A style-based generator architecture for generative adversarial networks. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. pp. 4401–4410 (2019)

[10] Liu, J.M., Liu, A., Leal, J., McMillan, F., Francis, J., Greiser, A., Rider, O.J., Myerson, S., Neubauer, S., Ferreira, V.M., et al.: Measurement of myocardial native t1 in cardiovascular diseases and norm in 1291 subjects. Journal of Cardiovascular Magnetic Resonance **19**(1), 1–10 (2017)

[11] Liu, M., Maiti, P., Thomopoulos, S., Zhu, A., Chai, Y., Kim, H., Jahanshad, N.: Style transfer using generative adversarial networks for multi-site mri harmonization. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. pp. 313–322. Springer (2021)

[12] Meloni, A., Martini, N., Positano, V., D'Angelo, G., Barison, A., Todiere, G., Grigoratos, C., Barra, V., Pistoia, L., Gargani, L., et al.: Myocardial t1 values at 1.5 t: Normal values for general electric scanners and sex-related differences. Journal of Magnetic Resonance Imaging **54**(5), 1486–1500 (2021)

[13] Rivaz, H., Karimaghaloo, Z., Fonov, V.S., Collins, D.L.: Nonrigid registration of ultrasound and mri using contextual conditioned mutual information. IEEE transactions on medical imaging **33**(3), 708–725 (2013)

[14] Taylor, A.J., Salerno, M., Dharmakumar, R., Jerosch-Herold, M.: T1 mapping: basic techniques and clinical applications. JACC: Cardiovascular Imaging **9**(1), 67–81 (2016)

[15] Tilborghs, S., Dresselaers, T., Claus, P., Claessen, G., Bogaert, J., Maes, F., Suetens, P.: Robust motion correction for cardiac t1 and ecv mapping using a t1 relaxation model approach. Medical Image Analysis **52**, 212–227 (2019)

[16] Viola, P., Wells III, W.M.: Alignment by maximization of mutual information. International journal of computer vision **24**(2), 137–154 (1997)