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Matching and Homogenizing Convolution Kernels for Quantitative Studies in Computed Tomography

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Abstract

The sharpness of the kernels used for image reconstruction in computed tomography affects the values of the quantitative image features. We sought to identify the kernels that produce similar feature values to enable more effective comparison of images produced using scanners from different manufactures. We also investigated a new image filter designed to change the kernel-related component of the frequency spectrum of a post-reconstruction image from that of the initial kernel to that of a preferred kernel. A radiomics texture phantom was imaged using scanners from GE, Philips, Siemens, and Toshiba. Images were reconstructed multiple times, varying the kernel from smooth to sharp. The phantom comprised 10 cartridges of various textures. A semi-automated method was used to produce $8 \times 2 \times 2 \text{ cm}^3$ regions of interest for each cartridge and for all scans. For each region of interest, 38 radiomics features from the categories intensity direct ($n = 12$), gray-level co-occurrence matrix ($n = 21$), and neighborhood gray-tone difference matrix ($n = 5$) were extracted. We then calculated the fractional differences of the features from those of the baseline kernel (GE Standard). To gauge the importance of the differences, we scaled them by the coefficient of variation of the same feature from a cohort of patients with non-small cell lung cancer. The noise power spectra for each kernel were estimated from the phantom's solid acrylic cartridge, and kernel-homogenization filters were developed from these estimates. The Philips C, Siemens B30f, and Toshiba FC24 kernels produced feature values most similar to GE Standard. The kernel homogenization filters reduced the median differences from baseline to less than one coefficient of variation in the patient population for all of the GE, Philips, and Siemens kernels except for GE Edge and Toshiba kernels. For prospective CT radiomics studies, the scanning protocol should specify kernels that have been shown to produce similar feature values. For

retrospective studies, kernel homogenization filters can be designed and applied to reduce the kernel related-differences in the feature values.

Introduction

Intensity and texture quantitative features in imaging are directly affected by the sharpness of the images. In computed tomography (CT), the image sharpness is largely controlled by the convolution kernel used in image reconstruction. Thus, it is not surprising that CT radiomics features have been shown to depend on the kernel used for reconstruction (1–5).

Many studies have examined how image acquisition and reconstruction parameters such as the kernel affect radiomics features. For example, Mackin et al. previously scanned a CT radiomics phantom on 16 scanners using the chest protocol of each scanner. These scans showed that the variability due to the imaging parameters was of similar magnitude to the variability found in the same features calculated for the gross tumor volumes of a cohort of patients with non-small cell lung cancer(6). Other studies have focused on particular acquisition parameters. According to multiple studies, radiomics features are relatively insensitive to the tube current(7, 8) or peak voltage(9–11) of the CT scans. Radiomics features are affected by the image (slice) thickness(1, 3, 7, 12) and pixel size(13, 14), and it may be possible to reduce these effects by resampling the images(7), resampling and smoothing(13), or a applying a correction(14).

Several studies have shown that for radiomics studies, images should be acquired using protocols to reduce the effects of the acquisition and image reconstruction parameters. For example, to conclude their study showing that smooth and sharp kernels are incompatible in radiomics, Zhao et al asserted that their findings would “raise awareness of the importance of properly setting imaging acquisition parameters”(12). However, it is still not clear how to properly specify compatible reconstruction kernels in protocols, which vary widely by manufacturer. To address this difficulty in matching kernels, Solomon et al compared the peaks of noise power spectra for GE (GE Healthcare, Waukesha, WI) and Siemens (Siemens Healthcare, Germany) filtered back projection kernels(15). To match kernels using their approach, one matches the peak frequency of the noise power spectrum. This approach is applicable only to prospective studies because it requires matching kernels prior to image reconstruction.

Differences in CT reconstruction parameters are more problematic for retrospective radiomics studies because it is too late to change the parameters for these studies. One option for these studies is to restrict the scans to those using kernels previously shown to be comparable. A second option, investigated by a recent study, is to apply a kernel-specific correction for each feature(5). That study showed that such corrections could improve feature robustness by 38–78%. To build upon these results, researchers need to match kernels from the most common CT scanner makes and provide a matching system optimized for radiomics. Also, for retrospective studies, there is a need to develop a correction such that features created with non-matching kernels can be meaningfully compared.

The purpose of the current study was to address these needs. First, we sought to identify the comparable kernels from GE, Philips, Siemens, and Toshiba. To achieve this, we identified the kernels that produced the most similar radiomics feature values for the materials in a specially designed radiomics phantom. Second, we sought to develop a method for post-processing existing CT images to make them more comparable to images created with a different kernel. Such a method would allow radiomics studies to compare images originally acquired with incompatible kernels. Further, this method may make it possible to change the kernel related characteristics of an image to those known to improve the predictive power of the radiomics features used in a study. Though this study focused on quantifiable image characteristics, the visual characteristics of the images are affected as well. Thus, this method may have clinical applications when comparing images produced on scanners from different manufacturers or images produced on the same scanner using different kernels.

Methods and Materials

Phantom and scanners

The Credence Cartridge Radiomics (CCR) phantom was imaged on GE Lightspeed RT (GE Healthcare, Waukesha, WI, USA), Philips Brilliance 64 (Philips Healthcare, Amsterdam, Netherlands), Siemens Sensation Open (Siemens Healthineers, Erlangen, Germany), and Toshiba Aquilion ONE (Toshiba Medical Systems, Otawara, Japan) scanners. These scans were acquired and reconstructed using the parameters shown in Table 1. The reconstructions were repeated six to eight times per manufacturer while varying the kernels from smooth to sharp. The kernels are listed in Table 2. The CCR phantom comprises 10 cartridges of materials producing a range of CT image textures(6). In the current study, we used the acrylic, dense cork, and rubber particle cartridges. Because the acrylic is homogeneous, it was used for measuring the noise power spectrum. The dense cork and rubber particle cartridges, shown in Fig. 1, have textures shown to be similar to those of non-small cell lung cancer tumors. The CCR phantom has been used by numerous groups to study feature reproducibility(6, 13, 14, 16, 17) and the effects of scanner acquisition parameters on radiomics features(5, 8).

For each scan, $8 \times 8 \times 2 \text{ cm}^3$ rectangular regions of interest (ROIs) were created using a semi-automated method. We extracted 38 radiomics features from the categories of intensity histogram ($n = 12$), gray-level co-occurrence matrix(18) ($n = 21$), and neighborhood gray-tone difference matrix(19) ($n = 5$) using IBEX radiomics software(20). The features studied are listed in Table 3.

Identifying comparable kernels

The first aim in the current study was to identify the “matching” kernels, i.e., those that produce similar quantitative feature values. The best matches between kernels may be feature- and material-dependent. To reduce the number of comparisons, we selected the GE Standard kernel as the baseline and then compared the remaining kernels to it. Different kernels produce different feature values, but these difference may not be large enough to be important in radiomics studies. To gauge the importance of the differences, we used the patient-normalized feature difference, Δf_k , defined as

$$\Delta f_k = \frac{(f_k - f_{GE})/f_{GE}}{\sigma_{f_p}/f_p}. \quad (1)$$

where f is the feature, k is the kernel, and f_{GE} is the feature value for GE Standard. σ_{f_p}/f_p is the coefficient of variation for the same feature from a cohort of 106 patients with non-small cell lung cancer. Thus, a value of 1 for Δf_k is equivalent to one coefficient of variation of the same feature in the patient cohort. Similar metrics have been used in previous studies(6, 13, 16).

Patient normalization cohort

The patient normalization cohort, which was part of a prior study(21), was used to represent the expected variability in the CT images of patients used in radiomics studies. All procedures for this cohort were performed in accordance with the Declaration of Helsinki on Ethical Issues. Informed consent was obtained for participation in the trial, and the need for additional informed consent was waived by the institutional review board. The end-of-exhale phase of the treatment planning CT images was used for feature extraction. The gross tumor volumes were selected as the ROIs, and an image intensity threshold of -100 HU was applied before the features were calculated. The tumor ROIs had a mean volume of 96 cm^3 and median volume of 42 cm^3 (range $5\text{--}568 \text{ cm}^3$). ROIs smaller than 5 cm^3 were excluded. The patients were imaged on a GE Discovery ST or GE Lightspeed RT16. The peak tube voltage was 120 kVp. The peak tube current was 100 or 200 mA with rotation times of 0.5 or 0.8 seconds. The image thickness was 2.5 mm, and the pixel spacing was 0.98 mm. This cohort is described in more detail in the prior study(21).

Designing the kernel image filters

The second aim of our study was to investigate a method for changing the kernel-related characteristics of CT images that have already been reconstructed. The filters were developed using the same scans and kernels used for the first aim. Any digital image $f(x, y)$ can be represented in frequency space as the product of the power spectrum $|F(u, v)|$ and the phase angle ϕ ,

$$\mathcal{F}\{f(x, y)\} = F(u, v) = |F(u, v)|e^{-i\phi(u, v)}. \quad (2)$$

For CT images reconstructed using filtered back projection, the power spectrum is a combination of the image signal power spectrum $H(u, v)$ and the noise power spectrum $G(u, v)$:

$$|F(u, v)| = |G(u, v)H(u, v)|. \quad (3)$$

In this case, $|G(u, v)|^2$ is proportional to the noise power spectrum and $G(u, v)$ is largely determined by the kernel. Thus, applying a filter of form $\frac{|\overline{G}_b(u, v)|}{|\overline{G}_a(u, v)|}$ to image $f_a(x, y)$ created using an arbitrary kernel a produces a new image $f_{ab}(x, y)$ with a power spectrum more characteristic of the second kernel b :

$$f_{ab}(x, y) = \mathcal{F}^{-1} \left\{ \frac{|\overline{G}_b(u, v)|}{|\overline{G}_a(u, v)|} \mathcal{F} \{ f_a(x, y) \} \right\} = \mathcal{F}^{-1} \left\{ \frac{|\overline{G}_b(u, v)|}{|\overline{G}_a(u, v)|} |G_a(u, v) H(u, v)| e^{-i\phi(u, v)} \right\}. \quad (4)$$

Building such a filter requires a method for estimating $\overline{G}_a(u, v)$ and $\overline{G}_b(u, v)$. The noise power spectrum can be measured using scans of a homogeneous material, as described by Solomon et al(15). We used analogous methods to estimate $\overline{G}_k(u, v)$ for each kernel. The acrylic cartridge ROIs provided the necessary homogenous images. To reduce any effects from radial asymmetries, we rotated each slice of ROIs by 90° , 180° , and 270° , and these rotated slices were averaged with the original to produce the image $I(x, y)$. A second-degree, two-dimensional polynomial $P\{I(x, y)\}$ was then fit to this averaged image. $\overline{G}_k(u, v)$ for each kernel k was estimated as

$$\overline{G}_k(u, v) = \frac{1}{N} \sum_i^N |FFT[I_{ki}(x, y) - P\{I_{ki}(x, y)\}]| \quad (5)$$

where N is the number of slices in the acrylic ROI. Subtracting the second-degree polynomial $P\{I_{ki}(x, y)\}$ removes the low frequency components from the image and makes the average intensity equal to zero. To create a two-dimensional, radially symmetric filter, we computed a one-dimensional radial average of $G_k(u, v)$, and a one-dimensional cubic-spline, $f_k(r)$, was fit to the one-dimensional radial average. These one-dimensional cubic splines, $f_k(r)$, were used to represent the radial frequency magnitudes for each kernel. The two-dimensional estimates $\overline{G}_k(u, v)$ were generated from the one-dimensional cubic splines using $r = \sqrt{u^2 + v^2}$.

Applying the kernel-homogenization filters

We next applied the filters to images from all manufacturers using equation (4). Both the numerator and the denominator of the ratio $\frac{|\overline{G}_b(u, v)|}{|\overline{G}_a(u, v)|}$ were produced from the one-dimensional cubic splines. For kernel a , we used the cubic spline for the kernel used during image reconstruction. For kernel b , we used the kernel from manufacturer of b that most closely matched the baseline. For example, the filter applied to images produced using the Siemens B50f kernel a would be B50f, and b would be B30f, because B30f is the kernel that

best matches the GE Standard kernel. To evaluate the effectiveness of the filters, we again used the patient-normalized feature differences, Δf_k , defined in equation (1).

Results

Figure 2 shows unfiltered and filtered images of the rubber particle cartridge compared with an image reconstructed using the GE Standard kernel. The unfiltered Siemens image, produced using the B70f kernel, appears sharper than the image produced using the GE Standard kernel. However, we found that filtering the Siemens image using the filter shown in Fig. 2d made the image texture apparently more similar to that produced by the GE standard kernel.

Figure 3, which quantifies the qualitative comparisons of Fig. 2, shows the patient-normalized feature difference for four features extracted from the rubber particle cartridges of the CCR phantom. Each row shows the differences between kernel features from each manufacturer and features from the GE Standard kernel. The four features represent intensity direct (entropy), gray-level co-occurrence matrix (energy), neighborhood gray-tone difference matrix (coarseness), and the standard deviation of the CT numbers. The kernels are sorted by increasing standard deviation, and unfiltered values are represented by triangles and kernel-homogenization filtered values are represented by squares. The kernel-homogenization filters were used with the GE Standard, Philips C, Siemens B30f, and Toshiba FC08 kernels. One unit on the vertical axis represents one coefficient of variation for the feature in the non-small cell lung cancer patient cohort. The range of the unfiltered results (triangles), exceeding two coefficients of variation in most cases, demonstrates the effect of the kernels on the feature values. However, for GE, Philips, and Siemens, the kernel-homogenization filter reduced the range of the patient-normalized feature difference for all four of the features shown (squares). For Toshiba, the results were mixed; the difference was increased for some features and decreased for others.

Figure 4 shows results similar to Fig. 3 but includes all of the features from the study. The cells are color-coded to indicate patient-normalized feature differences of $S_i < 0.5$ (green), $0.5 < S_i < 1.0$ (yellow), and $S_i > 1.0$ (red). The first column shows the median S_i value of all features and is used as a metric for determining the degree of matching among the kernels. The top portion of the figure compares the features from images that have not been filtered. The bottom portion compares the same kernels after the kernel-homogenization filter has been applied. After normalization, the differences between the GE kernels were small except for the Edge kernel features and the two features InverseDiffNorm (gray-level co-occurrence matrix inverse difference normalized mean) and InverseDiffMomentNorm (inverse difference momentum normalized mean). These two features showed large differences for kernels from all manufacturers because the coefficient of variation in the patient cohort was small. With the exception of these two features, S_i was less than 0.5 after filtering for all features for Philips kernels A, B, C, E, and L and all but four features for kernel D. With the same two exceptions, the median S_i was less than 0.5 for all of the Siemens kernels after filtering, but for only two prior to filtering. Filtering was not as effective for the Toshiba kernels, reducing the differences for kernel FC18 but actually increasing them for kernel FC65.

Table 4 shows the kernels from each manufacturer that best matched the kernels from GE. The best match was defined as the kernel that produced the smallest median patient-normalized feature difference. The values of the differences are shown in parentheses in Table 4. In the current study, B30f was the softest Siemens kernel and the closest match to the three softest GE kernels, Soft, Detail, and Standard. All of the Philips kernels were smooth relative to the GE BonePlus and Lung kernels. The sharpest Philips kernels, YA and YB, were not included in our study and may have provided a better match to the sharp GE kernels such as Edge, Boneplus, and Lung.

Discussion

We have examined the effects of reconstruction convolution kernels on the corresponding quantitative feature values. Although the kernels have a large effect on the feature, choosing kernels that produce similar image characteristics can reduce the variability between kernels. Furthermore, we demonstrated that image filters can reduce the differences between most kernels.

An earlier study from Solomon et al quantitatively compared kernels from GE and Siemens(15). Their aim was to produce quantitative metrics to match kernels on the basis of human perception of the images. Therefore, they applied a human visible response filter to their images before quantifying the differences. Because our aim was to identify kernels that produce similar quantitative features, we did not apply the visible response filter(22). Although our kernel matching results were in general agreement—smoother kernels match smoother kernels—there were some differences in the results. For example, in the prior study, Siemens B40f and B45f were closer matches to GE Standard than was B30f, the closest match in our study. Similarly, in the current study the Siemens kernels B50f, B60F, and B70f all matched GE Lung more closely than did B80f, which was the best match in the prior study. The differences in the results may be due to the absence of the visual response filter or the difference in metrics or a combination of both.

A recent study from Shafiq-ul-Hassan et al investigated methods for developing corrections to reduce the effects of kernel sharpness on quantitative feature values(5). These corrections scaled the feature values by the square root or the inverse of the square root of the peak frequency of the noise power spectrum. This approach was shown to be effective and simple to apply. We consider this correction approach to be a complement to the kernel-filter approach presented in the current study. The correction approach requires only knowledge of the kernel used during reconstruction, rather than a separate phantom scan as in the kernel-filter approach. This correction may also apply to images collected under inconsistent conditions such as different reconstruction fields of view or slice thicknesses. However, the correction approach requires determining a correction for each feature in the study. Also, it is not clear that such corrections will have similar, positive effects when applied to patients rather than phantom scans. Furthermore, the corrections do not alter the images directly, and this lack of alteration could be a strength, a weakness, or both.

The current study has some additional limitations. Perhaps the most important is that only six to eight kernels were included for each manufacturer. For Philips, the sharp kernels YA

and YB were not included. For Siemens, the smoothest included body kernel was B30f and none of the head kernels were included. A large range of Toshiba kernels was included, but the kernel-homogenization filtering was not effective. A possible explanation is that the method used for estimating the noise amplitude, $G(u, v)$ in equation (3), is not effective for Toshiba's kernels. All of the images used in the study were reconstructed with 50-cm fields of view, 0.98 pixels/mm. Thus, the Nyquist frequency was limited to 0.51 cycles/mm. This frequency is below the peak frequency for some of the kernels used in the study. Lastly, the current study does not demonstrate that the kernel-homogenization filter can be used to reduce the inter-scanner variability in retrospective radiomics studies. Application of the kernel-homogenization filter to patient images should be the focus of future studies.

Many studies have demonstrated that statistical and model-based image reconstruction algorithms can improve the quality of low dose CT images(23–29). Recent advances in computer hardware have reduced the time required to generate the images, and it is now practical to use the compute-intensive methods routinely. Because these algorithms were not part of this phantom study, it is unknown if the kernel transformations described in this study will be as effective for these algorithms. Further, there are a wide array of methods and vendor implementations. Future studies should directly compare the advanced reconstruction methods of the most commonly used scanners. Reducing the noise in images using these methods may improve the effectiveness of CT radiomics biomarkers.

For this study, we used radiomics feature values extracted from the CT images of NSCLC patients to gauge the relative differences in feature values due to the kernel used in reconstruction. The values of the patient normalized feature difference depend on the feature values from the patient, eq. 1. However, changing the patient cohort only affects the denominator in eq. 1. Whereas, the filtering method described here targets the numerator. Therefore, changing the patient cohort would affect the specific values of the normalized feature differences, but would not change the overall conclusion that the filtering method presented in this study can reduce the differences due to the reconstruction kernels.

The results of our study indicate that for prospective studies, the kernel and other image acquisition parameters should be matched and controlled to minimize the variability due to differences in the scanners. For example, all four manufacturers have at least one kernel that produces images with quantitative features similar to the GE Standard kernel. However, for retrospective studies with mismatched kernels, a kernel filter can be applied. For the kernel to be applied, a phantom with homogenous regions and textured regions can be scanned using the acquisition parameters of the patient cohort to be studied. From this phantom scan, a kernel filter can be developed to improve the consistency of the frequency spectra of the images in the study. Scanning the phantom on all the scanners may be a problem, especially if the scanners are no longer in service. In these cases, it might be possible to use kernel filters developed from phantom scans on a similar CT scanner model.

Conclusion

Quantitative imaging features are highly dependent on the convolution kernels used for image reconstruction. Prospective studies should specify convolution kernels that have been

shown to produce similar feature values. For retrospective studies, kernel-specific frequency-space filters can be applied to reduce the difference in features caused by the use of incompatible kernels.

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Figure 1: Images of the rubber particle cartridges with matched smoother (top row) and sharper (bottom row) kernels.

The window width and level were (1600, 700) for all images.

Figure 2: Slices of the Credence Cartridge Radiomics phantom's rubber particles cartridge reconstructed using (a) the GE Standard kernel, (b) the Siemens B70f kernel, and (c) the Siemens B70f kernel filtered using the kernel filter shown in d.

The images in a-c were produced with window width 1500 and level -600.

Figure 3: Patient-normalized feature differences between kernels from four manufacturers and the GE Standard kernel.

The underlying images were unprocessed (triangles) or processed with a kernel-homogenization filter (squares). The values are scaled such that one unit on the vertical axis represents the magnitude of one coefficient of variation for the same feature in a cohort of 106 patients with non-small cell lung cancer. For display purposes, the vertical range is restricted to $(-2, 2)$. Points that fall outside this range are marked with a black +.

Figure 4: Patient-normalized feature difference between kernels from four manufacturers and the GE Standard kernel for all features in the study.

Applying the kernel-homogenization filter (bottom) reduced the patient-normalized feature difference, S_i , for most kernel/feature combinations. The kernels used for homogenization are indicated with a black background and white text. NGDM, neighborhood gray-tone difference matrix.

Table 1:

Scan acquisition parameters.

Manufacturer	Model	kVp	Image thickness, mm	mAs	CTDIvol, mGy	DFOV, mm	Pitch	Type
GE	LightSpeed RT	120	2.5	109	6.1	500	0.75	Helical
Philips	Brilliance 64	120	3	300	24.1	500	0.94	Helical
Siemens	Sensation Open	120	3	150	17.9	500	0.75	Helical
Toshiba	Aquilion ONE	120	3	110	13.6	500	0.83	Helical

CTDIvol, volume computed tomography dose index; DFOV, display field of view.

Table 2:

Kernels used in study ordered from smooth to sharp (smallest to largest standard deviation in the rubber particles cartridge).

GE	Philips	Siemens	Toshiba
Soft	A	B30f	FC18
Detail	B	B40f	FC12
Standard	C	B45f	FC65
Bone	E	B50f	FC24
Edge	L	B60f	FC08
Boneplus	D	B70f	FC50
Lung		B80f	FC30
			FC81

Table 3:

Features used in the analysis.

Intensity histogram	Gray-level co-occurrence matrix	Neighborhood gray-tone difference matrix
Energy	Autocorrelation	Busyness
Entropy	Cluster prominence	Coarseness
Kurtosis	Cluster shade	Complexity
Local entropy max	Cluster tendency	Contrast
Local entropy mean	Contrast	Texture strength
Mean	Correlation	
Median	Difference entropy	
Range	Dissimilarity	
Skewness	Energy	
Standard deviation	Entropy	
Uniformity	Homogeneity	
	Homogeneity2	
	Information measure correlation 1	
	Information measure correlation 2	
	InverseDiffMomentNorm *	
	InverseDiffNorm *	
	Inverse variance	
	Maximum probability	
	Sum average	
	Sum entropy	
	Sum variance	
	Variance	

* InverseDiffNorm, gray-level co-occurrence matrix inverse difference normalized mean; InverseDiffMomentNorm, inverse difference momentum normalized mean.

Table 4:
GE kernels and the closest matching kernels from Philips, Siemens, and Toshiba.

The matching kernels are those that produce the smallest median patient-normalized feature difference (in parentheses) compared with the GE kernel. Smaller median patient-normalized feature differences indicate a better match between the kernels.

GE	Philips	Siemens	Toshiba
Soft	C (0.12)	B30f (0.38)	FC65 (0.14)
Detail	E (0.11)	B30f (0.15)	FC24 (0.18)
Standard	E (0.08)	B30f (0.09)	FC24 (0.12)
Bone	D (0.45)	B45f (0.18)	FC50 (0.30)
Edge	D (0.66)	B50f (0.05)	FC30 (0.42)
Boneplus	D (0.71)	B60f (0.05)	FC30 (0.03)
Lung	D (0.72)	B60f (0.14)	FC30 (0.10)