iMEDiTEC 2017

ORIGINAL PAPER

# Structural Characterization of ECG-gated Cardiac CT Images: Texture Analysis on Systole and Diastole Phases

N.M. Salih [a,b], H.A. Hamid [c], N.A. Bakar [c], A. Yahya [b], D.E.O. Dewi [a,b,*]

[a] IJN-UTM Cardiovascular Engineering Centre, Universiti Teknologi Malaysia, Skudai 81310, Johor, Malaysia
[b] Faculty of Biosciences and Medical Engineering, Universiti Teknologi Malaysia, Skudai 81310 Johor, Malaysia
[c] Department of Radiology, Universiti Kebangsaan Malaysia Medical Centre, 56000 Cheras, Malaysia

* Corresponding author: dyah@utm.my

## ABSTRACT

Cardiac Computed Tomography (CT) is one of the important noninvasive approaches to evaluate Cardiovascular Diseases (CVDs). Structural characterization of systole and diastole states from ECG-gated cardiac CT images may provide a marker for CVDs. The aims of the study were to characterize muscle structures of normal cardiac CT images using statistical texture analysis and to compare between systole and diastole phases. The cardiac CT images were obtained from Osirix Dicom Image Library. The region of interest of each image was defined for upper, middle, and bottom region of the CT images. The RoI images were analyzed using First, Second, and Higher-order statistical texture analyses. The texture features of systole and diastole phases were obtained and analyzed. From the First-order texture analysis, the middle region shows the highest structural differences of systole and diastole, while from the Second- and Higher-order texture analysis, middle and bottom regions show the highest structural differences of systole and diastole.

## INTRODUCTION

Cardiovascular Diseases (CVDs) is the leading cause of death in Malaysia and it is in demand for noninvasive diagnostic approaches. Computed Tomography (CT) is one of the noninvasive approach that plays an important supplementary role in the evaluation of patients with CVDs (Goo *et al*., 2003). Cardiac CT can be used to detect and evaluate heart function problems related to heart muscle (myocardium) such as myocardial perfusion (Williams and Newby, 2016). The evaluation of heart muscle condition is believed can be performed using structural characterization of the cardiac CT images. ECG-gated cardiac CT on the other hand, plays important role in determining systolic and diastolic states based on the extraction of heart beat information. Cardiac structural characterization of systole and diastole states may provide a marker for CVDs such as heart failure and dilated cardiomyopathy.

Based on the concept of image processing, the anatomical view from ECG-gated CT images can be characterized based on two approaches: (1) geometrical and (2) structural techniques. The structural characterization technique can be realized using texture analysis which can be classified into statistical, model-based, and signal processing methods (Tuceryan and Jain, 1993). In this paper, the study was focused on the structural characterization of normal ECG-gated cardiac CT images using statistical texture analysis. Statistical texture analysis represents the texture indirectly by the way that the gray levels are distributed over the pixels in the region (Haralick, 1979). The statistical texture analysis can be divided into First-, Second-, and Higher-order. Each analysis has its own statistical texture features which represent different structural information. Therefore, it is expected that the statistical texture analysis may provide certain structural characteristics of normal systole and diastole phases as the baseline for normal cardiac states.

## METHODOLOGY

### Data Collection and Pre-processing

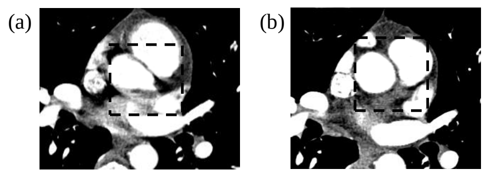


**Fig. 1** RoI location for upper region of cardiac CT images (slice 30) for (a) systole (b) diastole phases

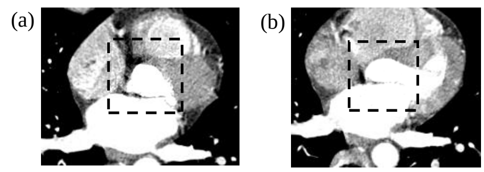


**Fig. 2** RoI location for middle region of cardiac CT images (slice 70) for (a) systole (b) diastole phases

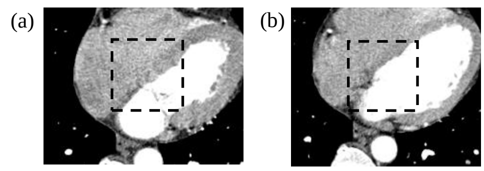


**Fig. 3** RoI location for bottom region of cardiac CT images (slice 110) for (a) systole (b) diastole phases



OPEN ACCESS Freely available online
eISBN 978-967-0194-93-6 FBME

Six axial multi-planar reconstruction (MPR) cardiac CT images of normal systole and diastole phases were obtained from FOURDIX file in Dicom Image Library (OsiriX, 2016). The images were visually inspected and analyzed. All images were standardized to 0 to 255 gray level range. The full cardiac CT images of each systole and diastole phases contain 188 slices. With the consultation from the radiologist, the specific slice for each upper, middle, and bottom regions were chosen. Fig. 1 until Fig. 3 show the CT images for upper (slice 30), middle (slice 70), and bottom (slice 110) regions of systole and diastole phases image. The dashes boxes are indicating the Region of Interest (RoI) locations for each image of systole and diastole phases.

The RoI of each image was defined for upper, middle, and bottom regions of the cardiac CT images. The inclusion criteria for the RoIs selection is the area that includes the heart and coronary artery. The exclusion criteria for the RoIs selection is the lung and bones. The RoI was selected in the same pixels location and size (100 x 100 pixels) for each slice of the CT images.

### Texture Analysis

The texture analysis was performed using the First-, Second-, and Higher-order statistical texture analyses. All approaches were implemented using MATLAB R2013a software. The First-order texture analysis was performed based on the intensity histogram texture measures that were calculated from the original image values. It describes the overall number of pixels with a certain gray level but independent of their location in the image (Aggarwal *et al*., 2012). Mean, Variance, and Kurtosis features were calculated for the First-order texture analysis.

The Second-order texture analysis was performed based on Gray Level Co-Occurrence Matrix (GLCM). This method is based on the joint probability distributions of pairs of pixels. It is used to estimate the properties of two or more pixel values occurring at specific locations relative to each other (Haralick *et al*., 1973). In this study, the GLCM was calculated for pixel distance equal to one (d = 1) with four orientation angle (horizontal (0 ˚), diagonal (45˚), vertical (90˚), and anti-diagonal (135˚)). Contrast, Energy, and Correlation features were calculated for the Second-order texture analysis.

Then, the Higher-order texture analysis was performed based on gray level run length matrix (GLRLM). This texture analysis method gives information about the connected length of a particular pixel in a definite direction. The matrix is defined by specifying the direction and then count the occurrence of runs for each gray levels and length in this direction (Galloway, 1975). Gray Level Non-uniformity (GLN), Run Length Non-Uniformity (RLN), and Run Percentage (RP) features were calculated for the Higher-order texture analysis.

Eventually, the extracted texture features from each analysis were evaluated and the values were compared to differentiate between systole and diastole phases. The values were also compared between upper, middle, and bottom region images.

## RESULTS AND DISCUSSION

The results from the First-, Second-, and Higher-order texture analyses are shown in Fig. 4 until Fig. 12. Each graph in the figures shows the feature values of systole and diastole phases for upper, middle, and bottom region of the cardiac CT images. From Fig.4 to Fig. 6, the graphs show that in all cardiac CT image regions (upper, middle, and bottom), the diastole images produced higher values for all First-order texture features (Mean, Variance, and Kurtosis) compared to those of in systole images.

The Mean feature can be refered to the central tendency of the gray level value (Tamura *et al*., 1978). Higher Mean value describes a central tendency of higher gray level value which represents larger bright area, while lower Mean value describes a central tendency of lower gray level value which represent larger dark area. The Variance value simply contains textural regularity information in the image (Tamura *et al*., 1978). Higher Variance value represents higher textural regularity. The Kurtosis feature describes the uniformity of gray level distribution based on the histogram flatness (Aggarwal *et al*., 2012). A positive Kurtosis value represents a fairly uniform gray level distribution with sharper peak. While a negative Kurtosis value represents a mid-level gray levels uniform distribution with flatter peak. The uniformity increases with the increment of positive Kurtosis value. Then, from the Mean, Variance, and Kurtosis features result, the middle region RoIs produced the highest differences between systole and diastole phases. From this finding, it can be described that the middle region RoIs are more promising for structural characterization of systole and diastole phases.

Graphs in Fig. 7 to Fig. 9 show that the diastole images produced higher value for Contrast feature in all regions (upper, middle, and bottom), Energy feature in the upper region and Correlation feature in the middle region. Then, the systole images produced higher value for Energy feature in middle and bottom regions, and Correlation feature in bottom region. The Contrast feature represents the softness of the image (Gebejes and Huertas, 2013). Higher Contrast value indicates heavier textures and lower Contrast values image indicates softer textures. Energy feature is a measure of homogeneity of an image which defines the uniformity of the image (Albregtsen, 2008). Higher Energy feature value indicates a more uniform image. The Correlation feature describes the gray level linear dependency on those of neighboring pixels in an image (Gebejes and Huertas, 2013).

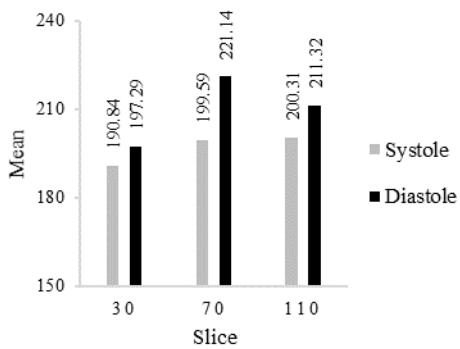


**Fig. 4** Mean feature profile of First-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images

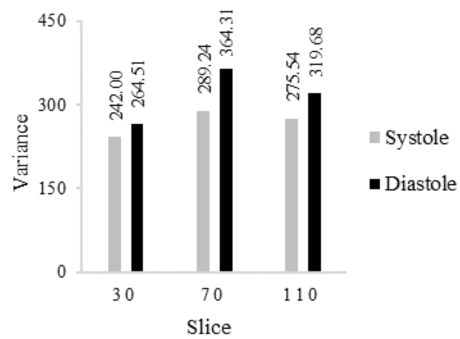


**Fig. 5** Variance feature profile of First-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images



OPEN ACCESS Freely available online
eISBN 978-967-0194-93-6 FBME

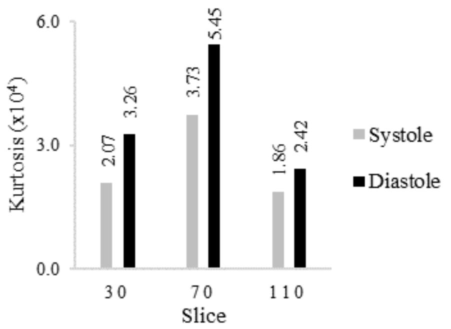


**Fig.6** Kurtosis feature profile of First-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images

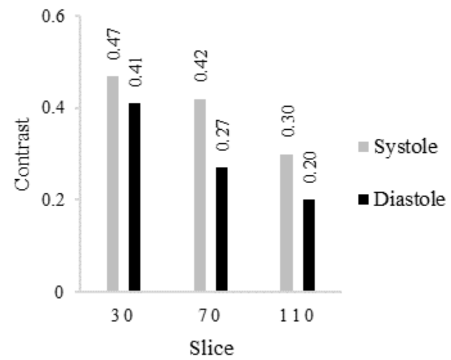


**Fig. 7** Contrast feature reasult of Second-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images

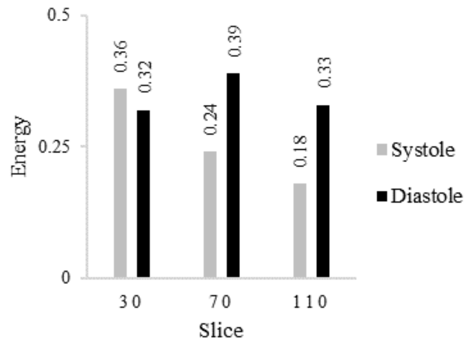


**Fig. 8** Energy feature profile of Second-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images

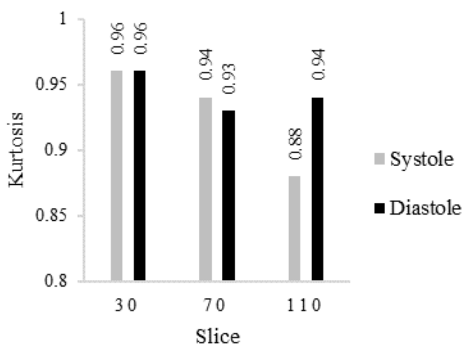


**Fig. 9** Kurtosis feature profile of Second-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images

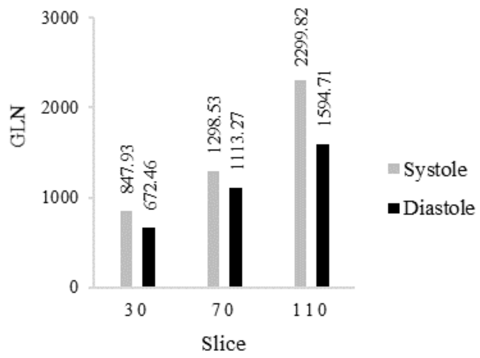


**Fig.10** GLN feature profile of Higher-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images

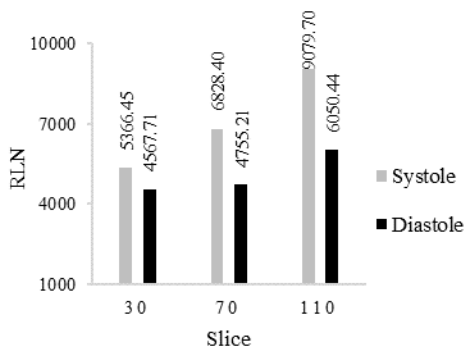


**Fig.11** RLN feature reasult of Higher-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images

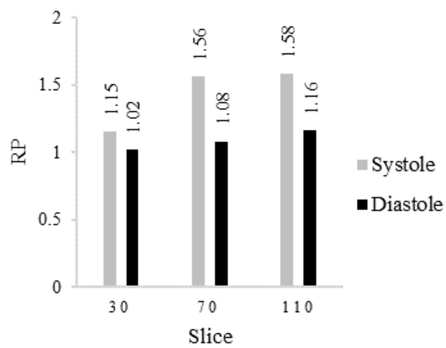


**Fig.12** RP feature profile of Higher-order texture analysis for slice 30 (upper), 70 (middle), and 110 (bottom) images

Correlation feature represents displacement and strain characteristics which rely on unique image patterns to track displacement (Bay, 1995). Higher Correlation value indicates higher pixels displacement in an image. Then, from the Contrast and Energy features result, the middle region RoIs produced the highest differences between systole and diastole phases. Next, from the Correlation feature result, the bottom region RoIs produced the highest difference between systole and diastole phases. It can be described that the middle and bottom region RoIs are more promising for structural characterization of systole and diastole phases.

From Fig.10 until Fig. 12, the graphs show that in all cardiac CT image regions (upper, middle, and bottom), the systole images produced higher values for all Higher-order texture features (GLN, RLN, and RP) compared to systole images. The Higher-order texture



OPEN ACCESS Freely available online
eISBN 978-967-0194-93-6 FBME

analysis used the concept of gray level run which is defined as the length in number of pixels of consecutive pixels that have the same gray level value. The GLN feature measures the uniformity of run distribution in an image (Martí-Bonmatí and Alberich-Bayarri, 2016). Higher GLN value represents higher uniformity of the run distribution. The RLN measures the uniformity of run length and increases with the number of runs of same length (Martí-Bonmatí and Alberich-Bayarri, 2016).. The RP is the ratio between the number of runs over the number of pixels in the image (Martí-Bonmatí and Alberich-Bayarri, 2016).. Higher RP value indicates that the number of runs is higher than the number of pixels in the image. Then, from the GLN and RLN features result, the bottom region RoIs produced the highest differences between systole and diastole images. Next, from the RP feature result, the middle region RoIs produced highest difference between systole and diastole phases. It can be described that the middle and bottom region RoI images are more promising for structural characterization of systole and diastole phases.

From the results, it can be summarized that the First-, Second-, and Higher-order statistical texture analysis can produce structural characterization for systole and diastole phases from ECG-gated cardiac CT images. It can be described that different position of muscles and tissues of the heart and coronary anatomy produced different structural characterization. From this finding, the statistical texture analysis of ECG-gated cardiac CT images may provide useful information that can be related to the heart muscle (myocardium) condition. The result from this study may serve as the baseline findings for normal heart muscle condition. In the future, it is expected that statistical texture analysis of cardiac CT images become more valuable in assisting the evaluation of CVDs condition that related to heart muscle including cardiomyopathy and heart failure (Sparrow, 2009).

## CONCLUSION

In this paper, cardiac CT image characterization of systole and diastole phases was performed using statistical texture analysis. Based on the study, the upper, middle, and bottom region of the cardiac CT images produced different structural characterization of systole and diastole phases. From the First-order texture analysis, the middle region shows the highest structural differences of systole and diastole phases, while from the Second- and Higher-order texture analysis, middle and bottom regions show the highest structural differences of systole and diastole phases. This paper is a proof of concept that texture analysis can be used to characterize the cardiac structures during systole and diastole phases using an open source data. In the future, this study can be implemented for evaluation and characterization of multiple cardiac CT images obtained from retrospective or prospective data collection.

## ACKNOWLEDGEMENT

This work was financially supported by the Universiti Teknologi Malaysia and MOHE under FRGS Grant R.J130000.7845.4F764.

## REFERENCES

Aggarwal, N. and Agrawal, R K. 2012. First and Second Order Statistics Features for Classification of Magnetic Resonance Brain Images. *JSIP*. 3(2), 146-153.

Albregtsen, F. 2008. Statistical texture measures computed from gray level coocurrence matrices. *Image processing laboratory, department of informatics, university of oslo*. 5

Bay, B. 1995. Texture correlation: A method for the measurement of detailed strain distributions within trabecular bone. *Journal of Orthopaedic Research*, 13(2), 258-267.

OsiriX. DICOM Image Library. *Osirix-viewer*. [online] Available at: http://www.osirix-viewer.com/resources/dicom-image-library/. [Accessed December 2016]

Haralick, R. M., Shanmugan, K., and Dinstein, I. 1973. Textural Features for Image Classification. *IEEE Transactions on Systems: Man, and Cybernetics SMC*, 3, 610- 621.

Haralick, R. M. 1979. Statistical and structural approaches to texture. *Proceedings of the IEEE,* 67(5), 786-804.

Galloway, M. M. 1975. Texture Analysis Using Gray Level Run Lengths. *Computer Graphics Image Processing*. 4, 172-179.

Goo, H., Park, I., Ko, J., Kim, Y., Seo, D., Yun, T., Park, J. and Yoon, C. 2003. CT of Congenital Heart Disease: Normal Anatomy and Typical Pathologic Conditions. *RadioGraphics*, 23, S147-S165.

Martí-Bonmatí, L. and Alberich-Bayarri, A. 2016. Imaging Biomarkers: Development and Clinical Integration. *Springer*. 90-92.

Sparrow, P., Merchant, N., Provost, Y., Doyle, D., Nguyen, E. and Paul, N. 2009. CT and MR Imaging Findings in Patients with Acquired Heart Disease at Risk for Sudden Cardiac Death. *RadioGraphics*, 29(3), 805-823.

Tamura, H., Mori, S. and Yamawaki, T. 1978. Textural Features Corresponding to Visual Perception. *IEEE Transactions on Systems, Man, and Cybernetics*, 8(6), 460-473.

Tuceryan, M. and Jain, A. K. 1993. Texture Analysis. *World Scientific Publishing Co*. 2, 235-276.

Williams, M. and Newby, D. 2016. CT myocardial perfusion imaging: current status and future directions. *Clinical Radiology*, 71(8), 739-749.



OPEN ACCESS Freely available online
eISBN 978-967-0194-93-6 FBME