DuDoSS: Deep-Learning-Based Dual-Domain Sinogram Synthesis from Sparsely Sampled Projections of Cardiac SPECT

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Abstract

Purpose: Myocardial perfusion imaging (MPI) using single-photon emission computed tomography (SPECT) is widely applied for the diagnosis of cardiovascular diseases. In clinical practice, the tedious scanning procedures and long acquisition time might increase patient anxiety and discomfort, motion artifacts, misalignments of SPECT and computed tomography (CT). Reducing the number of projection angles is a feasible solution to reduce the scanning time. However, fewer projection angles might cause lower reconstruction accuracy, higher noise level, and reconstruction artifacts. We developed a deep learning-based approach to improve image quality reconstructed from sparsely sampled projections.

Methods: We propose a novel deep-learning-based dual-domain sinogram synthesis (DuDoSS) to recover the full-view projections from sparsely sample projections of cardiac SPECT images. The studying dataset includes a total of 500 anonymized clinical stress-state MPI studies acquired on a GE NM/CT 850c scanner with 60 projection angles. One-day stress-only low-dose protocol, with the mean administered dose of 15 mCi ^{99m}Tc-tetrofosmin, was used. DuDoSS applies the SPECT images predicted in the image domain as guidance for the synthesis of the full-view projections in the sinogram domain. The SPECT image reconstructed using sparsely sampled projections is first input to an image-domain neural network in the image domain to predict the SPECT image reconstructed using ground-truth full-view projections. The predicted SPECT image is then forward-projected to generate pseudo full-view projections, which are then input to another projection-domain neural network to predict the ground-truth full-view projections. The synthetic projections were then reconstructed into non-attenuation-corrected (NAC) and attenuation-corrected (AC) SPECT images with or without CT-derived attenuation maps for quantitative evaluations. Voxel-wise evaluation metrics including normalized mean square error (NMSE) and segment-wise evaluation metrics including absolute percent error (APE) are applied for the quantitative evaluations.

Several testing groups are setup for comparison. CUSIP refers to a recently proposed approach, Convolutional U-Net-shaped Synthetic Intermediate Projections. CUSIP-DuRDN refers to the CUSIP method using a recently proposed deep learning algorithm Dual Squeeze-and-excitation Residual Dense Network (DuRDN). Direct Sino2Sino refers to predicting synthetic projections from zero-padded sparse-view projections directly. Direct Img2Img refers to predicting the full-view SPECT images from sparse-view SPECT images directly.

Results: Our proposed DuDoSS generated more accurate synthetic projections than CUSIP (NMSE 2.08 ± 0.81% versus 2.84 ± 0.97%, $p < 0.001$). The reconstructed images of DuDoSS are more accurate than CUSIP for both NAC (NMSE 1.89 ± 0.79% versus 3.02 ± 1.10%, $p < 0.001$) and AC images (NMSE 1.63 ± 0.72% versus 2.70 ± 0.94%, $p < 0.001$). In addition, the APE of the 17-segment polar maps of DuDoSS is significantly lower than CUSIP (APE 3.92 ± 3.20 % versus 12.23 ± 4.46%, $p < 0.001$).

Conclusions: Our proposed DuDoSS can generate accurate synthetic full-view projections from sparsely acquired projections for cardiac SPECT MPI. The synthetic projections generated by our DuDoSS are more accurate than the previous CUSIP approach. Besides, the reconstructed NAC and AC images using the synthetic projections by DuDoSS show lower errors than those of CUSIP.

KEYWORDS

Deep learning, sinogram synthesis, cardiac SPECT, myocardial perfusion imaging

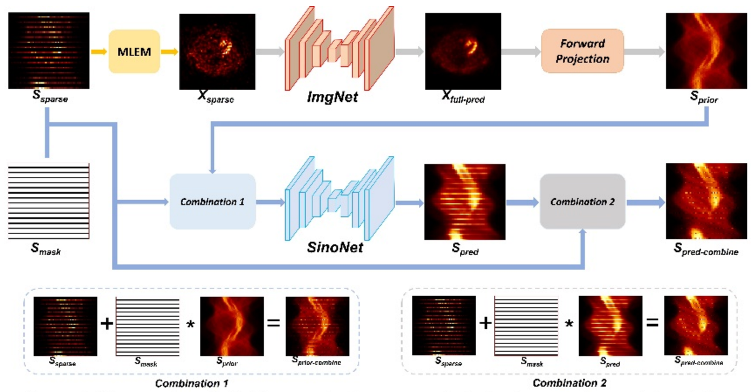

Figure 1. Diagram of our DuDoSS approach. X_{sparse} reconstructed using sparsely sampled projections S_{sparse} is input to the *ImgNet* to predict the full-view SPECT image $X_{full-pred}$. Then, $X_{full-pred}$ undergoes a forward projection to generate a prior sinogram S_{prior}, which is then combined with the ground-truth projections to get the $S_{prior-combine}$. Next, $S_{prior-combine}$ is input to the *SinoNet* to generate the predicted sinogram S_{pred}. Finally, S_{pred} is combined with the ground-truth projections to output the combined projections $S_{pred-combine}$.

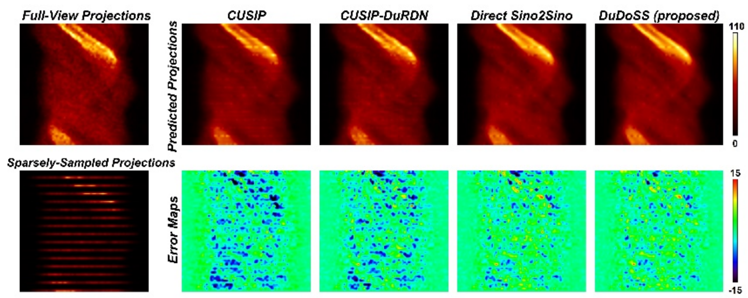

Figure 2. Synthetic projections of the slice crossing the center of the patient heart. *CUSIP-DuRDN* refers to the *CUSIP* method using a novel deep neural networks Dual Squeeze-and-excitation Residual Dense Network (DuRDN). *Direct Sino2Sino* refers to predicting synthetic projections from zero-padded sparse-view projections directly. Our proposed *DuDoSS* outputs more accurate synthetic projections than other groups, while *CUSIP* and *CUSIP-DuRDN* shows obvious under-estimations.

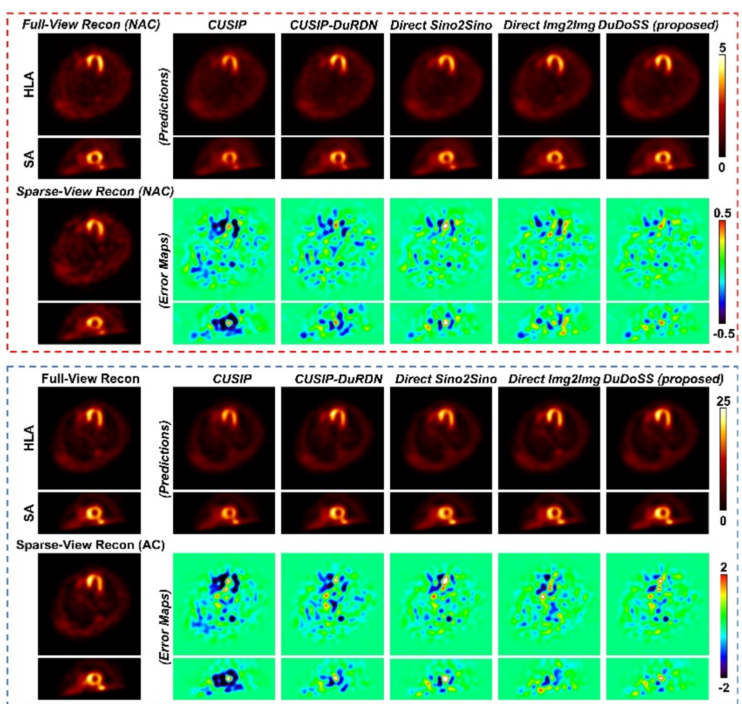

Figure 3. Reconstructed or predicted NAC/AC SPECT images. The NAC SPECT images are shown in the top red dash box, and the AC SPECT images are shown in the bottom blue dash box. *Direct Img2Img* refers to predicting the full-view SPECT images from sparse-view SPECT images directly. *DuDoSS* outputs the most accurate NAC and AC SPECT images, with the lowest errors.