## Metal

Marc Kachelrieß

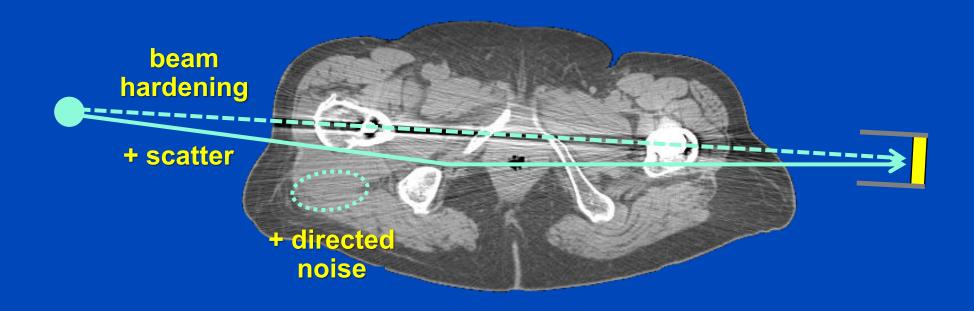
German Cancer Research Center (DKFZ)

Heidelberg, Germany

www.dkfz.de/ct



#### **Metal artifacts are**

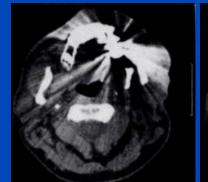


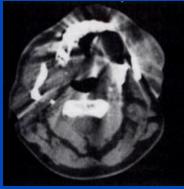
+ increased susceptibility to sampling artifacts and motion.

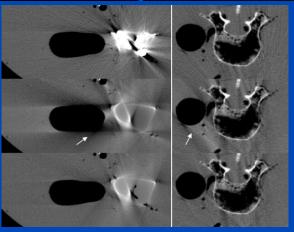


## Metal Artifact Reduction (MAR)

- With linear interpolation (MAR1)
  - [1] W. A. Kalender, R. Hebel and J. Ebersberger, "Reduction of CT artifacts caused by metallic implants", Radiology, vol. 164, no. 2, pp. 576-577, August 1987.
- With simple length-normalization (MAR2)
  - [2] J. Müller and T. M. Buzug, "Spurious structures created by interpolation-based CT metal artifact reduction", SPIE Medical Imaging Proc., vol. 7258, no. 1, pp. 1Y1-1Y8, March 2009.
- Our generalized normalization (NMAR)
  - [3] E. Meyer, F. Bergner, R. Raupach, and M. Kachelrieß.
     "Normalized metal artifact reduction (NMAR) in computed tomography", IEEE Medical Imaging Conference Record, M09-206, October 2009.







## GE's Solution Combines DECT Acquisition with Data Inpainting ...

Gastrointestinal Imaging · Original Research

Metal Artifact Reduction Software
Used With Abdominopelvic
Dual-Energy CT of Patients
With Metal Hip Prostheses:
Assessment of Image Quality and
Clinical Feasibility

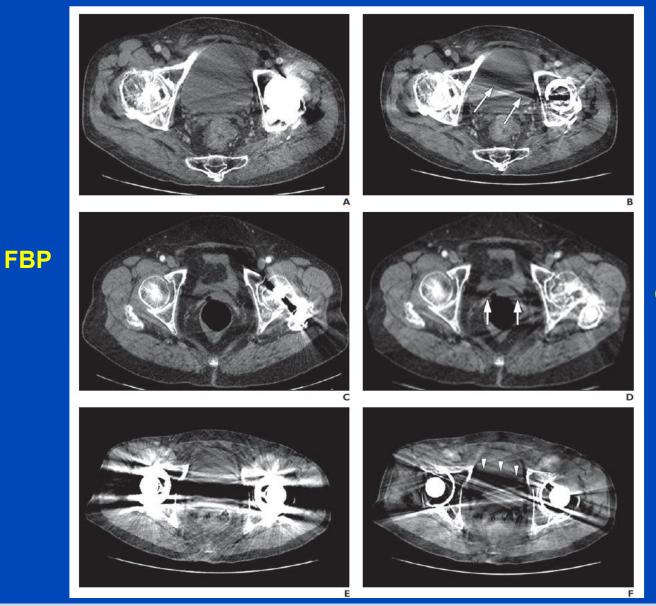
Seung Chol Han<sup>1</sup> Yong Eun Chung<sup>1</sup> Young Han Lee<sup>1</sup>

**OBJECTIVE.** The objective of our study was to determine the feasibility of using Metal Artifact Reduction (MAR) software for abdominopelvic dual-energy CT in patients with metal hip prostheses.

MATERIALS AND METHODS. This retrospective study included 33 patients (male



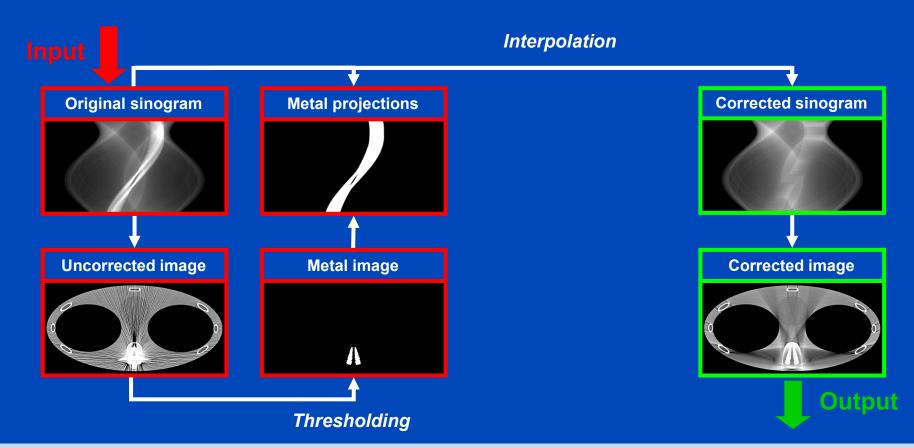
## ... but the Results are not Convincing!



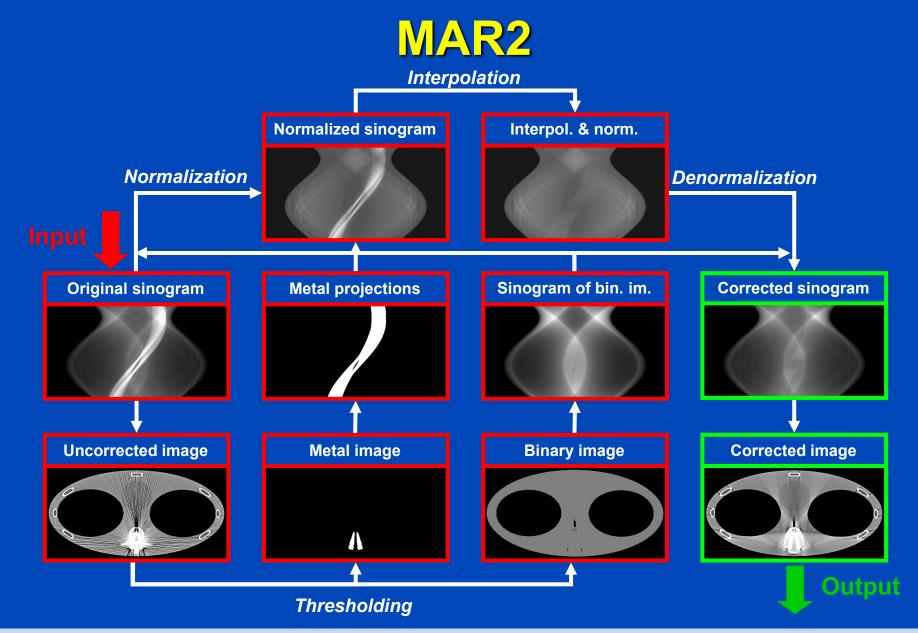




#### MAR1

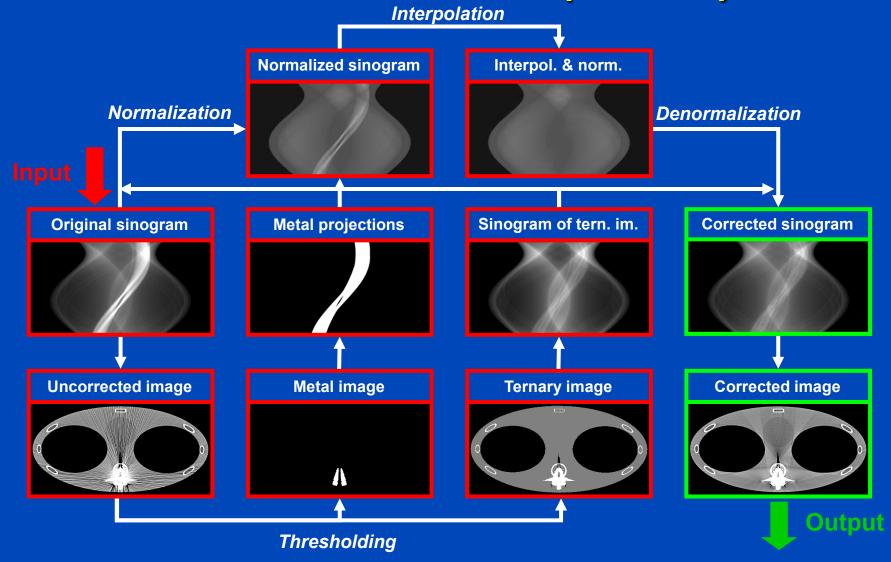






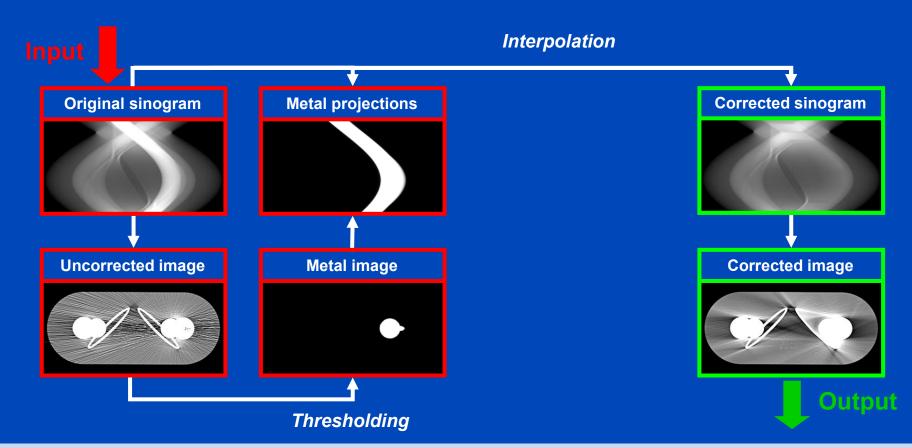


## Normalized MAR (NMAR)

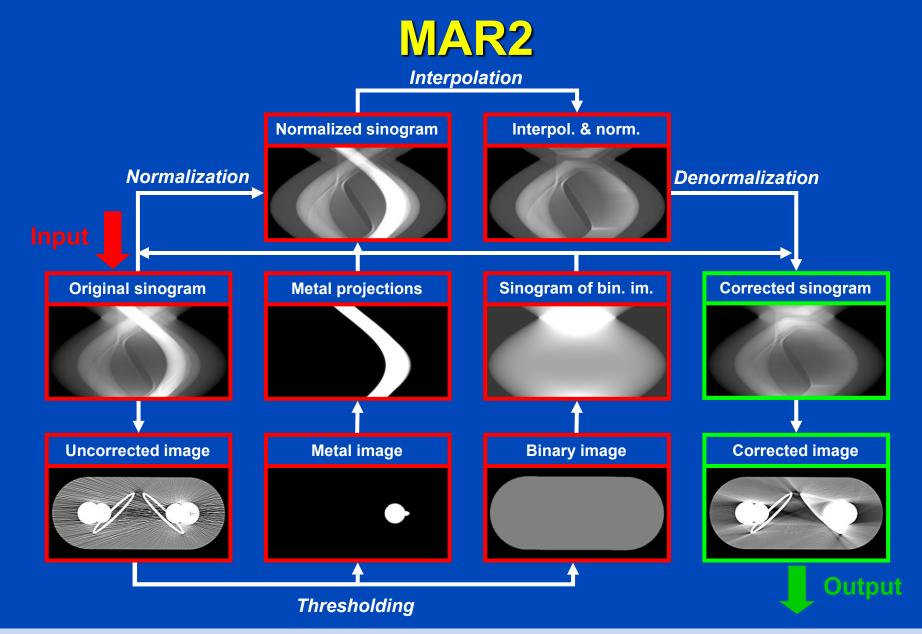




#### MAR1

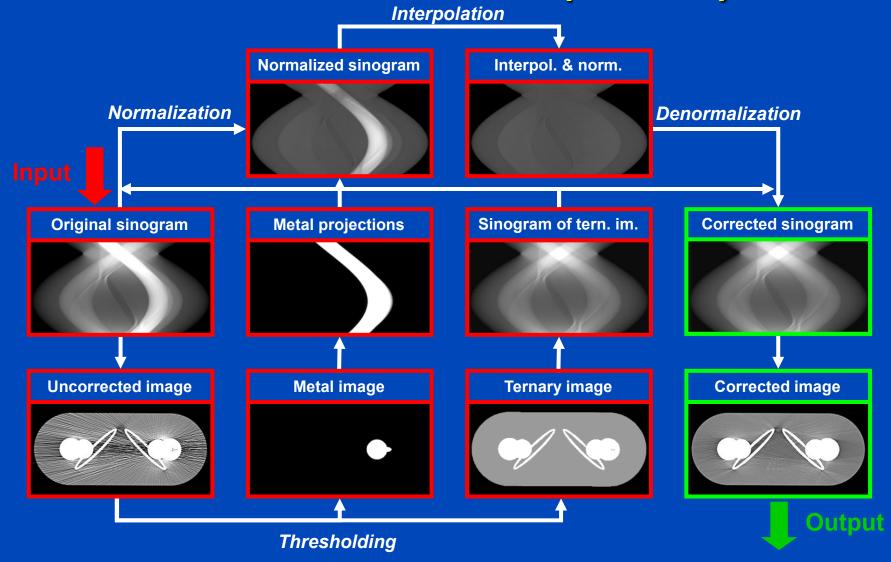






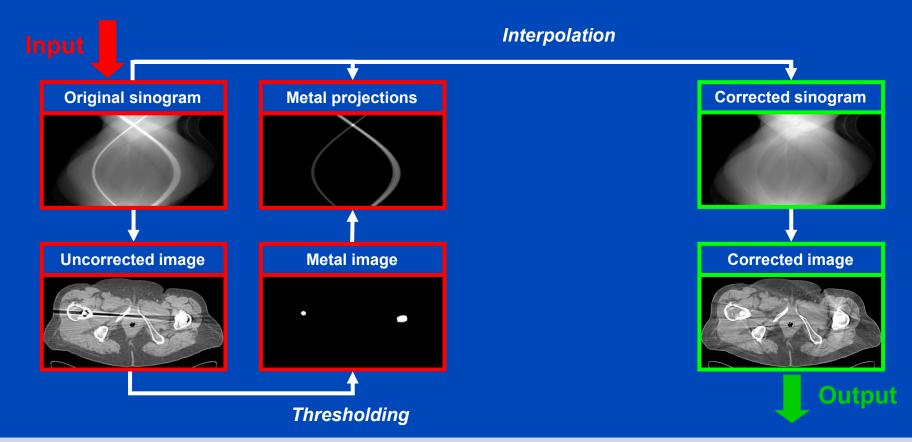


## Normalized MAR (NMAR)

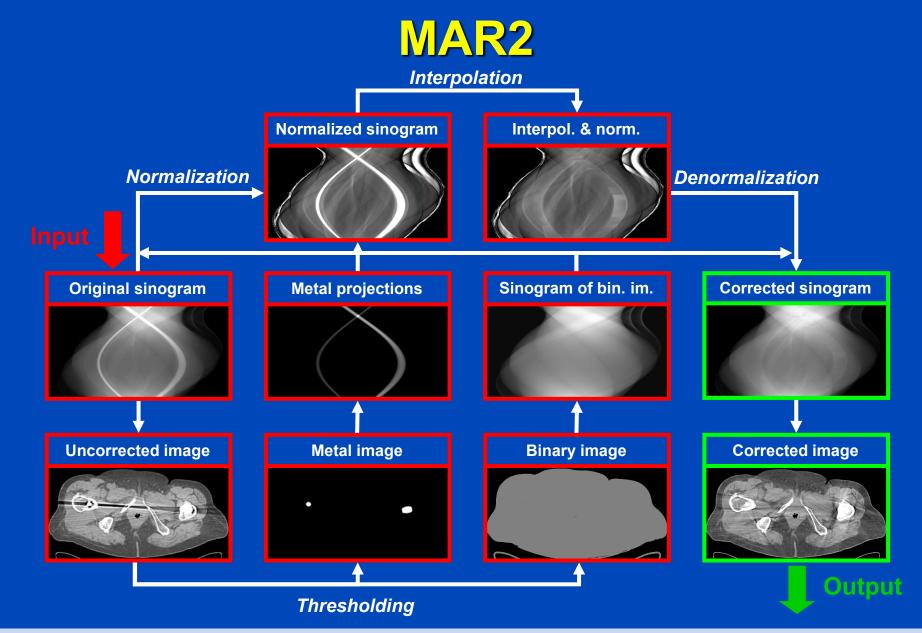




#### MAR1

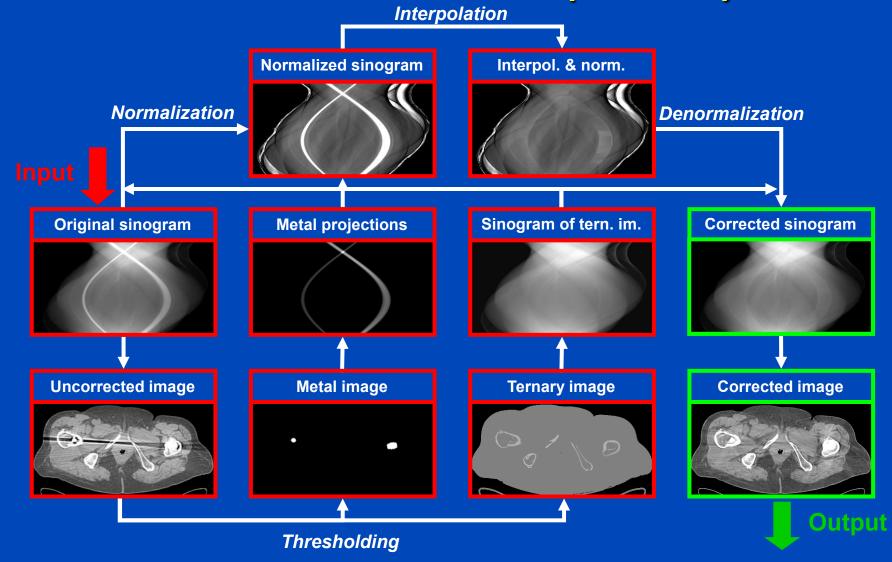








## Normalized MAR (NMAR)





## Results and Comparison: Patient Data

Uncorrected MAR1 MAR2 **NMAR** 

Patient with hip implants, Sensation 16, 140 kV, (C=0/W=500)



## Results and Comparison: Patient Data

Uncorrected MAR1 MAR2 NMAR

Patient with hip implants, Sensation 16, 140 kV, (C=500/W=1500)



# Results and Comparison: Patient Data MAR1 MAR2

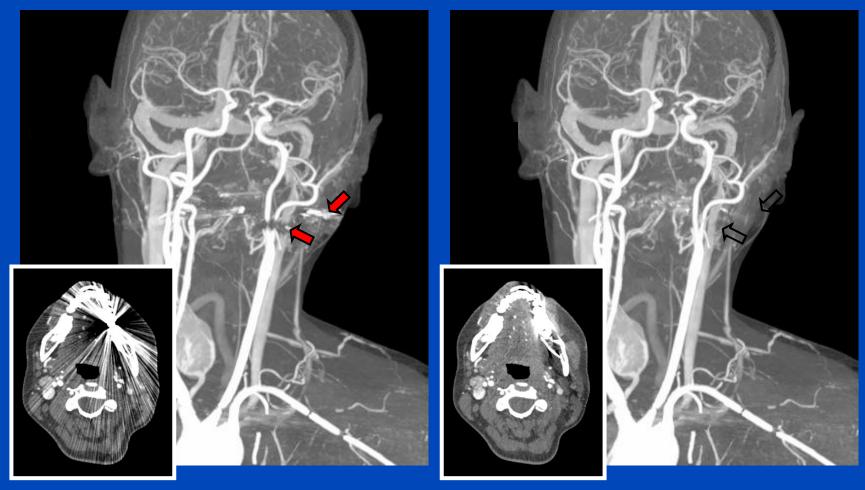
MAR1 Uncorrected **NMAR** 

Patient dental fillings, slice 110, Somatom Definition Flash, pitch 0.9. Top and middle row: (C=100/W=750). Bottom row: (C=1000/W=4000)



## **NMAR: Results**

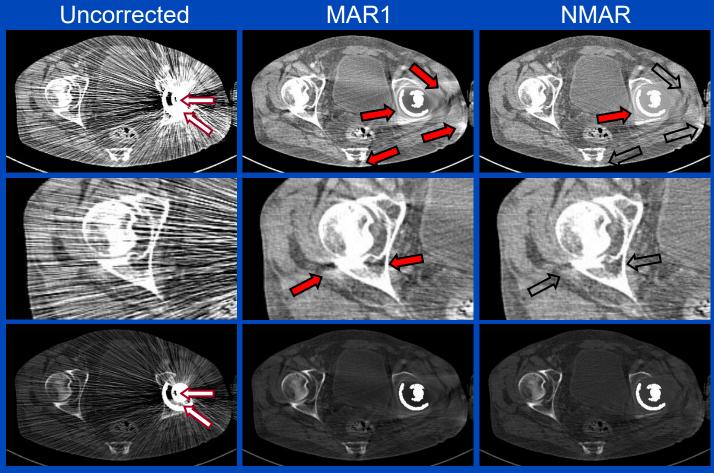
Uncorrected NMAR



Bone removal (with scanner software), (C=40/W=500).



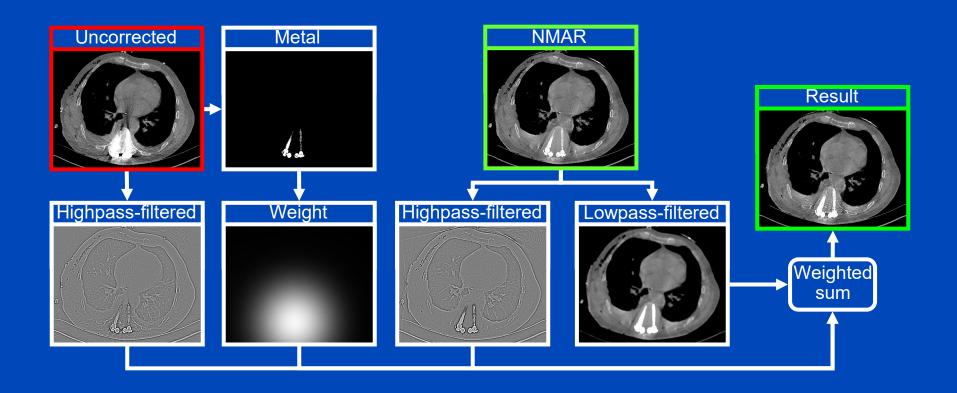
#### **NMAR: Results**



Patient with hip implant, Somatom Definition Flash, pitch 2.7. Top and middle row: (C=0/W=500). Bottom row: (C=500/W=1500).



#### **FSMAR: Scheme**





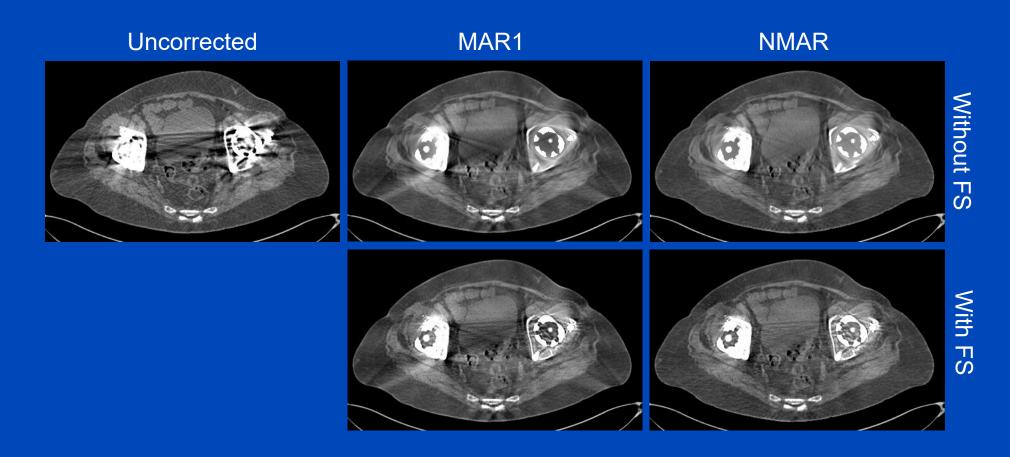
Uncorrected MAR1 **NMAR** Without FS With FS Patient with spine fixation, Somatom Definition, (C=100/W=1000).

dkfz.

Uncorrected MAR1 **NMAR** Without FS With FS

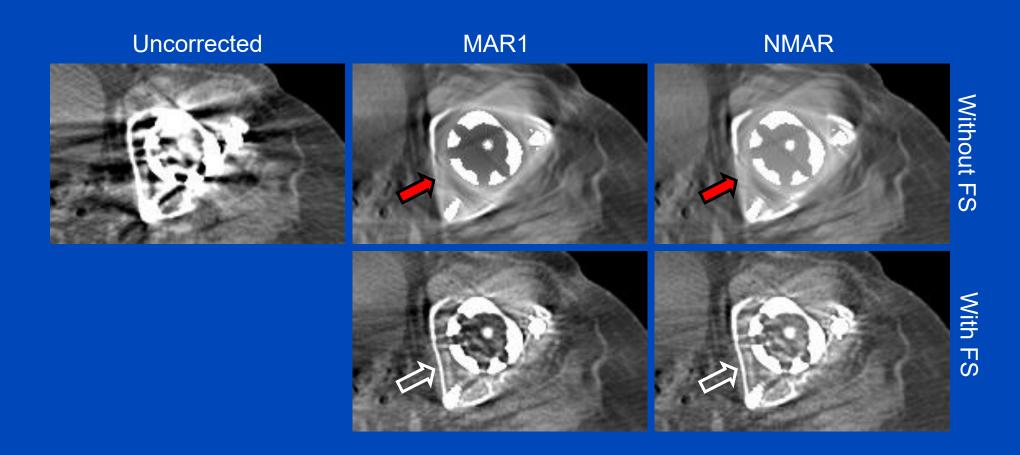
Patient with spine fixation, Somatom Definition, (C=100/W=1000).





Patient with bilateral hip prosthesis, Somatom Definition Flash, (C=40/W=500).

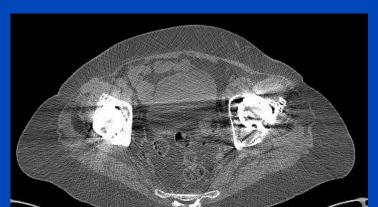




Patient with bilateral hip prosthesis, Somatom Definition Flash, (C=40/W=500).



Uncorrected



**NMAR** 



**FSNMAR** 

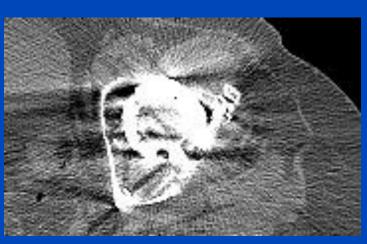


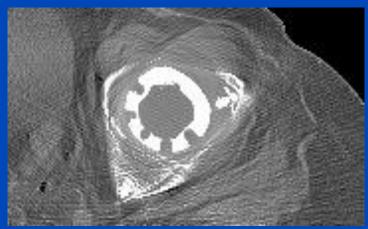
(C40/W800),  $S_{eff} = 1.5 \text{ mm}$ 



Uncorrected







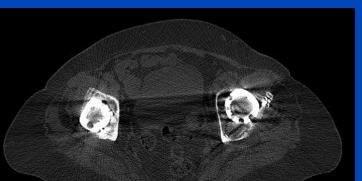
**FSNMAR** 



(C40/W800),  $S_{eff} = 1.5 \text{ mm}$ 



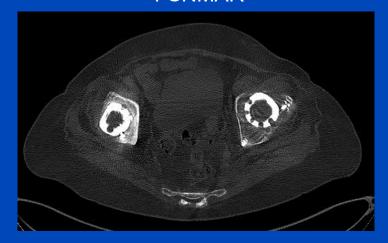
Uncorrected



**NMAR** 



**FSNMAR** 

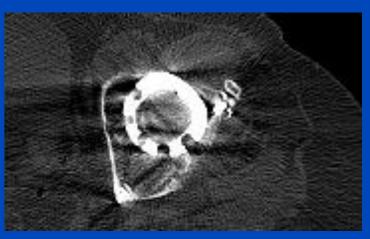


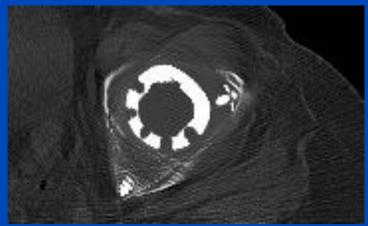
(C440/W1500),  $S_{eff} = 1.5 mm$ 

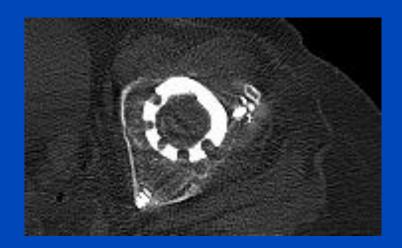


Uncorrected

**NMAR** 

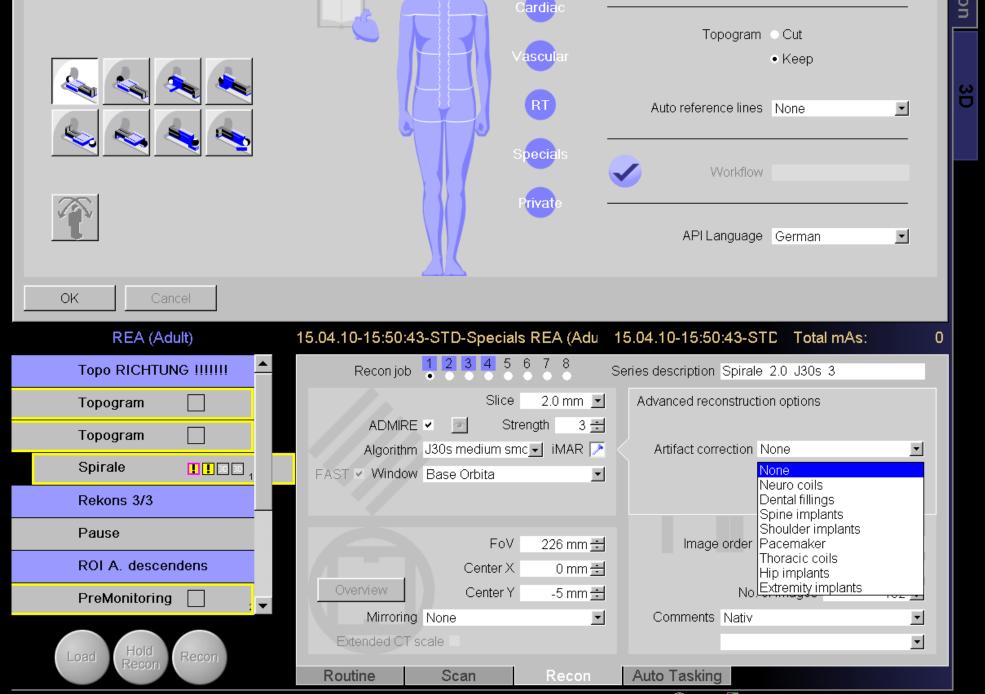


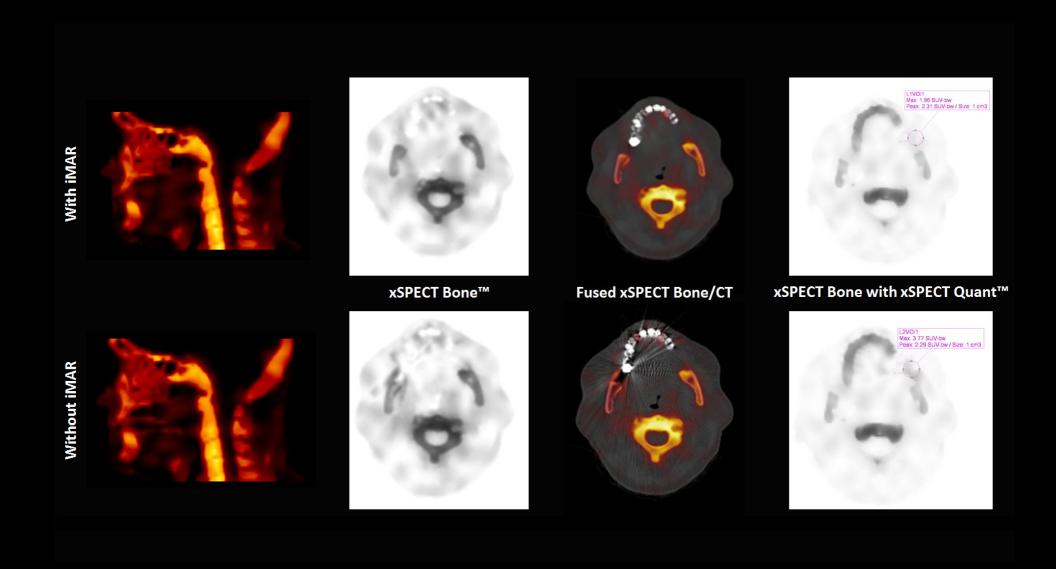




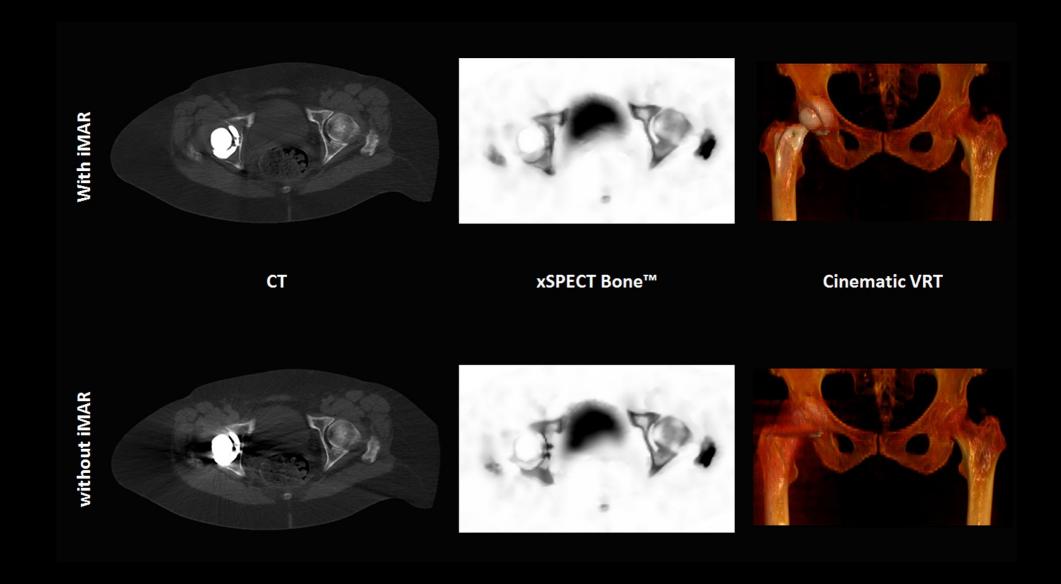
(C440/W1500),  $S_{eff} = 1.5 \text{ mm}$ 







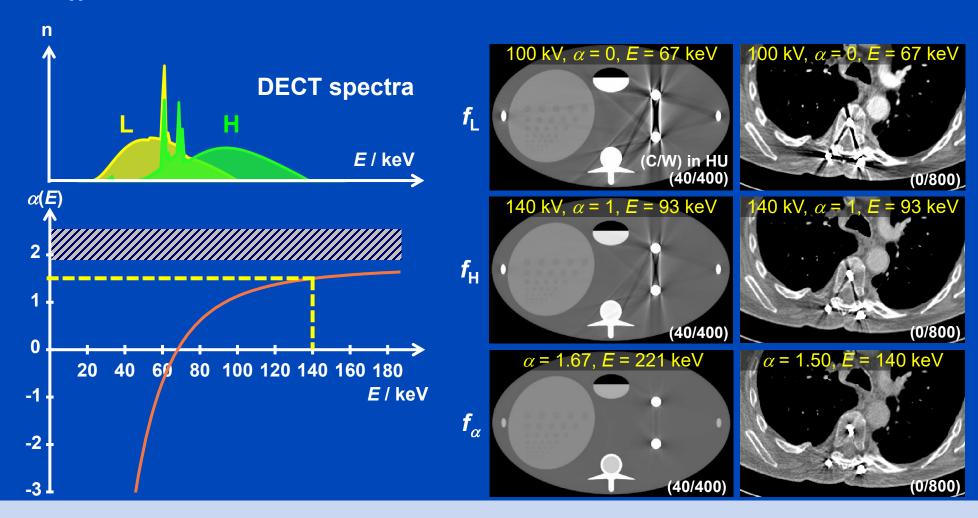






#### **DECT and Pseudo Monochromatic Imaging**

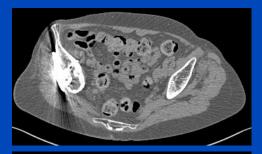
Pseudo monochromatic imaging is a linear combination of DECT's  $f_{\rm L}$  and  $f_{\rm H}$  volumes:  $f_{\alpha}=(1-\alpha)\,f_{\rm L}+\alpha\,f_{\rm H}$ 





#### **Pseudo Monochromatic Imaging**

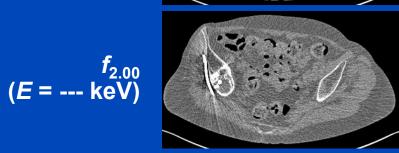
$$f_{\rm L} = f_0$$
  
(E = 67 keV)



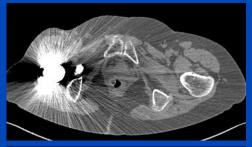
$$f_{\rm H} = f_1$$
  
(E = 93 keV)

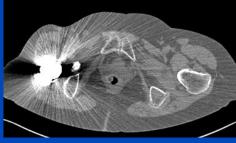


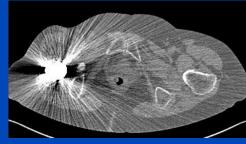
 $f_{1.55}$  (E = 154 keV)



z = -723 mm

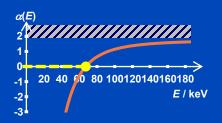


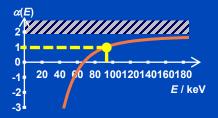


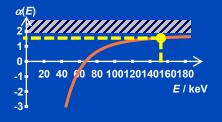


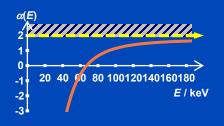


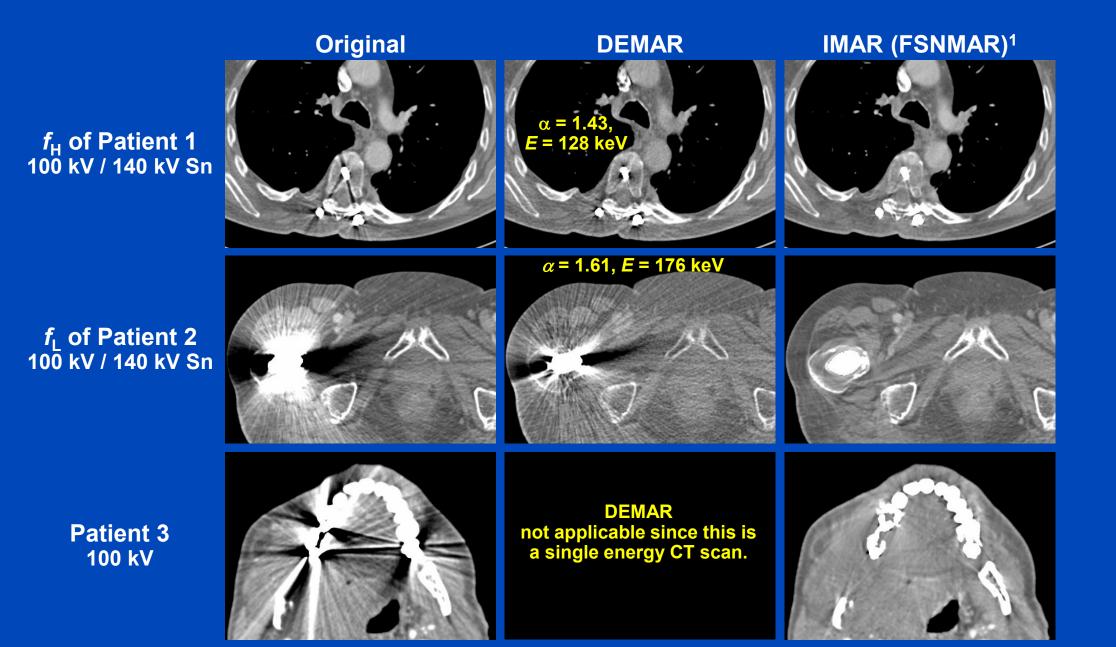
z = -792 mm













#### **Further Reading**

- Maik Stille, Matthias Kleine, Julian Haegele, Jörg Barkhausen, and Thorsten M. Buzug. Augmented Likelihood Image Reconstruction. IEEE Transactions on Medical Imaging 35(1), 158–173, July 2015.
- Webster J. Stayman, Yoshito Otake, Jerry L. Prince, Jay A. Khanna, and Jeffery H. Siewerdsen. Model-based tomographic reconstruction of objects containing known components. IEEE Transactions on Medical Imaging 31(10), 1837–1848, October 2012.
- Yi Zhang, Yifei Pu, Jin-Rong Hu, Yan Liu, Ji-Liu Zhou. A new CT metal artifacts reduction algorithm based on fractional-order sinogram inpainting. J Xray Sci Technol. 19(3), 373-84, January 2011.

A PCCT-based method to generate better prior images for NMAR and FSNMAR

## MAR FOR PHOTON-COUNTING CT



#### Photon-counting normalized metal artifact reduction (NMAR) in diagnostic CT

#### Achim Byla) and Laura Klein

Division of X-Ray Imaging and CT, German Cancer Research Center (DKFZ), Heidelberg 69120, Germany Department of Physics and Astronomy, Ruprecht-Karls-University Heidelberg, Heidelberg 69120, Germany

#### Stefan Sawall

Division of X-Ray Imaging and CT, German Cancer Research Center (DKFZ), Heidelberg 69120, Germany Medical Faculty, Ruprecht-Karls-University Heidelberg, Heidelberg 69120, Germany

#### Sarah Heinze

Institute of Forensic and Traffic Medicine, University Hospital Heidelberg, Heidelberg 69115, Germany

#### Heinz-Peter Schlemmer

Division of Radiology, German Cancer Research Center (DKFZ), Heidelberg 69120, Germany

#### Marc Kachelrieß

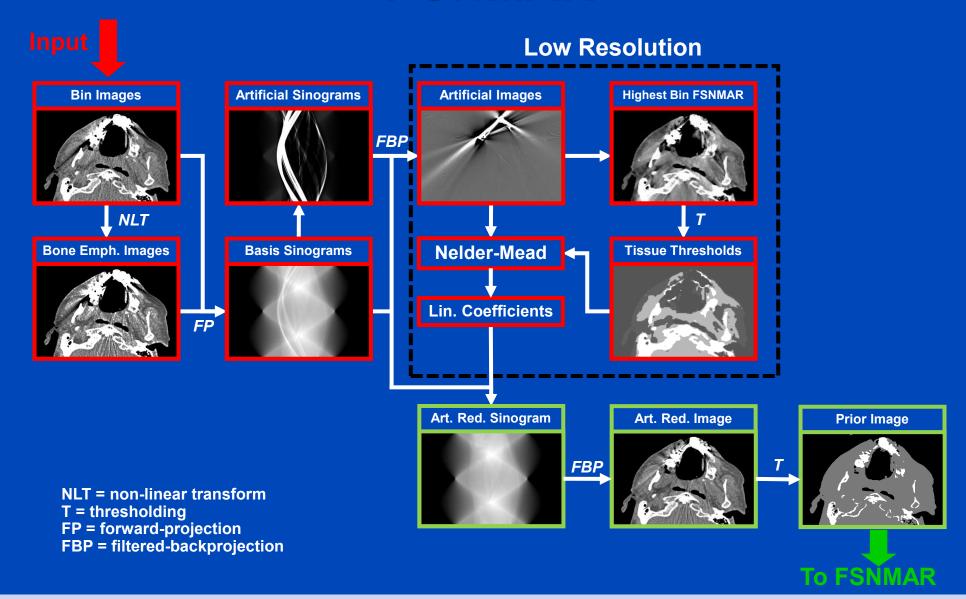
Division of X-Ray Imaging and CT, German Cancer Research Center (DKFZ), Heidelberg 69120, Germany Medical Faculty, Ruprecht-Karls-University Heidelberg, Heidelberg 69120, Germany

(Received 3 December 2020; revised 2 April 2021; accepted for publication 12 April 2021; published 28 May 2021)

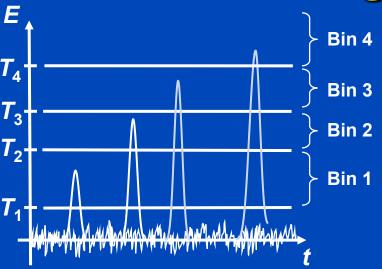
**Purpose:** Metal artifacts can drastically reduce the diagnostic value of computed tomography (CT) images. Even the state-of-the-art algorithms cannot remove them completely. Photon-counting CT inherently provides spectral information, similar to dual-energy CT. Many applications, such as material decomposition, are not possible when metal artifacts are present. Our aim is to develop a prior-based metal artifact reduction specifically for photon-counting CT that can correct each bin image individually or in their combinations.

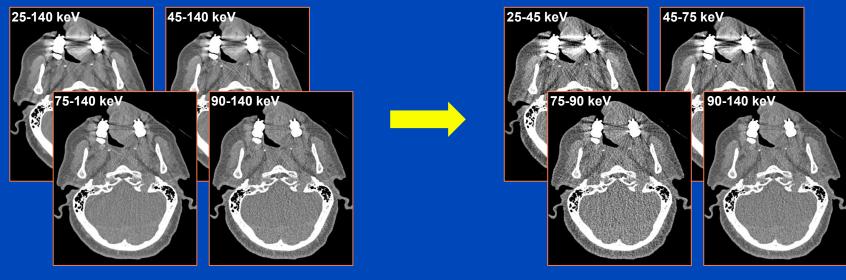


#### **PCNMAR**



# Threshold & Bin Images





**Threshold images** 

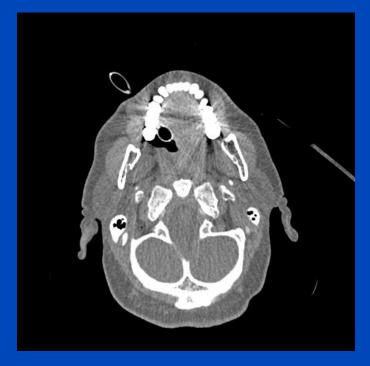
Bin images



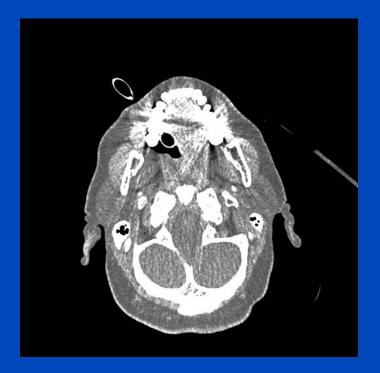
## **Bone-Emphasized Images**

 Instead of segmenting bone, we can apply a non-linear function to the input bins:

- 
$$I'(i,j) = I(i,j)$$
, if  $I(i,j) < 0$  and  $I'(i,j) = I(i,j) + 0.01I(i,j)^2$ , if  $I(i,j) \ge 0$ 







**Bone Image** 

C = 50 HU, W = 700 HU



## **Basis Sinograms**

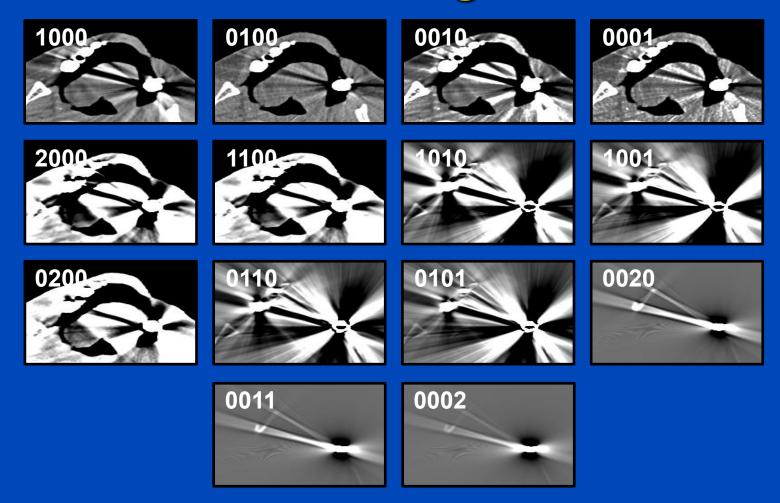
- The artificial sinograms approximate higher order beam-hardening artifacts.
- Each artificial sinogram  $p_{ijkl}$  is an element-wise product of two basis sinograms (i.e. from the bin or bone images):

$$p_{ijkl} = p_{\text{bin,low}}^i \cdot p_{\text{bin,high}}^j \cdot p_{\text{bone,low}}^k \cdot p_{\text{bone,high}}^l, i+j+k+l=2$$

- All sinograms are individually backprojected.
- For four bins, there are eight basis sinograms.



# **Basis Images**



 $f_{i,j,k,l} = X^{-1}(bin_1^{i*}bin_2^{j*}bone_1^{k*}bone_2^{l}) => ijkl, e.g. 0101 for bin_2^{*}bone_2^{l}$ 

## **Optimal Linear Combination**

• All basis images  $f_{ijkl}$  are linearly combined to produce an artifact-reduced image:

$$f_{\text{cor}} = \sum_{i,j,k,l} c_{i,j,k,l} f_{i,j,k,l}, \qquad c_{1,0,0,0} = (1 - c_{0,1,0,0})$$

where the condition ensures that the coefficients of the original bin images add up to one.

 To find the coefficients, we minimize a cost function with a Nelder-Mead algorithm.

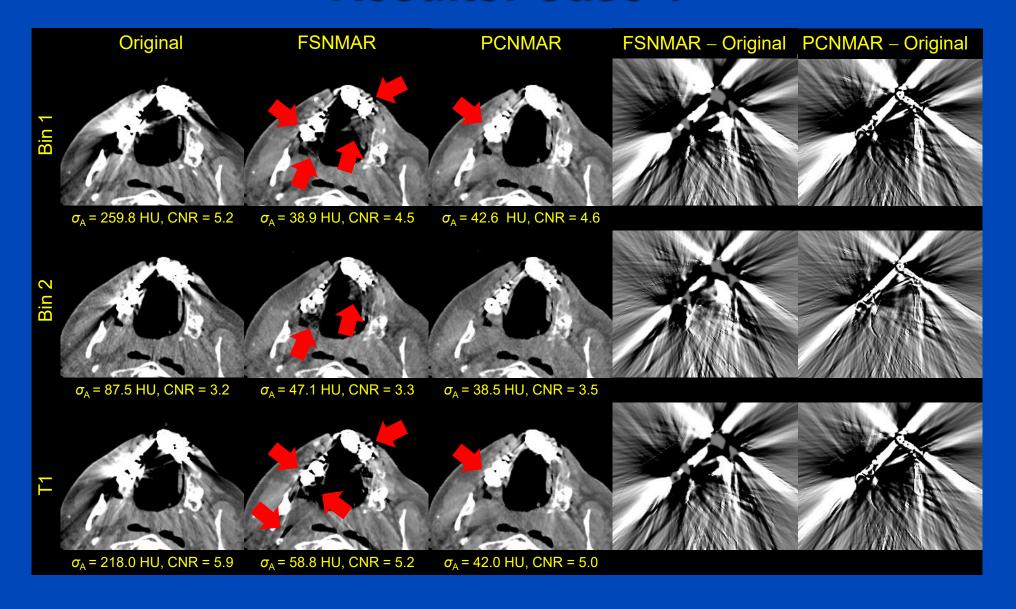


#### **Measurements**

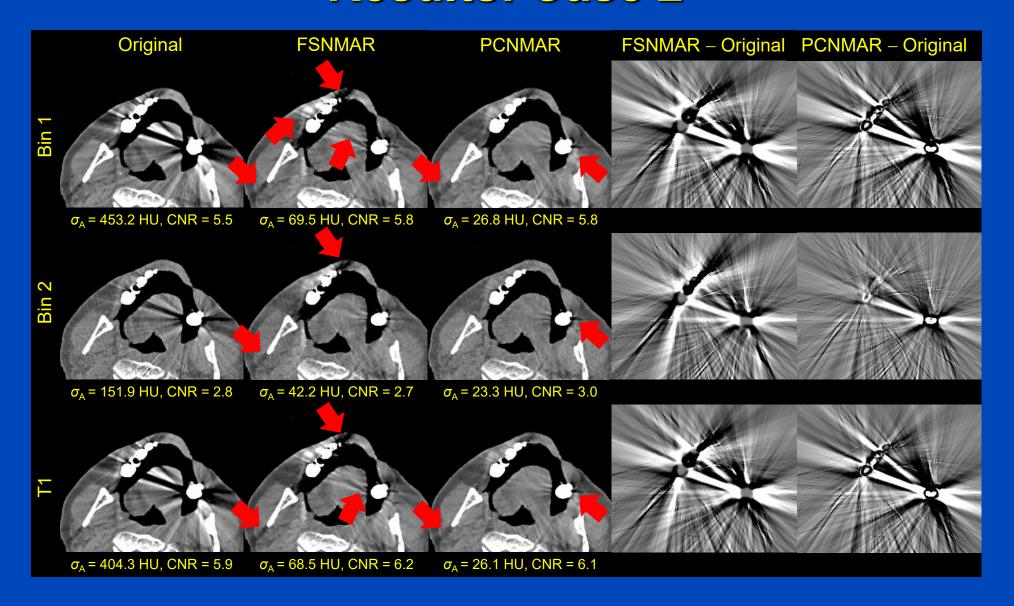
- CT data of seven forensic specimen
- Siemens Somatom CounT
- Voltage: *U* = 140 kV
- Tube current:  $I_{\text{eff}} = 300 \text{ mAs}$
- Eff. slice thickness:  $S_{eff} = 0.6 \text{ mm}$
- Pixel size:  $\triangle x = \triangle y = 0.5 \text{ mm}$
- Energy thresholds chess mode: 25/45/75/90 keV
- Energy thresholds macro mode: 25/90 keV
- Reconstruction kernel: B40f



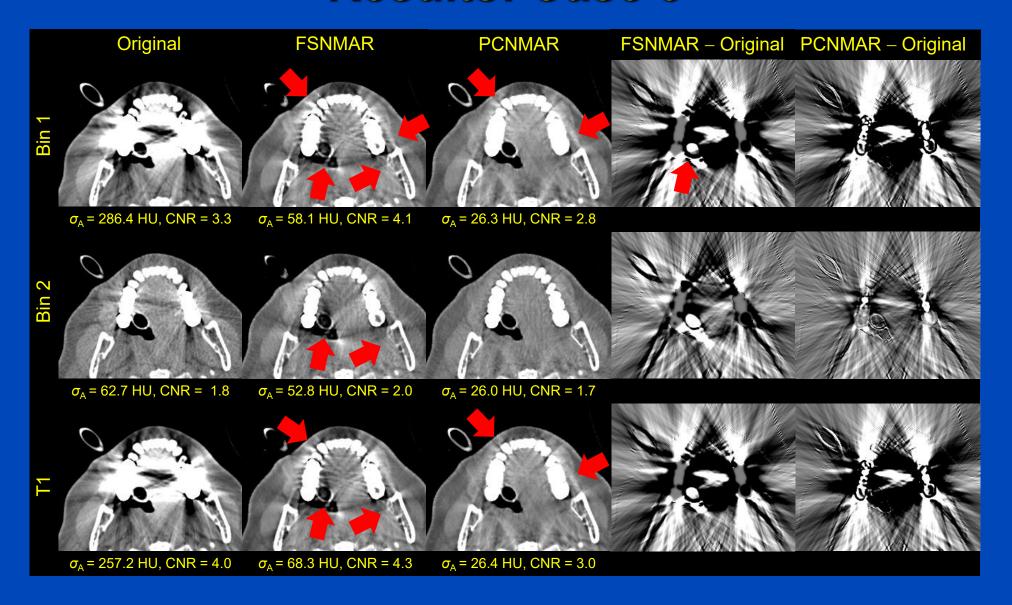
#### **Results: Case 1**



#### **Results: Case 2**

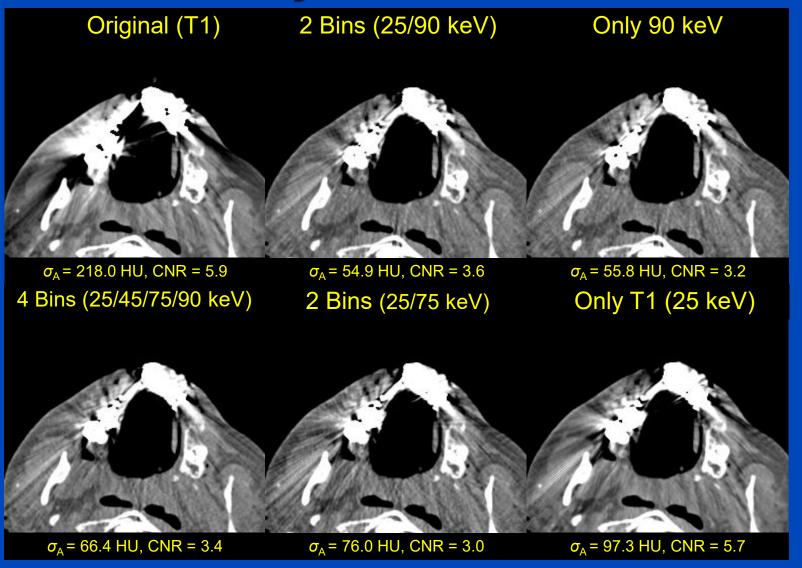


#### **Results: Case 3**





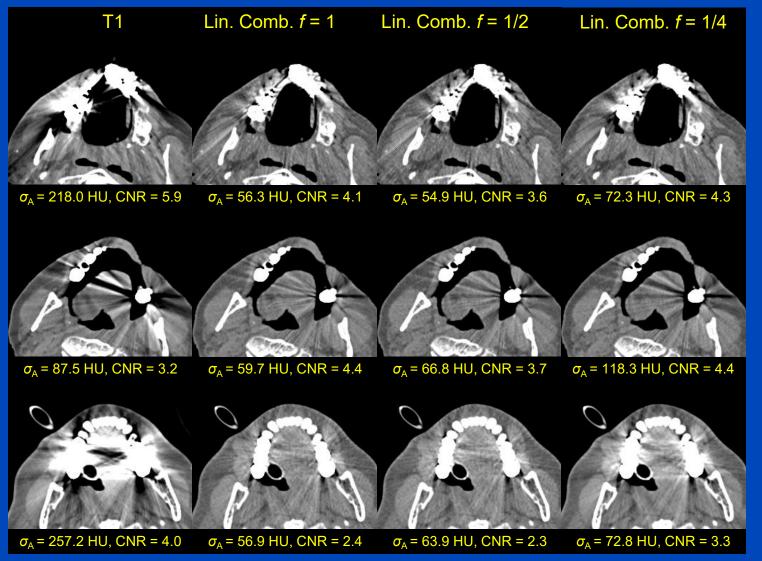
# **How Many Bins are Useful?**



Images show the linear combination result (i.e. without FSNMAR)



## Low- vs High-Res Linear Combination



f is the sampling relative to full resolution (in x, y, and  $\theta$ ) during optimization



#### Conclusions on PCMAR

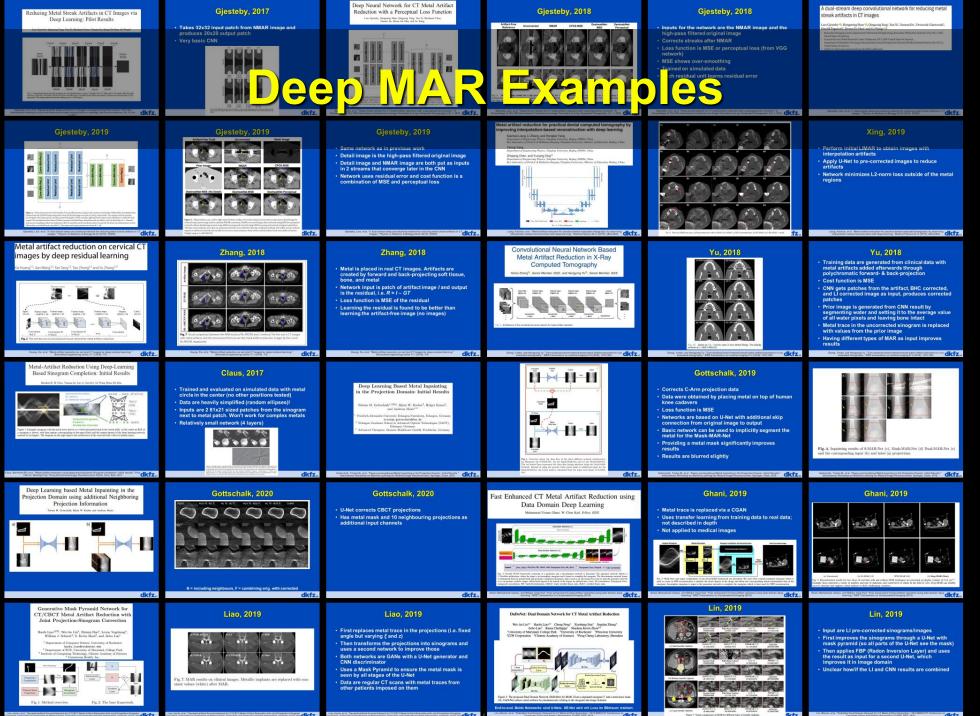
- PCNMAR is able to reduce artifacts better than conventional FSNMAR, keeping more structures intact.
- The extra spectral information from the energy bins is beneficial for the artifact reduction, especially the high energy bin.
- Using 4 bins instead of 2 bins did not yield better results, but allows more freedom in the selection of thresholds.
- The linear coefficients can be found with low-resolution images, but for a sampling of  $\frac{1}{4}$ , the results were visibly worse.

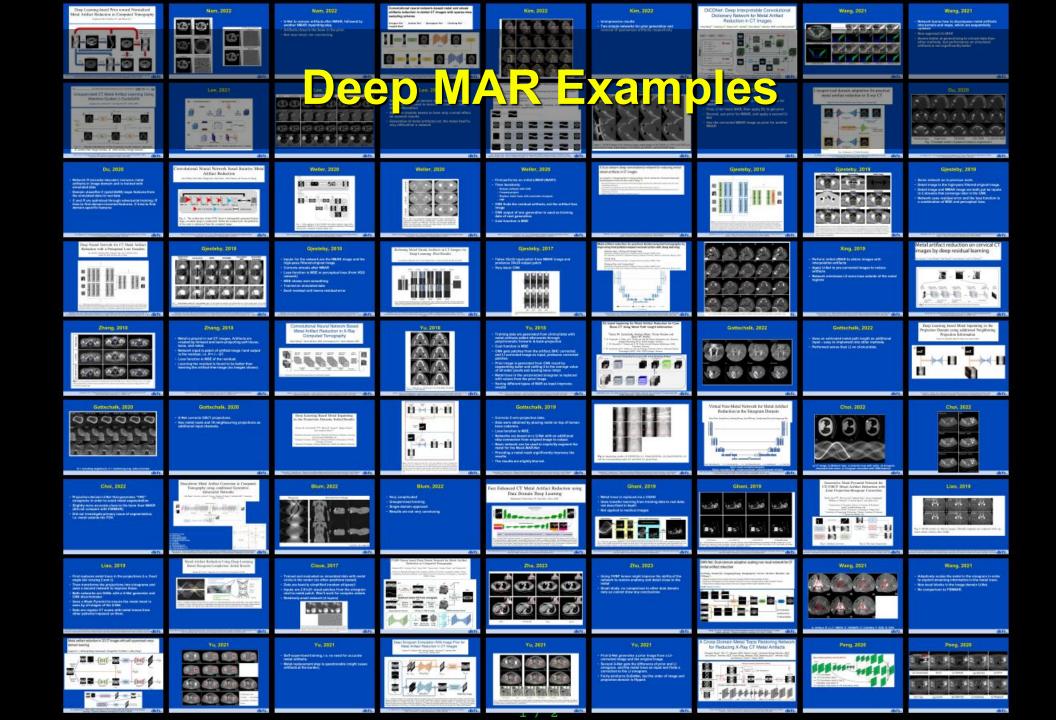


Often, these are methods to generate better prior images for NMAR and FSNMAR

# **DEEP MAR**

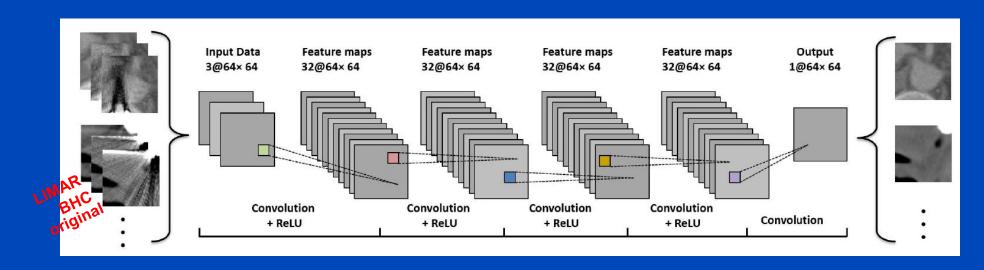






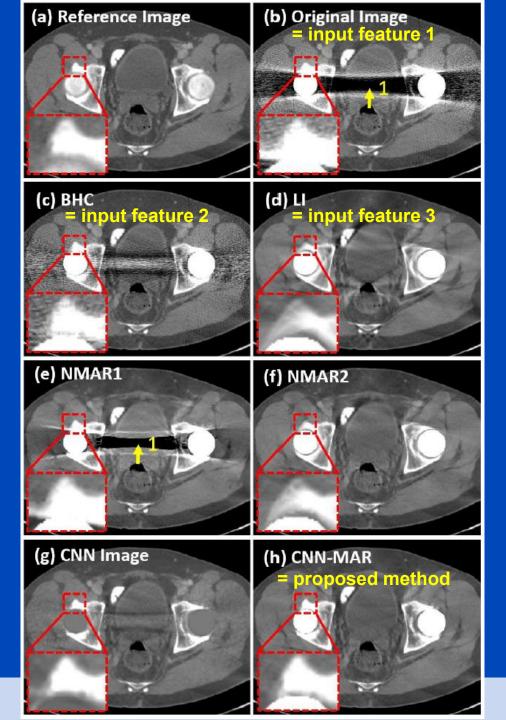
## **MAR Example**

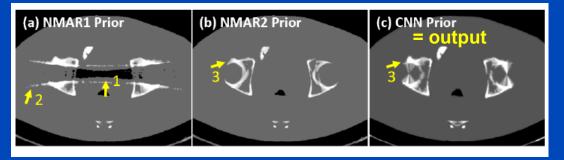
 Deep CNN-driven patch-based combination of the advantages of several MAR methods trained on simulated artifacts



- followed by segmentation into tissue classes
- followed by forward projection of the CNN prior and replacement of metal areas of the original sinogram
- followed by reconstruction



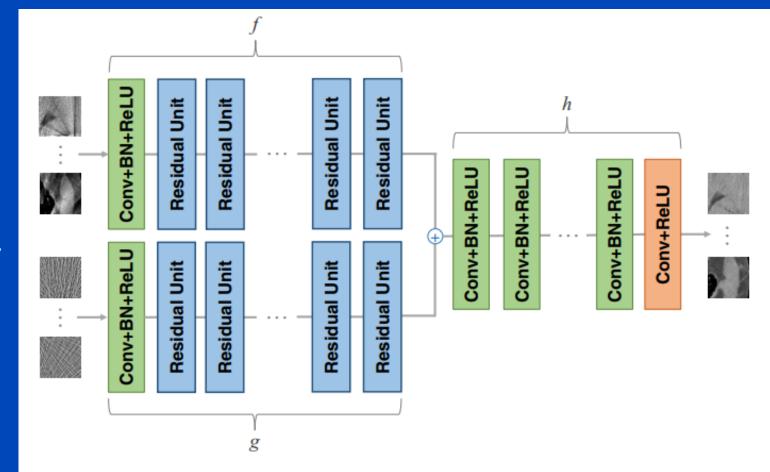






## MAR Example 2

- Detail image is the highpass filtered original image.
- Detail image and NMAR image are both put as inputs in 2 streams that converge later in the CNN.
- Network uses residual error and the loss function is a combination of MSE and perceptual loss.

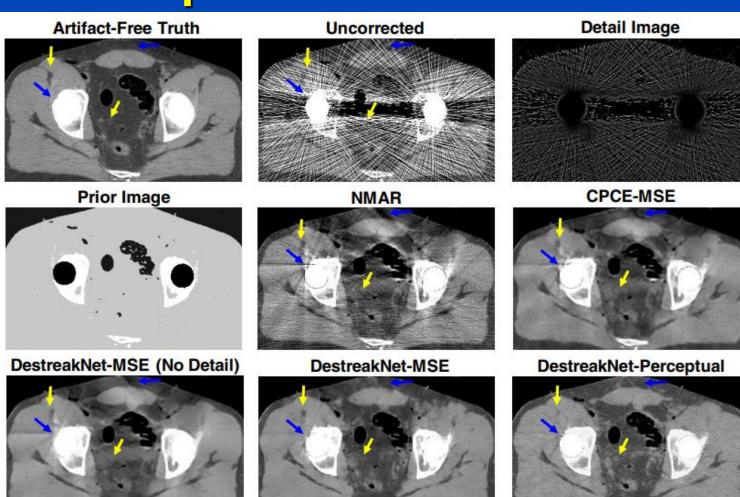


**Figure 2.** Network structure for *DestreakNet*. Two parallel streams, f and g, each contain an initial layer followed by 20 residual units. Patches from the NMAR image and patches from the detail image are input to f and g, respectively. The outputs of these streams are merged in the feature space, and then passed through h, which contains eight parameter layers and a final layer, to yield the final output. All convolution layers have 32 filters (except for the final layer, which has only one filter), each of which has a  $3 \times 3$  kernel and uses zero-padding. Batch normalization (BN) is used after each convolution layer (except for the final convolution layer), and is followed by a rectified linear unit (ReLU). The input and output patches are of size  $56 \times 56$ .



#### MAR Example 2

- Detail image is the highpass filtered original image.
- Detail image and NMAR image are both put as inputs in 2 streams that converge later in the CNN.
- Network uses residual error and the loss function is a combination of MSE and perceptual loss.



**Figure 5.** Hip prostheses case. Left to right, top to bottom: artifact-free truth; initial uncorrected reconstruction; detail image for network input; prior image used to calculate NMAR correction; NMAR-corrected image; direct network using MSE loss; proposed network without detail image stream using MSE loss; proposed network using MSE loss; proposed network using perceptual loss. The blue arrows indicate areas that our proposed network recovered better than the compared methods. The yellow arrows indicate regions in which our network was not able to recover accurate anatomy. Some of the created artifacts look very similar to lesions. Display range is [-200 300] HU.

# Metal artifact reduction for practical dental computed tomography by improving interpolation-based reconstruction with deep learning

#### Kaichao Liang, Li Zhang, and Hongkai Yang

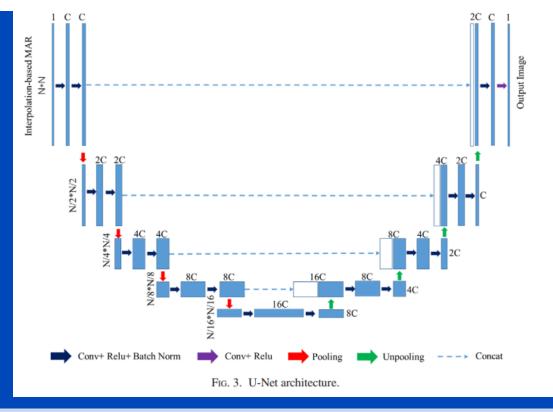
Department of Engineering Physics, Tsinghua University, Beijing 100084, China Key Laboratory of Particle & Radiation Imaging (Tsinghua University), Ministry of Education, Beijing, China

#### Yirong Yang

Department of Engineering Physics, Tsinghua University, Beijing 100084, China

#### Zhiqiang Chen, and Yuxiang Xing<sup>a)</sup>

Department of Engineering Physics, Tsinghua University, Beijing 100084, China Key Laboratory of Particle & Radiation Imaging (Tsinghua University), Ministry of Education, Beijing, China





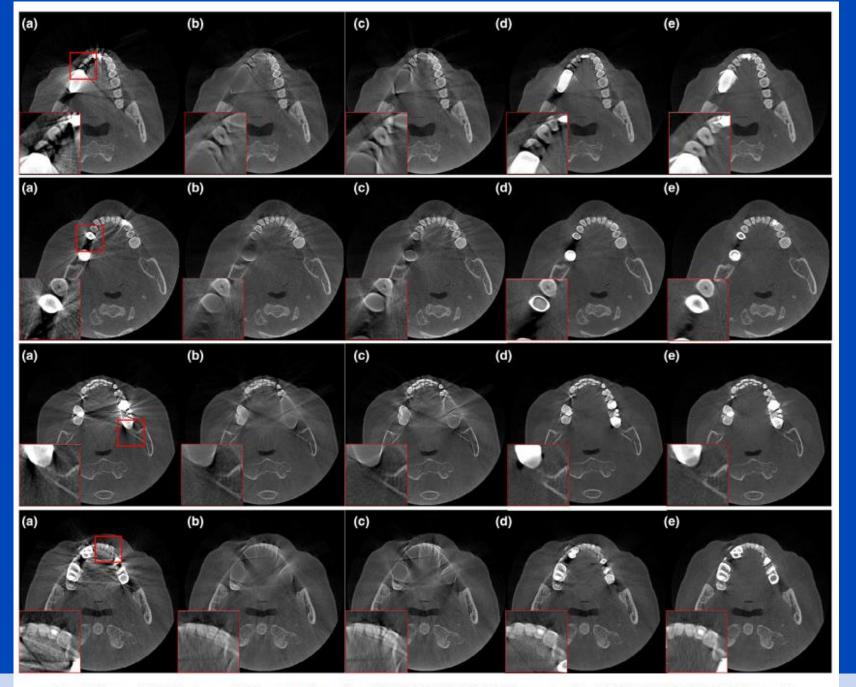
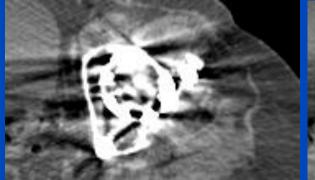


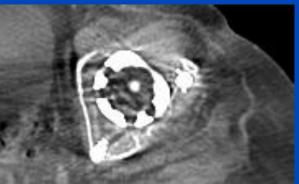
Fig. 8. Four real MAR test cases. (a) Reconstructions with no MAR, (b) I-MAR, (c) WLS reconstruction, (d) DL-MAR, (e) I-DL-MAR + metal.

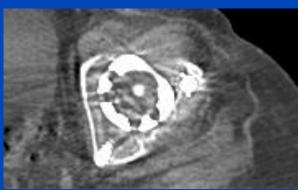


# MAR without Machine Learning is a Good Alternative: Frequency Split Normalized MAR<sup>1,2</sup>

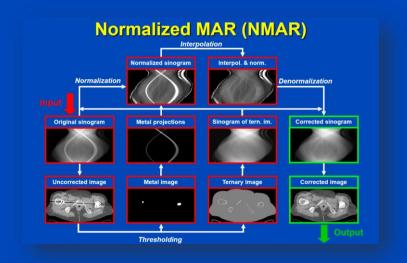
Uncorrected FSLIMAR FSNMAR

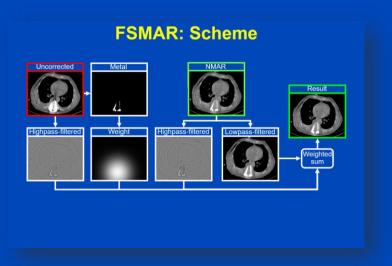






Patient with bilateral hip prosthesis, Somatom Definition Flash, (C=40/W=500).







# Why do NNs Appear to Always Outperform Classical Solutions?

The answer is:

#### **Novelty Bias**

- This means
  - the proposed (new) method is highly optimized by the author
  - the gold standard (old) method is implemented with less rigor
- Today, avoiding novelty bias is simple:
  - For any method, be it a NN or a conventional algorithm one has open parameters (millions for NN, dozens for conventional).
  - Determine them using
    - » the same non-linear minimization framework
    - » the same training data
    - » the same objective function
- If this is not done, any comparison with the conventional method is invalid.



# **Summary on Deep MAR**

#### Most common uses for networks:

- Improve image quality in image domain after MAR
- Use network for the sinogram inpainting
- Produce a prior image, e.g. for NMAR

#### Additional observations:

- Training data are often produced by segmenting an artifact-free CT image, adding metal and applying a polychromatic forward projection to different types of tissue separately.
- As of today, it seems hard to outperform FSNMAR, or hard to give convincing clinical examples.



## **Thank You!**

- This presentation will soon be available at www.dkfz.de/ct.
- Job opportunities through DKFZ's international PhD or Postdoctoral Fellowship programs (marc.kachelriess@dkfz.de).
- Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.

