Published in final edited form as:

Eur J Radiol. 2008 December ; 68(3): 409–413. doi:10.1016/j.ejrad.2008.09.017.

Evaluation of non-linear blending in dual-energy computed tomography

David R. Holmes III^{a,*}, Joel G. Fletcher^b, Anja Apel^c, James E. Huprich^b, Hassan Siddiki^b, David M. Hough^b, Bernhard Schmidt^c, Thomas G. Flohr^b, Richard Robb^a, Cynthia McCollough^b, Michael Wittmer^b, and Christian Eusemann^c

^aBiomedical Imaging Resource, Mayo Clinic College of Medicine, 200 First Street SW, Rochester, MN 55905, United States

^bDepartment of Radiology, Mayo Clinic College of Medicine, United States

^cSiemens Medical Solutions USA, Inc., United States

Abstract

Dual-energy CT scanning has significant potential for disease identification and classification. However, it dramatically increases the amount of data collected and therefore impacts the clinical workflow. One way to simplify image review is to fuse CT datasets of different tube energies into a unique blended dataset with desirable properties.

A non-linear blending method based on a modified sigmoid function was compared to a standard 0.3 linear blending method. The methods were evaluated in both a liver phantom and patient study. The liver phantom contained six syringes of known CT contrast which were placed in a bovine liver. After scanning at multiple tube currents (45, 55, 65, 75, 85, 95, 105, and 115 mAs for the 140-kV tube), the datasets were blended using both methods. A contrast-to-noise (CNR) measure was calculated for each syringe. In addition, all eight scans were normalized using the effective dose and statistically compared. In the patient study, 45 dual-energy CT scans were retrospectively mixed using the 0.3 linear blending and modified sigmoid blending functions. The scans were compared visually by two radiologists.

For the 15, 45, and 64 HU syringes, the non-linear blended images exhibited similar CNR to the linear blended images; however, for the 79, 116, and 145 HU syringes, the non-linear blended images consistently had a higher CNR across dose settings. The radiologists qualitatively preferred the non-linear blended images of the phantom. In the patient study, the radiologists preferred non-linear blending in 31 of 45 cases with a strong preference in bowel and liver cases.

Non-linear blending of dual energy data can provide an improvement in CNR over linear blending and is accompanied by a visual preference for non-linear blended images. Further study on selection of blending parameters and lesion conspicuity in non-linear blended images is being pursued.

Keywords

Dual-energy computed tomography; Image processing; Data fusion

1. Introduction

In X-ray based imaging, attenuation depends on the type of tissue scanned, the linear attenuation coefficient, and the average energy level of the X-ray beam, which can be adjusted via the X-ray tube potential. Since attenuation varies by X-ray energy, multiple energies can be used to improve the characterization of the composition of tissue. Multi-energy scanning was clearly described in Hounsfield's 1973 description of computed tomography [1]. Although there were several published studies on multiple energy scanning in the 1970s, recent technical improvements in scanner technology have led to the redevelopment of multi-kV scanning across a variety of hardware platforms. One practical challenge of multi-energy scanning is reviewing and interpreting the data acquired with these scanners. In addition to independent evaluation of the separate energy-level datasets, it is possible to mathematically mix the two dataset to yield a single "blended" datasets with desired features of each energy-level dataset. The purpose of this work is to evaluate linear and non-linear mixing of dual energy computed tomography (DECT) datasets.

Following the development of CT scanners in the 1970s, several researchers including Zatz [2] and others [3,4], verified the ability to better discriminate tissues with multiple energy scanning than single energy scanning. As Hounsfield described, using multiple energies during a CT scan allows to determine the effective atomic number and electron density of materials (e.g. tissues) scanned. In one paper by Rutherford et al. [5], DECT scans were used to determine the effective atomic number of colloid cysts and meningioma. In the same year, DECT was used for bone-mineral content in the radius and ulna [6]. At that time, DECT was accomplished by scanning the patient two or more times at different energies. Also, during the 1970s and early 1980s, a multiple source CT scanner, called the dynamic spatial reconstructor, was being developed for research which consisted of 14 X-ray sources and 14 detectors [7]. While research on both dual-source and dual-energy scanning continued, it was not until 2006 that a new clinical dual-source/dual-energy CT scanner with sufficient performance and noise characteristics became available [8]. The SOMATOM Definition (Siemens Healthcare, Erlangen, Germany) contains two sources and detectors in an orthogonal configuration. The energy level of each source can be programmed independently allowing for concurrent dual-energy scanning of a patient. Other CT manufacturers have developed alternative approaches such as rapid kV switching or sandwich detectors to generate multiple kV datasets using a single CT system. Because DECT can provide elementary chemical composition of the tissues, it can be used for automated bone removal [9], kidney stone characterization [10], gout detection [11], pulmonary embolism detection [12], and iodine contrast removal [9].

DECT imaging may be used in application other than composition analysis. In particular, multiple scans may be acquired to improve upon the SNR characteristics of an equivalent single energy scan. For example, a 140-kV scan is generally less noisy than a 120-kV scan; however, the benefit of improved noise characteristics is offset by the decrease in signal and loss of contrast resolution. An 80-kV scan can resolve iodine contrast better than a 120-kV scan but the resulting dataset contains more noise. Fused 140-kV and 80-kV scans yield a result which balances the advantages/disadvantages of both. Historically, linear blending functions have been used for this type of mixing. Specifically, it has been shown that a blending image with a ratio of 70% 140-kV and 30% 80-kV yields an image with similar image characteristics as a standard 120-kV single energy scan [9]. Fig. 1 shows a 140-kV and 80-kV scan of a patient with a liver lesion. The 140-kV image contains less noise; however, because of poor image contrast, it is difficult to clearly delineate the lesion. In contrast, the 80-kV scan can resolve the lesion at the expense of image noise. The linearly blended image provides some improvement in contrast while suppressing the noise.

While linear blending provides some improvement in image quality compared to any single scan (simply from an SNR perspective), it will also yield a sub-optimal image when evaluating the image contrast and visual conspicuity of lesions. Referring back to Fig. 1, the high contrast lesion seen in the 80-kV image is somewhat muted as a result of the contributions of the 140-kV data during the blending process. As a result, linearly blended images will likely result in a low-noise image, but reduce the likelihood of clearly identifying a lesion. As an alternative to linear blending, several non-linear blending functions have been developed which can be used to optimize the blending processing. Fig. 1 also shows the application of a modified sigmoid blending approach. A detailed analysis of such blending functions can be found in [13].

In short, the goal of non-linear blending is to maintain the contrast of the low-energy scan while achieving the noise characteristics of the high-energy scan. In the particular case of 140/80-kV scanning, the high-intensity regions of the 80 kV correspond to iodine contrast enhancement. Preferential blending functions will maintain the high image contrast in regions of high iodine concentration. By contrast, low-intensity levels, which correspond to air, water, and various soft tissues, are less noisy in 140-kV scan and should be preferred in the blending process. To achieve this aim, several non-linear blending functions were developed and evaluated including a binary blending function, a slope blending function, a gaussian function, and a modified sigmoid function. Preliminary analysis suggested that the modified sigmoid function (referred to as moidal blending function) was preferred by radiologists [13]. A moidal blending method has been commercially implemented in the Siemens Multi Modality Workplace (MMWP) and Wizard under the name of “Optimum Contrast.”

The moidal function provides a flexible blending paradigm in which the relative weight of the 140-kV and 80-kV data is dependent on the HU value. Fig. 2 illustrates the moidal function used for moidal blending. Intuitively, the selection of the level (λ), or point of inflection, should be near the point of divergence between the 140 and 80 kV. The width (ω) adjustment can be used to provide a sharper or smoother transition between the two datasets. To evaluate the effect of non-linear blending on DECT datasets, a study comparing linear and moidal blending was conducted in both a phantom and IRB-approved patient study.

2. Materials and methods

2.1. Phantom study

A liver phantom was created using bovine liver containing 6 cm³ syringes submerged in a 30-cm diameter water bath and wrapped in Superflab® tissue-simulating material to a diameter of 40 cm. Each of the syringes was filled with a different iodine concentrations ranging from 15 to 145 HU as measured at 140 kV (15, 45, 64, 79, 116 and 145 HU) to simulate hyperdense and hypodense liver lesions.

The phantom was scanned eight times at different dose settings using a dual source CT scanner (SOMATOM Definition from Siemens Medical Solutions). Each scan used a dual energy protocol for abdomen/liver without automatic exposure control and a tube rotation time of 0.5 s. The tube currents for the 140 kV tube were 45, 55, 65, 75, 85, 95, 105, and 115 mAs; the corresponding tube currents for the 80-kV tube were 192, 234, 276, 318, 361, 403, 446, and 488 mAs. Representative images collected from the liver phantom are shown in Fig. 3.

Following acquisition, the image datasets were mixed using linear blending and moidal blending. A linear blend ratio of 0.3 was chosen to simulate attenuation of standard 120-kV CT images. For moidal blending, two independent operators manually chose the λ and ω parameters which yielded the preferred visual contrast. Following blending, regions of interest (ROI) were selected for the water (ROI_W), liver (ROI_L), and each syringe (ROI_S). The contrast-

to-noise ratio (CNR) of each syringe was calculated as
$$\text{CNR} = (\bar{\text{ROI}}_s - \bar{\text{ROI}}_L) / \sigma(\text{ROI}_w)$$
 where $\bar{\text{ROI}}$ is the mean value and $\sigma(\text{ROI})$ is the standard deviation. In order to evaluate the difference between linear and moidal blending independent of dose, a figure of merit (FOM) was calculated using the method presented in [14]. Because the different scans were obtained at different dose settings, a direct comparison is only possible by normalizing the scans to an FOM. The FOM is based on the effective dose (ED) and is defined as CNR^2/ED . A Wilcoxon signed rank test was used to determine significance between the FOM of the ROIs for the linear blended image versus moidal blended image.

To evaluate the visual preference of blending images, two radiologists were blindly presented linear and moidal blended images for visual assessment. For this task, the same 0.3 linear blend was used; however, two moidal blended datasets were generated. One of the moidal blended images was generated using the previously selected blending parameters. The other moidal blended image was generated from the λ and ω parameters which yielded the maximal CNR in the previously defined ROIs. Each of the three blending approaches was applied to each of the eight scans at different dose settings, yielding 24 total images. The images were presented to the radiologists in a random blinded fashion (six panels of eight images) with each of the images presented at least twice. The observers were asked to choose their three preferred and least preferred image based on lesion conspicuity and visual appeal. In addition, both the lowest dose images and the highest dose images were directly compared in a blind manner.

2.2. Patient study

To evaluate the visual preference of blending images in patient data, 45 DECT patient scans were also compared. The scans were selected for organ-specific evaluation, and included 17 focused on the small bowel (i.e., dual-energy CT enterography), 13 focused on the liver (i.e., dual-energy late arterial phase), 5 focused on the pancreas (dual-energy pancreatic phase), 5 renal (dual-energy CT urography) and 5 adrenal (5 dual-energy adrenal scans). For each exam, two radiologists in consensus panned up and down through four datasets simultaneously: the 140-kV dataset, the 80-kV dataset, the 0.3 linear blended image, and a moidal blended image. The λ and ω parameters were selected manually in a manner similar to the phantom study. One senior radiologist chose parameters which provided the preferred visual contrast of the particular anatomy. The four sets of images were ranked from 1 (most preferred) to 4 (least preferred) with respect to organ conspicuity (for the organ of interest) and disease conspicuity (when disease was present).

3. Results

3.1. Phantom study

The CNR measurements for the linear and moidal blended images are shown in Fig. 4. For each syringe, there are eight pairs of measurements—one for each of the eight dose settings. The paired measurements are ordered from lowest to highest dose. For the 15, 45, and 64 HU syringes, the linear blended images and moidal blended images had similar CNR; for the other three syringes, the moidal blended images had a higher CNR consistently across the dose settings. Moreover, in several cases, the non-linear blended images had a higher CNR at a low-dose setting than the linear blended images at a high-dose setting.

The results of the dose independent FOM analysis comparing the CNR of linear and moidal blending images are shown in Table 1. In the case of the 15 and 45 HU syringes, there was no statistical difference between the linear and moidal blended images. The 64-HU syringe showed a significantly higher FOM in the linear blended image compared to either observer ($p = 0.008$ for both observers). For the remaining three syringes (79, 116, and 145 HU),

however, there was a significant difference in FOM (p -values ranging from 0.008 to 0.023) favoring the moidal blended images. The measured HU of the liver in the phantom was 72.

In the blinded visual analysis, both reviewers exclusively chose the moidal blending as their preferred three images when available in the eight panel display and the linear blending image as the least preferred when shown in the display. The moidal blending was preferred independent of the mA level (e.g. in both the lowest dose and highest dose comparisons). Images collected with higher mA levels were preferred over lower mA images; however, it was observed by the radiologists that even the 45-mAs data blended with the moidal blending function was approaching diagnostic quality.

3.2. Patient study

Overall the moidal blended were ranked the best (over the 0.3 linear blend, the 140-kV and 80-kV dataset) in displaying organ conspicuity in 69% (31/45), and best in displaying pathology in 61% (17/28) of patients. Table 2 shows the percent of cases in which moidal blending and 0.3 linear blending were ranked as the best image set for each organ of interest. Importantly, both bowel and liver pathologies (which are highlighted by the presence of iodine) were best seen using the moidal blending technique. Moidal images were preferred in 73% (vs. 9% in which linearly blended images were preferred) of bowel pathologies and 56% (vs. 11%) of liver lesions.

4. Discussion

There is significant opportunity to use dual-energy CT for disease identification and classification. However, in collecting dual-energy data, the radiologist is presented with twice the data obtained from a normal CT scan which can hinder the clinical evaluation. One way to simplify image review is to fuse CT datasets of different tube energies into a unique blended dataset with desirable properties. Important properties include high contrast and low noise, optimal lesion conspicuity, and artifact suppression. Linear blending has been shown to generate 120 kV-like datasets with a reduction in noise compared to a single source scan; however, uniform application of a fixed weighting function for all pixels reduces both noise and high signal. Non-linear blending can be used to refine the blending process. The use of a modified sigmoid blending function strongly weighs the low HU values toward the 140 kV image and the high HU values toward the 80 kV. Accordingly, since it is high HU values which are differentiated between 140-kV and 80-kV scans, there is the potential for improved contrast. The phantom study confirms in most cases the increase in CNR with non-linear blending. For lesions which are equal to or lower than the background (in this case HUs equal to or lower than liver), non-linear blending does not provide much improvement. This is expected given that the ROIs have HU which are not indicative of hyper-enhancement. Instead, non-linear blending (such as moidal blending) should be targeted to clinical applications in which hyper-enhancement may indicate disease.

CNR provides a quantitative evaluation of the blending methods because visual contrast and lesion conspicuity are of primary importance in radiologic detection and characterization. Towards this end, the phantom data was blended and used in a blind comparison. There was a clear preference for the non-linearly blended images even at different dose settings; however the study design compared the moidal method to a fixed linear blend of 0.3. The use of a different linear blend, 0.7 for example, may yield different results. One of the challenges in assessing non-linearly blended images is the issue of parameter selection by scan type and dose settings. In the future, it is likely that default settings should be incorporated into the blending algorithm with the ability to define the parameters prior to a clinical review of the images.

The patient study provides some qualitative evidence that nonlinear blending may have clinical merit. In the bowel and liver, the unique properties of the non-linear blending along with the selective hyper-enhancement of disease generate images which are visually appealing. For these anatomies, the radiologist found presets which appear to work well and would be reasonable defaults although they were organ-specific (e.g. bowel- λ : 341, ω : 281 and liver- λ : 16, ω : 428). Non-linear blending was less effective in the kidney and pancreas because these organs normally show considerable enhancement. Nevertheless non-linear blending may yet prove to have a role in evaluation of these organs, for example in detection of subtle hyper-enhancing neuroendocrine tumors of the pancreas.

5. Conclusions

Non-linear blending of dual energy data can provide an improvement in CNR over linear blending, but its advantages over tunable linear blending is unknown. The improvement in CNR is accompanied by a visual preference for non-linear blended images. One of the primary challenges is optimizing the selection of nonlinear blending parameters which may be organ-specific. Further study on selection of parameters and lesion conspicuity in nonlinearly blended images is being pursued.

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Fig. 1.

Patient with metastatic melanoma of small bowel. The modified sigmoid blended image was ranked superior to the 0.3 linear blend because of improved conspicuity, and better than the 80 kV dataset because of reduced image noise.

$$\%Blend = \frac{1}{1 + e^{\frac{I_{low} - \lambda}{\omega}}}$$

Fig. 2.

Moidal blending function for dual-energy CT data. The blending ratio varies according to CT Number. The % blend is the contribution of the low-energy data (80 kV, in this case). λ is point of inflection and ω defines the rate of change in transition from a low blending ratio to a high blending ratio. I_{low} is the pixel intensity level of the 80-kV image.

Fig. 3.
Optical photo (left) and scan images at two energy levels (center, right) from liver phantom with six syringes filled with contrast.

Fig. 4.

CNR measurement of each syringe after linear and moidal blending for each dose. In the plot, each pair of linear (black) and moidal (gray) blended image is shown for each syringe. The pairs are ordered by the 140-kV dose setting from lowest to highest (e.g. 45, 55, 65, 75, 85, 95, 105, and 115 mAs).

Table 1

Figure of merit (FOM) comparison between linear blended images and non-linear blended images in phantom. The FOM is calculated as CNR^2/ED . Wilcoxon signed rank test used for comparison. For reference, liver HU was measured at 72.

ROI	Linear blend	Non-linear blend (Obs 1)	Non-linear blend (Obs 2)
145-HU syringe	3.0	2.9	2.7
45-HU syringe	1.7	1.7	1.6
64-HU syringe	0.9 [*]	0.3	0.2
79-HU syringe	0.1	0.9 [†]	0.9 [†]
116-HU syringe	1.8	2.9 [†]	2.7 [†]
145-HU syringe	3.1	5.1 [†]	4.8 [†]

* Significantly higher FOM with linear blending ($p < 0.05$).

† Significantly higher FOM with non-linear blending ($p < 0.05$).

Table 2

Number of organ-specific cases in which either the moidal blend or 0.3 linear blend was ranked best in 45 contrast-enhanced dual-energy CT exams, as described.

	Moidal blend		0.3 linear blend	
	Organ	Lesion	Organ	Lesion
All cases	69% (31/45)	61% (17/28)	9% (4/45)	7% (2/28)
Bowel	88% (15/17)	73% (8/11)	6% (1/17)	9% (1/11)
Liver	77% (10/13)	56% (5/9)	15% (2/13)	11% (1/9)
Pancreas	20% (1/5)	50% (1/2)	0% (0/5)	0% (0/2)
Kidney	20% (1/5)	50% (1/2)	20% (1/5)	0% (0/2)
Adrenal	80% (4/5)	50% (2/4)	0% (0/5)	0% (0/4)