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# Improved coronary artery calcium (CAC) detection in conventional CT with deep-learning image de-blurring

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## Abstract

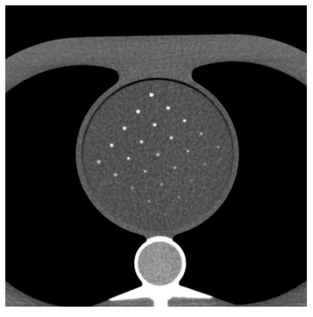
We investigated the impact of a CNN-based deep-learning (DL) algorithm for image de-blurring on coronary artery calcium (CAC) detection performance in conventional CT imaging. Our approach comprises first de-noising the image with a state-of-the-art CNN-based image de-noising algorithm. With improved SNR, it is then possible to sharpen the image with a CNN-based image de-blurring algorithm. We train such networks using natural images, *i.e.*, a large set of diverse photographs. The de-noising strength in the final image can be adjusted by blending back the estimated noise from the first step to the desired degree. To assess the impact of the de-blurring algorithm, we scanned an anthropomorphic phantom containing 100 small calcifications on a CT system using a CAC scoring protocol. Data were acquired at clinical and high radiation dose, and subsequently reconstructed with and without the DL de-blurring algorithm, using 25% de-noising strength. For each small CAC, detectability was defined as the ability to calculate an Agatston score (at least 3 adjacent voxels exceeding 130 Hounsfield units). For the high dose scans, CAC detectability increased from 39% for the standard reconstruction to 49% with de-blurring. The same 39% CAC detectability at high dose without de-blurring was obtained with routine dose with de-blurring. In this work, we also show some visual impressions of applying our DL de-blurring method to clinical cardiac data.

## Introduction

- CT imaging suffers both from **noise** and **system blur**, which both impair **readability,** general **image quality** and the **diagnostic value** of any CT acquisition.
- This is in particularly relevant for all clinical tasks involving the detection of small objects, such as **coronary artery calcification (CAC) detection**.
- In this work we assess the impact of a deep-learning, **CNN-based de-blurring** solution which we use together with a **CNN-based denoising** algorithm [1, 6], on the performance of CAC detection.
- For the quantification we evaluate CAC detection on a one-of-a-kind **anthropomorphic phantom** [3, 4], containing many various small cylindrical CACs of different sizes and densities.
- Algorithmically we use a separate denoising CNN followed by a de-blurring CNN (**two-steps**), giving us more flexibility and control in the output definition as opposed to a single end-to-end algorithm.

## Methods

- The anthropomorphic **chest phantom** was scanned on a Philips CT7500 dual-layer system with a central **insert containing 100** small cylindrical **calcifications**.
- Calcifications are varying in **size** (0.5 - 2mm) and **density** (90 - 540mg hydroxyapatite per cc).



**Data acquisition parameters**

- 120 kVp, 0.27s rot. time, 128 x 0.625 mm coll.
- 512 x 512 FBP recon with Philips standard res. C-filter and 220m FOV
- two dose settings: **clinical** dose (4.0 mGy CTDIvol) and **high** dose (20.8 mGy CTDIvol)

**Figure 1** Axial view of the used phantom with the different calcifications clearly visible in the central insert. Figure taken from Ref. [3].

## DL - deblurring workflow

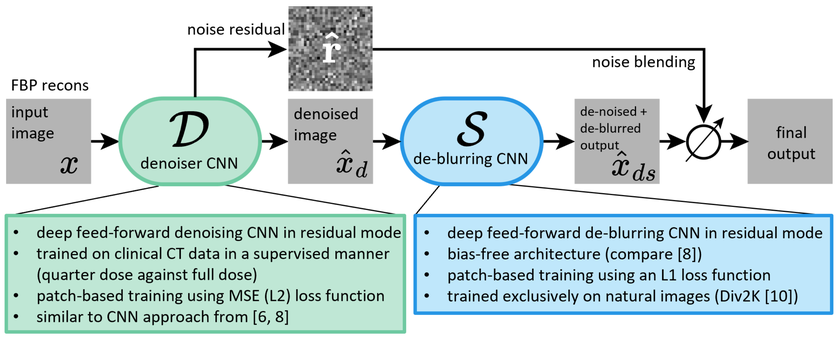



**Figure 2** Schematic depiction of the introduced AI-deblurring solution. Starting with conv. FBP CT recons, we feed the images first to a denoising CNN, giving us a denoised image and an estimate for the noise residual in the image. In a second step we apply the AI-deblurring CNN to remove system blur from the images. Final noise blending with the stored noise residuals allows to control the noise level in the final output image.

## Results

- CAC performance was assessed using a previously validated, automated quantification method [11], where for each **CAC detectability** was defined as the ability to calculate an Agatston score.

**CAC detection accuracy**

| dose setting | standard | AI de-blurred |
|---|---|---|
| clinical | 37 % | 39 % |
| high | 39 % | 49 % |

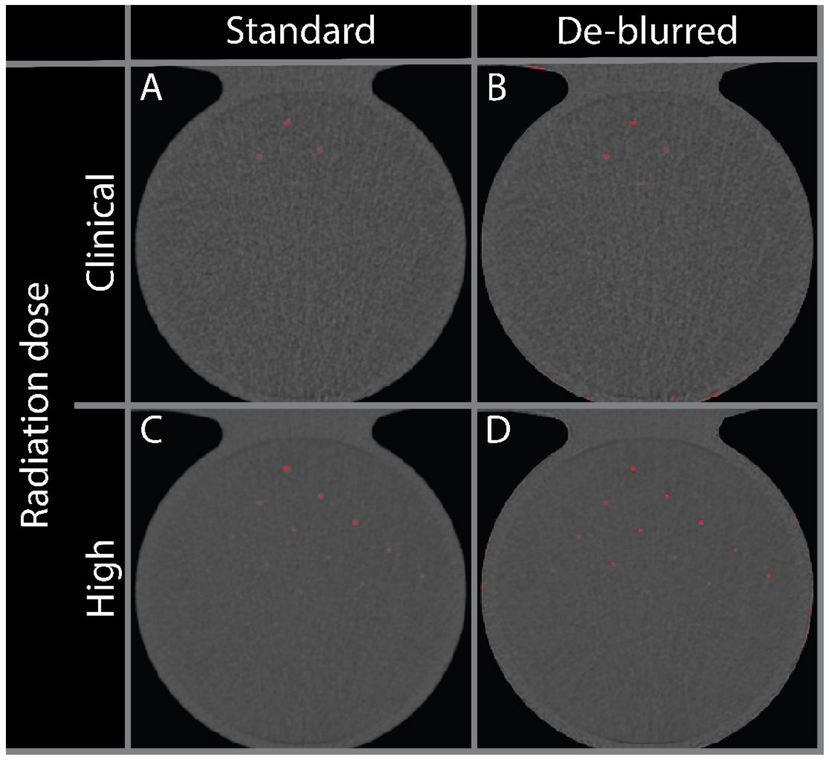



**Figure 3** Representative images of the CAC phantom with voxels exceeding the Agatston scoring threshold of 130 HU labeled in red. The slice shown contains the 25 smallest (0.5 - 1.0 mm) and highest density (240 - 540 mg hydroxyapatite/cc) calcifications. Results are shown for (**A**) clinical dose and standard reconstruction, (**B**) clinical dose and DL de-blurred reconstruction, (**C**) high dose and standard reconstruction, and (**D**) high dose and DL de-blurred reconstruction. All images are shown at a level of 90 HU and window width of 750 HU.

## Application to clinical cardiac CT

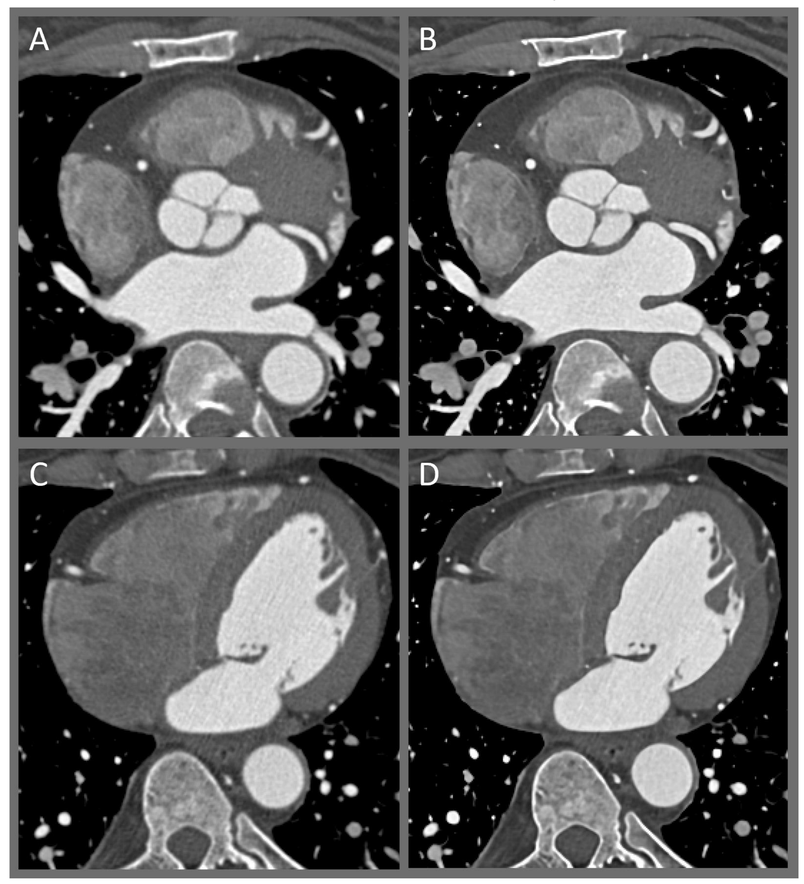



**Figure 4** Gated cardiac CT acquisition shown at two different axial slice locations. **A** and **B** depict the same axial cross section with the conventional cardiac reconstruction shown in **A** compared to the DL-based image de-blurring method shown in **B**. **C** and **D** show a lower axial slice. Again, conventional processing in **C** is compared to the processing with DL image de-blurring active as shown in **D**.

## Conclusions

- We investigated the impact of a generic DL image de-blurring algorithm on **CAC detection** and perceived **image sharpness**, showing improvements, both quantitatively for the chest phantom as well as qualitatively on the clinical cardiac scans.
- Further, we want to promote this intricate interplay between **denoising** and **de-blurring** with AI algorithms, where we herein introduce a quite generic AI de-blurring algorithm trained on **natural images**.
- Last, we want to promote the use of **clinical task-based metrics** to assess **image formation** algorithms such as the CAC detection task.

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