# Towards Material Decomposition on Large Field-of-View Flat Panel Photon-Counting Detectors — First *in-vivo* Results

Kerstin Müller, Moiz Ahmad, Martin Spahn, Jang-Hwan Choi, Silke Reitz, Niko Köster, Yanye Lu, Rebecca Fahrig, and Andreas Maier

Abstract-Dual-energy CT imaging allows to separate materials and tissue based on their attenuation behavior using two different X-ray spectra. Various techniques exist to acquire X-ray and CT images with two different energies. One approach utilizes a specific detector technology to discriminate the photons in the emitted X-ray spectrum by their energy instead of integrating the energy as in current applied detector technology. Photon-counting detectors (PCDs) offer several advantages compared to traditional energy integrating detectors such as improved detective quantum efficiency (DQE). However, due to manufacturing challenges, PCDs are still part of on-going research and not applicable in a clinical scanner, yet. In this paper, a first step towards invivo material decomposition for iodinated contrast agent from background tissue in a porcine study using a large field-ofview photon-counting detector is presented. First preliminary results are encouraging to further exploit material decomposition methods using the presented photon-counting detector. However, major challenges remain with the current technology that need to be investigated and addressed in future work.

Keywords—C-arm Angiography, Photon-Counting Energy-Resolving Detectors, Material Decomposition, Image Formation

## I. INTRODUCTION

Photon-counting detectors (PCD) offer significant advantages to current energy-integrating flat panel detectors (FDs) such as improved detective quantum efficiency (DQE) and photon energy resolution [1], [2], [3]. In particular the ability to differentiate material properties dependent on photon energies has attracted significant attention as it allows material decomposition with a single scan, as data with both energies is acquired simultaneously. This enables 2-D projection-based decomposition of materials [4], [5], [6]. The acquisition of a high energy (HE) and total energy (TE) image at the same time point with a PCD, assuming 2 energy bins, solves the problem of degraded image quality due to motion artifacts. For example for a 2D digital subtraction angiography (DSA), where the mask and the fill images are acquired at different time points, severe motion artifacts can occur as visible in Fig. 1. Modern C-arm systems allow to select the mask image and also provide motion correction algorithms. However, these cannot eliminate severe motion between mask and fill images.



Fig. 1. Prominent motion artifact in DSA image may occur because mask and fill image were acquired at different time points.

Current photon-counting detector technology still poses significant challenges. Amongst other problems, an excess of detected photons results in pulse pile-up and the detected count rates are energy dependent and spatially varying [2], [3]. So called homogenization approaches to compensate those effects exist which result in significant improvements of the acquired image stacks [7], [8]. Assuming a PCD with two energy bins, a total energy (TE), high energy (HE), and low energy (LE) image stack is acquired. The most benefit of the homogenization techniques exists for the TE image. Results for the individual energy bins (HE, LE), however may be inferior (cf. Fig. 2). As pulse pile-up favors lower count rates, detectors typically can only account for smaller pixel sizes and the Xray tube needs to be set to low exposure rates. As a result, the acquired 2-D images have a noisy appearance and material separation is not possible on the raw 2-D images.

All the previously mentioned challenges make it difficult to advance from simulated phantom PCD experiments towards integration into a clinical system. In this paper, a first attempt towards projection-based material decomposition with a large field-of-view photon-counting detector in an *in-vivo* porcine study is presented. A non-linear denoising technique is applied to the generated 2-D (LE, HE) image stacks to perform a simple linear material decomposition. To the best of our knowledge, this is the first study on *in-vivo* material decomposition using a large field-of-view PCD.

## II. MATERIALS AND METHODS

#### A. Photon-Counting Detector (PCD) Imaging

A large field-of-view dual-energy photon-counting detector (XCD) for its application in interventional radiology was "piggy-back" mounted to the flat panel detector (FD) of

K. Müller, M. Ahmad are with the Radiological Sciences Lab, Department of Radiology, Stanford University, Stanford, CA, USA. E-mail: kmuell@stanford.edu. M. Spahn, S. Reitz, and N. Köster are with Siemens Healthcare GmbH, Forchheim, Germany. J.-H. Choi and Rebecca Fahrig were with the Radiological Sciences Lab, Stanford University, Stanford, CA, USA. R. Fahrig is now with Siemens Healthcare GmbH, Forchheim, Germany. Y. Lu and A. Maier are with the Pattern Recognition Lab, Department of Computer Science, Friedrich-Alexander-Universität Erlangen-Nürnberg.



Fig. 2. Homogenization algorithms improve spatially varying detection behavior, but detector module artifacts are still present in the HE and LE processed images.

an Artis zeego system (Siemens Healthcare GmbH, Forchheim, Germany). The detector is a customized OEM product manufactured by XCounter ABB (Danderyd, Sweden). The detector features a 1 mm cadmium telluride (CdTe) layer to convert absorbed X-ray energy to an electrical signal. The detector covers an active area of  $30 \times 5$  cm<sup>2</sup> made up of several individual modules, each having a size of 1.25×2.5  $cm^2$ . Overall the 2D image matrix is  $3072 \times 512$  pixel with an isotropic pixel resolution of  $100\mu m$ . The exposure integration range is from 100 $\mu$ s-5s. The XCD features two energy bins per pixel with an adjustable threshold with a counter depth of 12 bit. The adjustable thresholds are only mean values and can vary between different pixel modules. The two bins allow synchronous acquisition of a total energy (TE) and a high energy (HE) image can be performed. The detector also features a charge sharing correction feature to restore the energy that may spread over several neighboring pixel due to fluorescence or charge dispersion and to count the event only once. The detector design is similar to the small PCD presented in Ullberg et al. [1]. The readout of the XCD is performed over a gigabit ethernet connection and the generated 2D images are visualized and stored on an external workstation. The same pre-processing and conditioning as described in Ahmad et al. was applied to the TE and HE image stacks [9].

## B. TE-guided Bilateral Filtering

As previously mentioned, the 2D HE and LE image stacks suffer from severe pixel noise compared to the TE image stack (cf. Fig. 2). In order to improve image quality and to reduce noise, a non-linear joint bilateral filtering (JBF) technique is applied [10], [11], [12]. The approach exploits the improved image quality of the TE image  $I_{\text{TE}}(\boldsymbol{x})$  to filter the respective (HE, LE) image under guidance at position  $\boldsymbol{x}$ . The bilateral filtered image  $I'_b(\boldsymbol{x})$  from the non-filtered image  $I_b(\boldsymbol{x})$ , where  $b \in \{\text{HE}, \text{LE}\}$  can be computed by

$$I'_b(\boldsymbol{x}) = \frac{1}{c(\boldsymbol{x})} \sum_{\boldsymbol{u}} g_s(\boldsymbol{x}, \boldsymbol{u}) g_I(\boldsymbol{x}, \boldsymbol{u}) I_b(\boldsymbol{x}), \quad (1)$$

$$c(\boldsymbol{x}) = \sum_{\boldsymbol{u}} g_s(\boldsymbol{x}, \boldsymbol{u}) g_I(\boldsymbol{x}, \boldsymbol{u}), \qquad (2)$$

$$g_s(\boldsymbol{x}, \boldsymbol{u}) = e^{-\frac{||\boldsymbol{x}-\boldsymbol{u}||_2^2}{2\sigma_s}}$$
(3)

$$g_I(\boldsymbol{x}, \boldsymbol{u}) = e^{-\frac{(\Lambda_{\rm IE}(\boldsymbol{u}) - \Lambda_{\rm IE}(\boldsymbol{u}))}{2\sigma_I}}$$
(4)

Here,  $\sigma_s$  denotes the spatial standard deviation and  $\sigma_I$  denotes intensity standard deviation used for the joint bilateral filter.

#### C. Material Decomposition

Due to the non-linearity of the photon count rate and since the material decomposition is spatially quite variant, we chose a simple linear model for material separation and assume that this model is valid in a small patch of the image. In order to compute a soft tissue suppressed image that only shows contrast agent, we analyzed a small area  $\Omega_{\text{ST}}$  containing only soft tissue to compute regression coefficients m and t solving the least-square problem:

$$\underset{m,t}{\arg\min} = \sum_{\boldsymbol{x} \in \Omega_{\text{ST}}} ||\ln(I'_{\text{HE}}(\boldsymbol{x})) - (m \cdot \ln(I'_{\text{LE}}(\boldsymbol{x})) + t)||_2^2.$$
(5)

The contrast projection  $I_{\rm C}(\boldsymbol{x})$  showing only iodinated contrast agent can be computed by

$$I_{\rm C}(\boldsymbol{x}) = \ln(I_{\rm HE}'(\boldsymbol{x})) - (m \cdot \ln(I_{\rm LE}'(\boldsymbol{x})) + t). \tag{6}$$

#### D. Evaluation

1) Digital Subtraction Angiography (DSA): The PCD generated iodine images  $I'_{\text{HE}}(x)$  were compared to DSA-like data. DSA is a popular method in angiographic imaging for visualization of iodine-based contrasted vessels. For DSAimaging, the reference frame  $I'_{b,\text{ref}}(x)$ , without contrast injection is acquired and subtracted to get only the contrast-filled projection  $I_{b,\text{DSA}}(x)$ :

$$I_{b,DSA}(\boldsymbol{x}) = I_b'(\boldsymbol{x}) - I_{b,ref}'(\boldsymbol{x}).$$
(7)

This procedure can be performed for both energy bins b (HE, LE).

2) Contrast-to-Noise Ratio (CNR): In order to quantitatively evaluate the contrast within vessel structure to background, the contrast-to-noise ratio (CNR) was computed.

#### **III. EXPERIMENTS**

Stanford Universitys Administrative Panel on Laboratory Animal Care approved the protocol for this *in-vivo* animal study. Arterial femoral access was established using percutaneous puncture for hemodynamic monitoring, administration of medications, and the injection of contrast agent. For the 2D scan a 20 mL of 100% iodinated contrast agent (Omnipaque 350 mg/mL, GE Healthcare, Princeton, NJ) was administered over a pigtail catheter placed in the aortic root. The contrast was delivered with a rate of 8 mL/s using a power injector (Medtron, Saarbrücken, Germany). The 2D acquisition was performed with requesting 81 kV, 10 ms and 800 mA from the X-ray tube and the thresholds of the XCD were set to 8 keV for the lower and 39 keV for the higher energy bin.

#### IV. RESULTS

In the following section, the results of the TE-Guided filtering and the material decomposition are presented in comparison to conventional DSA-imaging. All algorithms were realized using the CONRAD software package [13].

### A. TE-guided Bilateral Filtering

In a first experiment, we explored whether TE-guided JBF filtering reduces noise, improves image quality and still allows to identify tissue clusters in a HE/LE channel scatter plot. A  $1 \times 1$  cm<sup>2</sup> patch of the image showing a contrasted vessel and soft tissue background was selected for the scatter plot. Fig. 3 shows the LE versus HE scatter plot for a small region of interest containing an iodinated contrasted vessel and water-like background tissue. It can be seen that without smoothing, no materials can be differentiated. Only after extensive smoothing, material clusters for separation of different materials form even though spatial resolution is drastically reduced. As shown in Fig. 4, with TE-guided bilateral filtering similar tissue clusters as seen with strong spatial smoothing appear, but preserving the spatial resolution. Spatial smoothing with  $\sigma_s = 5$  and a TE-guided filtering with  $\sigma_s = 5$  and  $\sigma_I = 10$  were compared. Visual comparison before and after filtering of the LE channel which contains the most noise also confirms the effectiveness of the TE-guided filtering, while Gaussian smoothing enables the same differentiation and degrades severely the spatial resolution (cf. Fig. 5).

### B. Material Decomposition

Subsequently, we explored different methods to emphasize the contrast filled right coronary vessel tree. As a first attempt we investigated only a single detector tile as a first proof of concept due to the large differences in energy count behavior between the different detector modules. Fig. 6 displays the results of the different methods. DSA of the HE channel shows the contrast filled vessel with a CNR of 1.66. Using the TEguided filter improves the CNR to 2.46. On the LE channel, the contrast is barely visible at a CNR of 0.64. There is only high contrast at the top of the vessel, while contrast is significantly reduced in most parts. TE-guided filtering also improves contrast to a CNR of 1.32. The material decomposition image also shows sub-optimal contrast compared to the denoised HE channel. But the material decomposed image does not suffer from any motion artifact. Its CNR is also higher than the HE



Fig. 3. Scatter plot for LE and HE photon counts. Identification of underlying material or tissue in the non-filtered 2D HE and LE stack is not possible, due to the excessive noise and spatially variant energy discrimination. Extensive spatial filtering (2D-Gaussian filter) allows to form clusters for water and iodine while decreasing spatial resolution.



Fig. 4. TE-guided filtering improves the ability to identify material and tissue clusters in the 2D TE raw data, comparable to Gaussian filtering using a strong spatial sigma.

raw image with 2.00 as noise is greatly reduced. The nonuniformity of the energy counts across the single tile causes the top part of the image and the bottom left to loose contrast. Note that the water calibration was performed in the left center of the tile which delivers the best signal-to-noise characteristics in the image.

#### V. DISCUSSION AND CONCLUSION

In this proof-of-concept study the goal was to investigate the first attempts towards material decomposition using invivo data acquired with a large field-of-view photon-counting detector. As a first feasibility test a simple and local method for material separation was chosen due to the detectors spatial variations. After pre-processing of the TE image stacks using homogenization methods, the spatially variant energy resolution and noise still pose the biggest challenges. TE-guided filtering reduces noise drastically while preserving spatial information. This results in increased CNR rates in DSA images for HE and LE. However, DSA has the large disadvantage that motion artifacts are introduced. Material decomposition techniques are not effected, as the image is computed from simultaneously acquired TE and HE image stacks. The current detector shows significant differences in energy sensitivity and energy resolution abroad detector modules. In particular at the tile borders neighboring pixels may have significantly different



Fig. 5. LE channel before and after TE-guided filtering: The filtering reduces noise significantly and preserves the edges of the contrast filled vessel. Note that also the impression of the patches between the detector elements is reduced as these are less apparent in the TE images.



Fig. 6. Patches of the different techniques to extract iodinated contrasted vessel from background and respective CNR.

properties in terms of spectral separation. To alleviate this, we investigated only a single tile for material decomposition. Still, the CNR of the decomposed image is only slightly better than the DSA of the LE projection of the same patch. It should be mentioned that the trimming of the detector is not sufficient and will be addressed in future work. Overall, we believe that further investigations using more sophisticated methods found in literature [14], [15], [16], [17] will help to improve material decomposition that will finally enable applications as single shot DSA.

**Disclaimer:** The concepts and information presented in this paper are based on research and are not commercially available.

#### ACKNOWLEDGMENT

The authors gratefully acknowledge funding support from the NIH Shared Instrument Grant S10 RR026714 supporting the zeego@StanfordLab, and Siemens Healthcare GmbH Advanced Therapies. Special thanks also goes to Yamil Saenz for his help with the in-vivo pig experiment.

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