Identifying Robust Radiomic Features Extracted From Images Generated by a 0.35T MR-Linac

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INTRODUCTION

Assessing imaging biomarker (feature) robustness is an essential prerequisite before investigating predictive power or building reliable radiomic models [1]. However, radiomic features aim to describe pathophysiological changes or treatment outcomes may be dependent on scanner and/or image acquisition parameters [2]. Models based on features sensitive to such factors may lead to unreliable models, thus emphasizing the requirement of identifying imaging biomarkers that are robust over a wide range of imaging conditions [3].

AIM

- To investigate radiomic features extracted from images acquired with a 0.35T scanner on an integrated MR-Linac.
- The main objective was to study **feature variability, reproducibility and repeatability** and identify features that are robust for various possible imaging conditions, in both phantom and patient data.

METHOD

- Eleven images (acquired monthly) using a Magphan RT® phantom and eleven images (acquired daily) using a ViewRay® Daily QA phantom, representing ideal imaging conditions.
- 50 images from ten stereotactic body radiation therapy (SBRT) pancreas cancer patients (5 daily fractions). Kidneys and liver were chosen to represent heterogeneous and invariant tissue.
- All images were acquired with a True Fast Imaging with Steady State Free Precession (TRUFI) pulse sequence, using two different protocols for the phantom and patient images.
- 1087 shape-based, first order, second order (GLCM, GLRLM, GLSZM and NGTDM[1]) and higher order statistical (LoG[2], fractal dimension, wavelets, Law's) radiomic features were extracted for each subject.
- Feature variability was investigated looking at the reproducibility and repeatability of each feature within and between the phantom and patient datasets.
- Stability was assessed with the Coefficient of Variation (CoV), where features with CoV<5% were classified as robust/stable.

[1] GLCM = Gray level co-occurrence matrix, GLRLM = Gray level run length matrix, GLSZM = Gray level size zone matrix and NGTDM = Neighborhood gray tone difference matrix.

[2] LoG = Laplacian of Gaussian.

RESULTS

Table 1: Shown in this table are the resulting features demonstrating high stability in both phantom and patient data within in each category.

Shape-based	First order	GLCM	GLRLM	LoG sigma=0.5mm	LoG sigma=1mm	LoG sigma=1.5mm	LoG sigma=2mm	LoG sigma=2.5mm	LoG sigma=3mm	Fractal dimension
V(voxels)	Volume fraction at 0.10 intensity	Entropy	Short-run emphasis	Energy	Entropy	Coeff vari	Coeff vari	Coeff vari	Coeff vari	MeanLac1
Volume	Nlenergy	Mean	Long-run emphasis	Entropy	Hist entropy	Energy	Energy	Energy	Energy	MeanLac2
Surface area	Entropy	Inverse difference moment	Run length non-uniformity	Hist entropy	Norm entropy	Entropy	Entropy	Entropy	Entropy	MeanLac3
Surface to volume ratio	Hist entropy	Inverse difference	Run percentage	Norm energy		Hist entropy	Hist entropy	Hist entropy	Hist entropy	
Volume density (axis)	Norm Nlenergy	Sum entropy		Norm entropy		Norm energy	Norm energy	Norm energy	Norm energy	
Area density (axis)	Norm entropy	Vnorm Mean				Norm entropy	Norm entropy	Norm entropy	Norm entropy	
Volume density (convex)		Gnorm Entropy								
Area density (convex)		Gnorm Sum Entropy								
Sphericity		Gnorm Mean								
Asphericity		Vgnorm Mean								
Compactness 1										
Spherical disproportion										
LongAxis(mm,COM)										
Maximum 3D diameter(mm)										

Wavelet LLL	Wavelet LLH	Wavelet LHL	Wavelet HLL	Wavelet LHH	Wavelet HLH	Wavelet HHL	Wavelet HHH	Laws EEE	Laws EEL	Laws EES
Coeff vari	Coeff vari	Entropy	Entropy	Entropy	Entropy	Entropy	Coeff vari	Hist entropy	Hist entropy	Hist entropy
Energy	Entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Energy			
Entropy	Hist entropy	Norm entropy	Norm entropy	Norm entropy	Norm entropy		Entropy			
Hist entropy	Norm entropy						Hist entropy			
Norm energy							Norm energy			
Norm entropy							Norm entropy			

Laws ELE	Laws ELL	Laws ELS	Laws ESE	Laws ESL	Laws ESS	Laws LEE	Laws LEL	Laws LES	Laws LLE	Laws LLL
Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Energy
										Entropy
										Hist entropy
										Norm energy
										Norm entropy

Laws LLS	Laws LSE	Laws LSL	Laws LSS	Laws SEE	Laws SEL	Laws SES	Laws SLE	Laws SLL	Laws SLS	Laws SSE
Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy	Hist entropy

Laws SSL	Laws SSS
Hist entropy	Hist entropy

- **130** radiomic features demonstrated **high stability** in both phantom and patient data (see table 1).
- Robust features were identified in all categories apart from two second order statistical groups (Gray level size zone matrix and Neighborhood gray tone difference matrix)
- **13** features in common with this result had predictive or discriminative power in MRI-based radiomics literature [4, 5, 6, 7, 8] (see table 2).

Table 2: Shown in this table are the 13 radiomic features that were identified as robust in this work and mentioned in MRI-based radiomics literature as having predictive/discriminative power.

Shape-based	**GLRLM**
Volume	Short-run emphasis
Sphericity	Long-run emphasis
Asphericity	Run length non-uniformity
Compactness 1	Run percentage
Spherical disproportion	
	GLCM
First order statistical	Entropy
Hist entropy	Sum entropy
	Inverse diff. Moment

CONCLUSIONS

- There are 130 features demonstrating high stability over a relatively wide range of imaging conditions.
- Results indicate that phantom measurements are useful for stability assessment, and that a 0.35 T scanner of an integrated MR-Linac is sufficiently stable over time for radiomics studies.
- A large number of features were robust. However, many features were not, thus emphasizing the value of stability assessment as a prior step.
- Several robust features are predictive/discriminative in literature which, even though preliminary, is a promising result meaning that we have identified potential features for further analysis and radiomics studies.
- More research, including texture phantoms mimicking tissue heterogeneity, should be investigated.

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