Twenty-five-fold temporal resolution in cardiac CT: Deep learning-based partial angle motion compensation

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Purpose or Learning Objective:

Cardiac motion, which can lead to motion artifacts, hinders the diagnostic values of cardiac CT. To deal with motion artifacts, there are several class of strategies. One such class are drug-based approaches that typically rely on the administration of beta-blockers to slow down the heart rate before acquisition [1]. Another class are software-based approaches that correct for motion post-acquistion. Among the latter, so-called partial angle-based motion compensation (PAMoCo) approaches have proven great potential [2]. While existing implementations are limited to coronary arteries only [3], this work presents a deep learning-based PAMoCo approach (Deep PAMoCo) that can correct for motion in the entire heart.

Methods or Background:

The principal idea of the PAMoCo is to divide the scan range into (2K+1) sub-ranges which can be reconstructed independently to derive a set of (2K+1) so-called partial angle reconstructions (PARs). While these PARs show severe limited-angle artifacts, they have (2K+1)-fold higher temporal resolution compared to a conventional reconstruction using all data. Therefore, it can be assumed that with a proper choce of K, any PAR represents a distinct quasi-static motion phase of the scan. Estimating inter-phase motion in the form of a motion vector field (MVF) allows to transform all PARs to the same reference phase, say the central motion phase at K = 0. Once transformed, all PARs can be summed up to get a motion compensated reconstruction as:

$$f_{moco}(r) = \sum_{-K}^{K} (r + s(r, t_k)) \qquad (1)$$

Fig 1

Above, **r** represents the spatial coordinate and **s** represents the MVF applied onto PAR at time **tk**. In deep learning-based PAMoCo, a U-net based neural network estimates the MVF **s** while a spatial transformer network (STN) applied the MVF onto the PARs as depicted in figure 1.

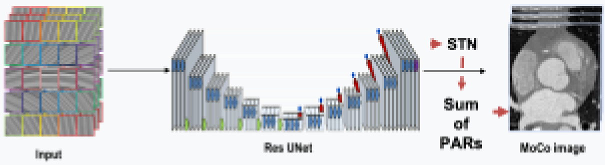

Fig 2: Schematic of the proposed Deep PAMoCo.

For the aforementioned approach, we used simulations that are based on clinical CT reconstructions with a motion model. Training the approach in a supervised setup requires input-label pairs, where the inputs are PARs and the labels are the reconstructions at motion state K=0. To generate training data with motion artifacts, we found the MVF between the systolic and diastolic phases then we generated 600 sub-volumes by deforming systolic phase iteratively with the sub-MVFs formed by scaling the MVF, which are then forward and back-projected to form the 25 PARs each with an angular interval of 7.2°. The ground truth corresponds to the motion state of the central PAR. Given the data, we trained 230 epochs, by minimizing the mean squared error between the ground truth and the prediction.

Results or Findings:

The performance was evaluated on 100 test samples generated as described in the previous section. In figure 2, as seen in the comparison and the difference images, the proposed method is able to remove motion artifacts in key cardiac features such as the coronary artery and the aortic valve by mapping all PARs to the central motion state.

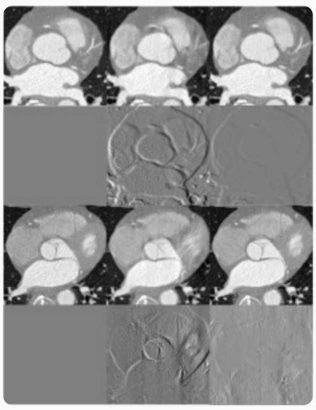

Fig 3: Left column represents the ground truth, middle column represent filtered-back project (FBP) reconstruction, right column represent the MoCo image. The even numbered rows are the differences images in relation to the ground truth.

Conclusion:

Other software-based motion compensation methods such as registration-based methods, which acquire multiple phases, thus needing extra dose. While recently, some deep-learning based methods seek to remove motion artifacts that through an image-to-image translation that are essentially cosmetic methods with no physical context. Compared to these methods, the deep PAMoCo method was able to compensate for cardiac motion and therefore remove motion artifacts without adding extra dose or compensating for non-existant “motion”. The proposed approach proved efficient in reducing motion artifacts, and thus improving the image quality of cardiac CTs.

References:

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[2] Hahn, J., Bruder, H., Rohlkohl, C., Allmendinger, T., Stierstorfer, K., Flohr, T., & Kachelrieß, M. “Motion compensation in the region of the coronary arteries based on partial angle reconstructions from short-scan CT data”, Med. Phys. 44 (11): 5795–5813 (2017).

[3] Maier, J., Lebedev, S., Erath, J., Eulig, E., Sawall, S., Fournié, E., Stierstorfer, K., Lell, M., & Kachelrieß, M. “Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT.” Medical Physics 48: 3559-3571(2021).

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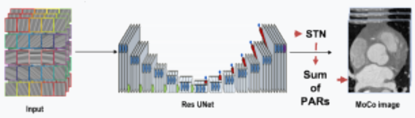
Fig 1



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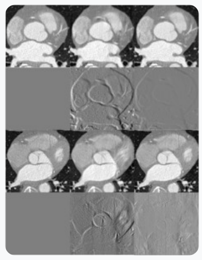

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