Impact of Quantization Parameters on Radiomic Texture Feature Variation in Low Field Strength Magnetic Resonance Images

G. Simpson[1], J. Ford[2], Fei Yang[2], Nesrin Dogan[2]
1 University of Miami, Coral Gables, Florida
2 University of Miami Miller School of Medicine, Miami, Florida

JULY 12–16 2020 VIRTUAL
Improving Health QUALITY. Increasing Global IMPACT
JOINT AAPM | COMP MEETING
EASTERN TIME [GMT-4]

SYLVESTER COMPREHENSIVE CANCER CENTER
UNIVERSITY OF MIAMI HEALTH SYSTEM

INTRODUCTION

- Magnetic resonance (MR) guided radiotherapy machines provide images with superior contrast to traditional cone beam computed tomography images.
- Daily low field strength MR images provide images during each daily treatment are under scrutiny for use with texture analysis.
- Texture analysis of low field strength MR images could provide valuable insight to disease response during radiotherapy.
- MR images require pre-processing before calculation of texture features to provide comparable gray levels between images..
- Selection of algorithm and the number of intensity gray levels impacts texture feature values.

AIM

- Determine how selection of quantization algorithm and the number of gray level intensity levels impacts the variation of texture features extracted low field strength MR images of a texture phantom.

METHOD

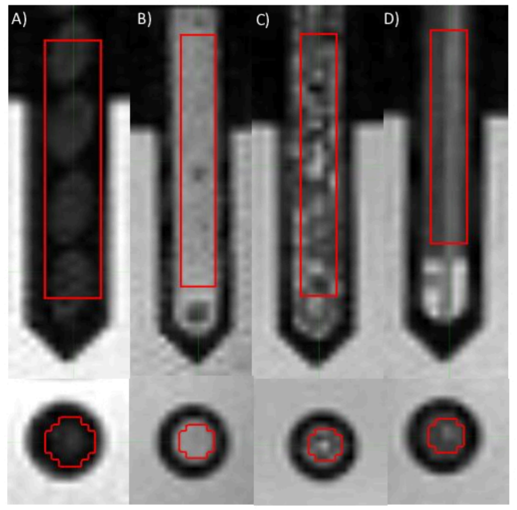
- Texture phantom constructed of four test tubes filled with various materials and water inserted to the daily image QA phantom (see Figure 1).
  1. Vitamin E pills
  2. Cut up sections of IV tubing
  3. Gauze
  4. Capillary tubes
- 37 phantom images acquired over 44 days.
- 39 texture features extracted from each ROI (see Table 1).
- Three quantization methods available in the publicly available Texture Analysis Toolbox in MATLAB (The MathWorks, Natick, Massachusetts) by Vallières[1] under consideration.
  1. Lloyd-Max Algorithm – minimizes the mean square error by optimizing the decision levels of the original intensities and the intensity bin.
  2. Uniform Probability Quantization – rescales the original intensities linearly to the intensity bins.
  3. Histogram Equalization – monotonic transform that reassigns intensities to the new bins with approximately equal probabilities.
- Four different gray level intensity levels
  - 32, 64, 128, and 256 levels
  - The number of bins can result in sparse or saturated matrixes that impact texture feature values.

TEXTURE FEATURES TABLE 1

Encoding Method	IBSI code/aggregation code	Texture feature:	IBSI Name
GLCM	LFYI/IAZD	Energy	8ZQL
		Contrast	ACUI
		Entropy	TU9B
		Homogeneity	IB1Z
		Correlation	NI2N
		Sum Average	ZGXS
		Variance	UR99
		Dissimilarity	8S9J
GLRLM	TPOI/IAZD	Short run emphasis (SRE)	22OV
		Long run emphasis (LRE)	W4KF
		Gray-level nonuniformity (GNU)	R5YN
		Run length nonuniformity (RLN)	W92Y
		Run percentage (RP)	9ZK5
		Low gray-level run emphasis (LGRE)	V3SW
		High gray-level run emphasis (HGRE)	G3QZ
		Short run low gray-level emphasis (SRLGE)	HTZT
		Short run high gray-level emphasis (SRHGE)	GD3A
		Long run low gray-level emphasis (LRLGE)	IVPO
		Long run high gray-level emphasis (LRHGE)	3KUM
		Gray-level variance (GLV)	8CE5
		Run length variance (RLV)	SXLW
GLSZM	9SAK/KOBO	Small zone emphasis (SZE)	5QRC
		Large zone emphasis (LZE)	48P8
		Gray-level nonuniformity (GNU)	BYLV
		Zone-size nonuniformity (ZSN)	4JP3
		Zone percentage (ZP)	P30P
		Low gray-level zone emphasis (LGZE)	XMSY
		High gray-level zone emphasis (HGZE)	5GN9
		Small zone low gray-level emphasis (SZLGE)	5RAI
		Small zone high gray-level emphasis (SZHGE)	HW1V
		Large zone low gray-level emphasis (LZLGE)	YH51
		Large zone high gray-level emphasis (LZHGE)	J17V
		Gray-level variance (GLV)	BYLV
		Zone-size variance (ZSV)	3NSA
NGTDM	IPET/KOBO	Coarseness*	-
		Contrast	65HE
		Busyness	NQ30
		Complexity	HDEZ
		Strength*	-

IBSI – Image biomarker standardisation initiative[2]
* Features calculated as originally defined by Amadasun and King[3]

TEXTURE PHANTOM FIGURE 1



Sagittal (top images) and axial (bottom images) slices of the four texture inserts with the region of interests (ROI), in red, defining the volume used to extract texture features. Column A is the vitamin E-pills (ROI_E), column B is the test tube stuffed with gauze (ROI_G), column C is cut sections of IV tubing (ROI_IV), and column D is the tube filled with capillary tubes (ROI_Cap).

RESULTS

Figure 2
Vitamin E Pills

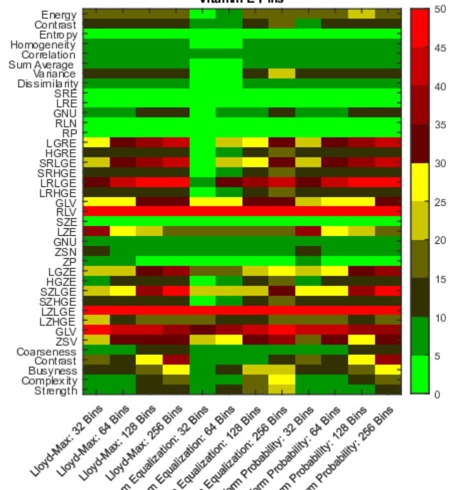


Figure 3
IV Tubing

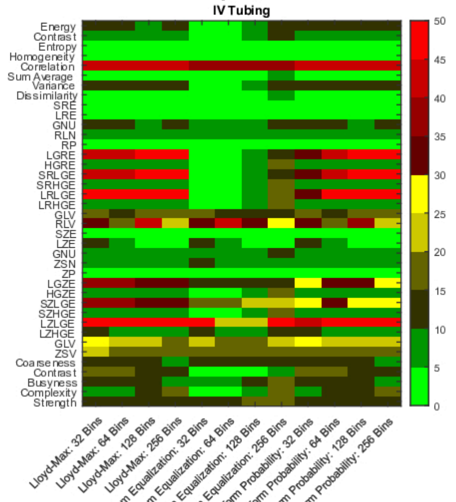


Figure 4
Gauze

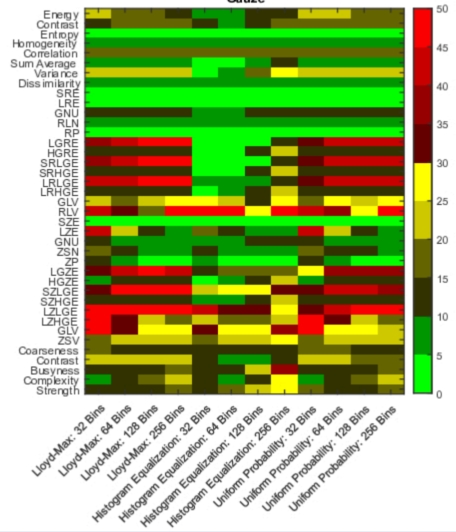
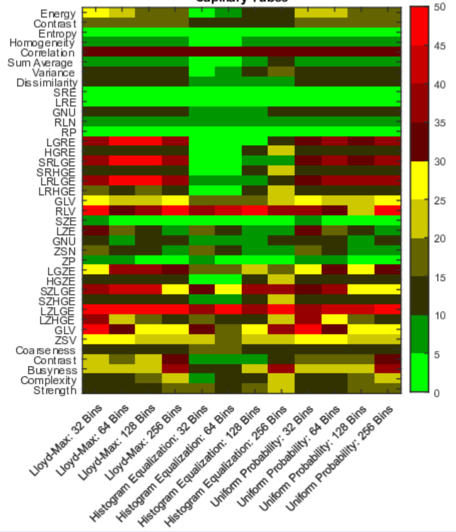


Figure 5
Capillary Tubes



- Feature variation over time expressed as the coefficient of variation (CV%) over time (Figures 2-5).
  - CV% was calculated for each texture feature as the standard deviation divided by the mean value multiplied by 100.
- The y-axis labels are the texture features and the x-axis labels are the quantization method and number of gray level intensities used to calculated the texture features.
- Histogram Equalization with 32 and 64 gray levels resulted in the most texture features with CV% below 10% (green and light green) and is apparent by viewing the columns of the respective columns of each combination.
- A number of features maintained low CV% across all texture inserts and combinations of quantization method and numbers of gray level intensity levels and is obvious when looking across the rows.

CONCLUSIONS

- Texture features calculated from the processed ROIs using Histogram Equalization to quantize the image intensities to 32 or 64 intensity levels resulted in the largest number of features with CV% < 10%.
- A number of features were stable across all synthetic textures and methods, maintaining a CV% < 10%.
  - GLMC-based texture features entropy and homogeneity
  - GRLRM-based SRE, LRE, RLN and RP
  - GLSZM-based SZE
- The low field strength MR produces images from which texture features can be extracted with an acceptable amount of variation.
- Though the pre-processing with Histogram Equalization and 32 or 64 gray level intensity values results in the most stable features, they may not be ideal for clinical exploration.

ACKNOWLEDGEMENTS

Special thanks to Dr. Ford for designing and imaging the phantom.

REFERENCES

1. Vallières M. *A radiomics model from joint FDG-PET and MRI texture features for the prediction of lung metastases in soft-tissue sarcomas of the extremities.* Physics in Medicine and Biology, 2015: **60**(14): p. 5471-5496.
2. Zwanenburg A, et al. *Image biomarker standardization initiative. 2019: p. arXiv preprint arXiv:1612.07003.*
3. Amadasun, M. and R. King, *Textural features corresponding to textural properties.* IEEE Transactions on Systems, Man, and Cybernetics, 1989. **19**(5): p. 1264-1274.

CONTACT INFORMATION

Garrett Simpson
University of Miami, Department of Biomedical Engineering
E-mail: gns24@miami.edu