Computed Tomography Texture Phantom Dataset for Evaluating the Impact of CT Imaging Parameters on Radiomic Features.

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Abstract:

Purpose: To describe the computed tomography (CT) dataset of the Credence Cartridge Radiomic (CCR) phantom we collected at our institution and shared with the research community.

Acquisition Method: Two hundred and fifty one CT scans of the CCR texture phantom were acquired on 8 scanners using various acquisition and reconstruction parameters, namely, slice thickness, reconstruction Field of View (FOV), reconstruction kernel, mAs, and Pitch. Multiple scanners and vendors were used to assess the inter-scanner and inter-vendor variability of CT radiomic features. A systematic scanning approach was followed in order to study the effects of varying imaging parameters on the numerical values of the extracted radiomic features.

Data format and storage location: CCR Phantom image files were stored in DICOM format in The Cancer Imaging Archive (TCIA, http://www.cancerimagingarchive.net/).

Key words: computed tomography, radiomics, texture, imaging, image, acquisition, reconstruction, phantom, dataset, feature, robustness.

1. **INTRODUCTION**:

The extraction of quantitative information from medical images, known as radiomics, promises to aid cancer detection, diagnosis and prediction of response to treatment [1-3]. However, medical images are typically acquired using a number of imaging parameters. Each of these parameters is typically manipulated during routine CT imaging to get a desired image quality. These parameters may affect the quantitative image information extracted in radiomic studies. Texture phantoms provide a stable geometry and material composition to study the robustness of radiomic features with respect to various imaging conditions [4].

Recent phantom studies have shown that CT radiomic features are significantly affected by imaging parameters [5, 6]. Also, intra- and inter-scanner variability of radiomic features has been reported [4]. Previously reported features identified as prognostic or predictive were later found to be intrinsically dependent on voxel size [5, 7]. Most second order texture features have been shown to be affected by CT image noise texture due to reconstruction kernels [6]. And many radiomic features were more pronounced to be affected by thinner CT slices as compared to thicker slices [8]. Therefore, comprehensive characterization of radiomic features is possible using texture phantoms.

For radiomics analysis, phantom CT scans are typically acquired using combinations of multiple imaging parameters. A practical approach to assess how a parameter affects radiomic feature values is to perform scans of a phantom varying such parameter while keeping all other parameters constant at nominal values. In this way mathematical relationships between radiomic features versus the varied parameter might be discerned and correction methods developed to reduce feature variability, as previously demonstrated [5, 6].

To describe the computed tomography (CT) dataset of the Credence Cartridge Radiomic (CCR) phantom we collected at our institution and shared with the research community.

The purpose of this work is to describe the CT dataset of the CCR phantom acquired on different scanners, different vendors and several commonly used imaging parameter combinations. These scans were acquired at the Moffitt Cancer Center and are available to other researchers in The TCIA website.

2. ACQUISTION

2.1 Systematic Scanning Approach

The CCR phantom [4] was used for all scans. This phantom is composed of ten different cartridges, each having a different material with unique textures to simulate a range of HU values similar to that found in the human body. In previous studies, the rubber cartridge was most frequently used because it was found to have HU values similar to those of non-small cell lung cancer (NSCLC) tumors [4, 9].

CT scans of the phantom were acquired on 8 CT scanners from three major manufacturers: Siemens, Philips and GE Healthcare. Multiple scanners and vendors were employed to assess the inter-scanner and inter-vendor variability of CT radiomics. Basic acquisition parameters, namely tube current (mAs) and pitch, were varied. For image reconstruction, the parameters varied were Field Of View (FOV), slice thickness and reconstruction kernels.

The scanning was performed such that only one parameter under investigation was a variable while all other imaging parameters were kept constant at nominal values. This scanning approach provided a way to discern relationships between a given parameter and the numerical values of extracted radiomic features.

2.2 CCR Phantom Dataset

Overall, 251 CCR phantom scans were acquired. The data were divided into four subcategories; each subcategory addressed one ‘variable’ CT parameter. These subcategories were variations in voxel size, reconstruction kernel, tube current-exposure time product (mAs), and Pitch. The nominal parameter values used for each ‘variable’ parameter are listed in Table 1 through Table

4. The variation in voxel size was obtained by changing pixel size (7 FOVs per scanner for 7 scanners & 5 FOVs for 1 scanner) or by changing slice thickness (3 slice thicknesses per scanner) for a total of 8 CT scanners. Therefore, there are total of 162 scans for voxel size variation (Table 1). The CCR phantom scans for variable kernel settings were acquired on 5 CT scanners (Table 2). The scans for variable mAs and Pitch were acquired on 4 CT scanners as listed in Table 3 and Table 4, respectively.

Table 1: CCR Phantom scans (total = 162) to evaluate the impact of voxel size on radiomic features.

CT Scanner	Recon. Kernel.	mAs	kVp	Scan Type	Detector Configuration (mm)	Voxel size (Variable) by varying Slice Thickness (mm)	Voxel size (Variable) by varying Reconstruction FOV (mm)
GE Discovery STE	Standard	250	120	Helical	Det. Coverage= 40	1.25, 2.5, 3.75	200, 250, 300, 350, 400, 450, 500
GE Lightspeed 32	Standard	250	120	Helical	Det. Coverage= 20	1.25, 2.5, 3.75	200, 250, 300, 350, 400, 450, 500
Philips Brilliance 64	Standard (B)	250	120	Helical	64 x 0.625	1.5, 2.0, 3.0	200, 250, 300, 350, 400, 450, 500
Philips Big Bore 16	Standard (B)	250	120	Helical	64 x 0.625	1.5, 2.0, 3.0	200, 250, 300, 350, 400, 450, 500
Siemens Definition AS	I31f-2	250	120	Helical	64 x 0.6	1.5, 2.0, 3.0	200, 250, 300, 350, 400, 450, 500
Siemens Sensation 64	B31f	250	120	Helical	64 x 0.6	1.5, 2.0, 3.0	200, 250, 300, 350, 400, 450, 500
Siemens Sensation 40	B31f	250	120	Helical	40 x 0.6	1.5, 2.0, 3.0	200, 250, 300, 350, 400, 450, 500
Siemens Sensation 16	B31f	250	120	Helical	16 x 0.6	1.5, 2.0, 3.0	200, 250, 300, 400, 500

Table 2: CCR Phantom scans (total = 28) to evaluate the impact of reconstruction kernels on radiomic features.

CT Scanner	Recon. FOV	mAs	kVp	Scan Type	Slice thickness, Recon. interval	Detector Configuration (mm)	Reconstruction Kernel (Variable)
GE Discovery STE	250	65	120	Helical	1.25 mm, Adjacent	Det. Coverage= 40	Soft, Standard, Detail, Lung, Edge
Philips Brilliance 64	250	65	120	Helical	1.5 mm, Adjacent	64 x 0.625	Smooth (A), Standard (B), Sharp(C), Lung enhanced (L), Y-Sharp (YA)
Siemens Definition AS	250	65	120	Helical	1.5 mm, Adjacent	64 x 0.6	I26f-2, I30f-2, I40f-2,I44f-2, I50f-2, I70f-2
Siemens Sensation 64	250	65	120	Helical	1.5 mm, Adjacent	64 x 0.6	B10f,B20f, B31f, B50f, B60f, B70f
Siemens Sensation 40	250	65	120	Helical	1.5 mm, Adjacent	40 x 0.6	B10f,B20f, B31f, B50f, B60f, B70f

Table 3: CCR Phantom scans (total = 20) to evaluate the impact of mAs on radiomic features.

CT Scanner	Recon. FOV (mm)	Kernel	kVp	Scan Type	Slice thickness, recons. interval	Detector Configuration (mm)	Radiation dose (mAs) (Variable)
GE Discovery STE	180	Standard	120	Helical	1.25 mm, Adjacent	Det. Coverage= 40	50, 100, 200, 300, 400
Philips Brilliance 64	180	Standard (B)	120	Helical	1.5 mm, Adjacent	64 x 0.625	50, 100, 200, 300, 400
Siemens Definition AS	180	I31f-2	120	Helical	1.5 mm, Adjacent	64 x 0.6	50, 100, 200, 300, 400
Siemens Sensation 64	180	B31f	120	Helical	1.5 mm, Adjacent	64 x 0.6	50, 100, 200, 300, 400

Table 4: CCR Phantom scans (total = 41) to evaluate the impact of Pitch on radiomic features.

CT Scanner	Recon. FOV (mm)	mAs	kVp	Scan Type	Recon. Kernel	Slice thickness, recon. interval	Detector Configuration (mm)	Pitch (Variable)
Philips Brilliance 64	250	65	120	Helical	Standard(B)	1.5 mm, Adjacent	64 x 0.625	0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3
Siemens Definition AS	250	65	120	Helical	I31f-2	1.5 mm, Adjacent	64 x 0.6	0.5, 0.6, 0.7, 0.8, 0.9, 1.0 1.1, 1.2, 1.3, 1.4, 1.5
Siemens Sensation 64	250	65	120	Helical	B31f	1.5 mm, Adjacent	64 x 0.6	0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4, 1.5
Siemens Sensation 40	250	65	120	Helical	B31f	1.5 mm, Adjacent	40 x 0.6	0.5, 0.7, 0.8, 0.9, 1.0 1.1, 1.2, 1.3, 1.4, 1.5

3. FILE NAMING FORMAT

All scans were stored at The Cancer Imaging Archive (TCIA) at the National Institute of Health (NIH) for long term repository [10, 11]. The scans were exported from GE-PACS in DICOM format. Each scan file name was formatted as follows:

Manufacturer_Scanner Model_kVp_mAs_slice thickness_Variable

For scan files, where mAs was the variable the file naming format was:

Manufacturer_Scanner Model_kVp_Slice thickness_mAs

For the variation of the reconstruction kernel using the Siemens Definition AS scanner for scanning parameters of 120 kVp, 65 mAs and 1.5 mm slice thickness, file names were formatted as:

Siemens_DefinitionAS_120_65_1.5_Kernel

In this particular case, the reconstruction kernel was varied from B10 (very soft) to B70 (very sharp). The file names for all other cases followed the same naming technique.

The entire dataset is under the name "CC-Radiomics-Phantom-2" on The TCIA website, http://www.cancerimagingarchive.net/. The total size of the dataset is 30.5 GB, consisting of 251 scan files in DICOM format.

4. DISCUSSION

Radiomics considers images as quantitative data and promises to contribute to the development of personalized oncology [12]. However, quantitative data extracted from computed tomography (CT) images is significantly affected by the variation of imaging parameters and stochastic noise [5,13]. There are large variations in the parameters employed currently in CT imaging; therefore, it is difficult to determine how these parameter variations affect radiomic feature values. Moreover, features values across institutions may also be affected by variations in imaging protocols and quality control procedures. The purpose of this work was to describe CCR phantom dataset, acquired at a single institution, to address the issue of variability in CT radiomics due to imaging parameters. This dataset was acquired using a systematic scanning approach facilitating variability assessments and subsequent corrections of radiomic features.

Texture phantoms provide stable geometries and material compositions useful for investigating the robustness of radiomic features before clinical investigations [4, 5]. These texture phantoms can be customized to match a range of HU values of different tumor types. For example, the rubber cartridge within CCR phantom has HU values similar to non-small cell lung cancer (NSCLC) tumors [4]. Another possible approach is the use of homogeneous and heterogeneous 3D-printed cylindrical inserts in combination with commonly used imaging quality assurance phantoms [14, 15].

The phantom dataset is also useful to identify a subset of robust radiomic features as well as to develop methods to correct for variability in CT radiomic features [5]. For example, a subset of scans was acquired by only varying voxel size while keeping all other parameters constant at nominal values. With this approach we were able to identify features that were robust to voxel size variations. Additionally, we proposed a normalization method to remove the voxel size dependency of several features, even for features that had been previously reported to have prognostic power [5]. In another study [6], we acquired scans with systematic variation of reconstruction kernels, and found that most texture features were sensitive to reconstruction kernel settings. Moreover, we correlated the variability in features to correlated noise texture introduced by the reconstruction process [6]. This dataset was also used to investigate the stability of deep features across different CT scanners and Field Of Views [16]. The important point is that the impact of an individual imaging parameter can be evaluated using the dataset and the approach reported in this paper.

The phantom dataset is also useful for comparing the numerical values of radiomic features extracted using different algorithms that are currently used in radiomic research [17-19]. It is known that feature definitions, and/or the implementation of these definitions, may vary among different research groups [20]. In this regard, this phantom dataset provides a useful repository for researchers to compare the performance of radiomics algorithms.

ACKNOWLEDGEMENTS

We would like to acknowledge Dr. Dennis Mackin from MD Anderson Cancer Center for providing the Credence Cartridge Radiomics (CCR) phantom. This project was partly supported by NIH/NCI grant RO1-CA190105-01. We would also like to acknowledge TCIA (NIH) team for curating the dataset and making it available for public.

CONFLICT OF INTEREST

None declared

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