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Apical Myocardium Texture Analysis In ECG-Gated Cardiac CT Images

N.M. Salih[1], A. Yahya[2], U.U. Sheikh[3]
[1](Department of Biomedical Engineering and Health Sciences, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Email: nurulazirah2@graduate.utm.my)
[2](Department of Electronic and Computer Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Email: azliyahya@utm.my)
[3](Department of Electronic and Computer Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Email: usman@utm.my)

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Abstract:

Structural characterization of the normal LV apical myocardium from ECG-gated cardiac Computed Tomography (CT) image using statistical texture analysis may provide baseline information for a potential LV apical disorder marker. However, conventional statistical texture analysis on small CT image region still suffers from low resolution and noises. This study proposed edge detection with statistical texture analysis to characterize small LV apical myocardium region and compared between systole and diastole phases. Suitable images were chosen from FOURDIX file in Dicom Image Library and Region of Interest (RoI) was defined for the LV apical myocardium region. Sobel, Canny, and Laplacian of Gaussian edge detection methods were implemented to the RoIs followed by First, Second, and Higher-order statistical texture analyses. The texture features of systole and diastole phases were obtained and analyzed. The result showed that edge detection RoIs produced more consistent differentiation between systole and diastole phases compared to the original RoIs.

Keywords — **Apical myocardium, Systole, Diastole, Texture Analysis, Edge detection**

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I. INTRODUCTION

Many cardiac disorders involve with left ventricular (LV) apex including Hypertrophic cardiomyopathy (HCM) and Left Ventricular Aneurysm (Tjahjadi et al., 2022, Bailey et al., 2024). However, they are sometimes difficult to differentiate, and cardiac imaging is important in assisting the diagnosis (Abraham et al., 2024). Computed Tomography (CT) is one of the reliable imaging approaches since it can be used to visualize and evaluate the morphology and function of the heart (Williams and Newby, 2016; Abraham et al., 2024). Based on heart functionality, LV apex disorders could affect the performance of the LV which include the inability of the LV to fill (diastolic performance) and/or eject (systolic performance) (Fukuta and Little, 2008). Therefore, the advancement of ECG-gated cardiac CT could provide better evaluation of LV apex disorders. In any attempt to relate structure to function, evaluating the heart muscle (myocardium) will provide important information for LV apex disorders. The myocardium structures may be altered due to abnormality and diseases (Grossman, 1990). Therefore, from the perspective of ECG-gated cardiac CT imaging, structural characterization of the apical myocardium image for systole and diastole phases may provide a potential marker for LV apex disorders.

Based on the concept of image processing, the structural characterization of CT images can be realized using texture analysis. The texture of medical image may consist of patterns that representing biological tissues, muscles, blood vessels, and bones. Various texture analysis techniques have been applied to medical image, which can be classified into statistical, model-based, and signal processing methods (Tuceryan and Jain, 1993; Haralick, 1979). Even though texture analysis had contributed in many image analyses, it still has some drawbacks when dealing with small size Region of Interest (RoI), low resolution, and noise from medical image. Due to these drawbacks, several studies had analyzed the performance of texture analysis together with edge detection method to obtain better medical image analysis. Edge detection can identify and locate edge in an image (Kumar, 2015). It is agreeable that edges in an image contain meaningful features and information. It can reduce noise and filters out redundant information, at the same time preserving the important structural properties of an image (Yuval, 1996, Sparr, 2000). Plus, it can improve noisy and low-resolution image by reconstructing the image into a more representable image that easier to be analyzed (Osuna et al., 1997).

Based on earlier work, it was proven that Gray Level Co-occurrence Matrix (GLCM) texture analysis with edge detection method can be used for separating soft tissue and bone in X-ray image (Chai, 2011). Then, GLCM and Sobel edge detection method was successfully implemented for bone fracture detection in X-ray and CT image (Anu et al., 2015). Several works were also reported for MRI image of brain and spine as well as Ultrasound image of kidney (Kumaran and Bhavani, 2014; Faro et al., 2010; Tamilselvi and Thangaraj, 2010). All mentioned works are basically relying directly on the texture analysis of binary image produced from edge detection method. It is expected that manipulation of the binary image from edge detection method could provide more interesting texture analysis outcome for medical image analysis. Therefore, this study focused on evaluating the texture characteristics of a manipulated edge detection image. Even though the proven report of texture analysis with edge detection method for certain medical image is increasing, the performance of such method on cardiac image is still not well investigated. This study took the challenge to investigate the performance of texture analysis with edge detection method for apical myocardium region in ECG-gated cardiac CT image.

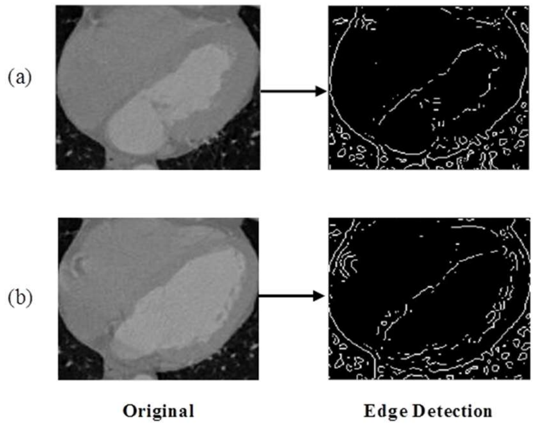

Fig. 1 Edge detection outcome for (a) systole and (b) diastole phases in cardiac CT image

Fig. 1 shows the edge detection outcome for whole four chamber view of cardiac region in CT image for normal systole and diastole phases. From the figure, it can be observed that systole and diastole phases contain different edge representation of cardiac region. Based on this ability of the edge detection method, it is expected could produce useful image representation and structural information of apical myocardium tissue for systole and diastole phases. It is also believed that edge detection method could improve the performance of statistical texture analysis on small size RoI from cardiac CT image. From these hypotheses, this study proposed a stronger structural characterization of ECG-gated cardiac CT images based on combination of texture analysis and edge detection. It is expected that this proposed design will produce better characterization of systole and diastole phases as the baseline for normal condition.

II. MATERIALS AND METHODS

This study used the axial multi-planar reconstruction (MPR) cardiac CT images of normal systole and diastole phases. The images were obtained from open-source datasets of FOURDIX file in Dicom Image Library (OsiriX, 2016). The images are available in dicom format with total 188 slices for systole phase and 188 slices for diastole phase. The image size for each slice is 512 x 512 pixels. The characteristics of the cardiac tissues in all image slices are normal.

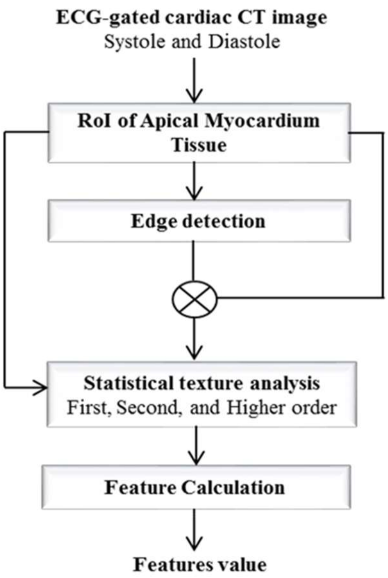

Fig. 2 Block diagram of the proposed methodology

Fig. 2 shows the block diagram of the proposed methodology for this study. The first step is the process to select and define the Region of Interest (RoI) for the Apical Myocardium Tissue in the CT images (for systole and diastole phases). The next step is the edge detection method with the objective to extract edge information from the RoI images. After that, texture analysis will be performed, and texture features will be extracted from the images. The extracted texture features will be analyzed and compared between systole and diastole RoIs. Each methodology step is explained and discussed in details the next sub-topics.Therefore, the authorities can make action faster in order to prevent more danger to road users.

A. *Region of Interest for Apical Myocardium Tissue*

This step involves with slice selection from the FOURDIX ECG-gated cardiac CT datasets and RoI selection for apical myocardium tissue. With the guidance from consultant radiologist, five slices of systole phase and five slices of diastole phase images were chosen from the datasets. All chosen images contained the four-chamber view of cardiac region with the appearance of left ventricular myocardium. The images consisted of slice number 105, 108, 111, 114, and 117 for both systole and diastole phases. Fig. 3 shows example of the selected cardiac CT images for this study which involve with systole and diastole phases. S code image represent the systole phase and D code image represent the diastole phase.

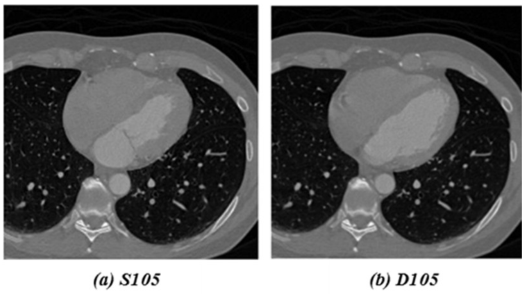

Fig. 3 Example of selected CT image slices for (a) systole and (b) diastole phases

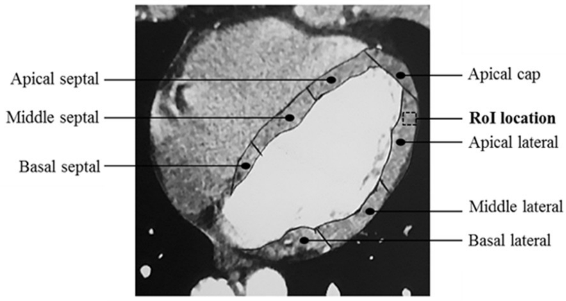

Fig. 4 The sketch of LV apical segments based on AHA recommendation (the image redrawn from slice D105) and RoI location

The RoI selection was performed by identifying the apical myocardium in the cardiac CT images. In 2002, the American Heart Association (AHA) recommended that the LV can be divided into total 17 segments that usually used for cardiac wall motion assessment (Cerqueira, 2002). In four chamber view of CT image, the apical, middle, and basal segments of LV myocardium can be clearly visualized. Based on the AHA recommendation, three LV apical segments can be identified including apical cap, apical lateral, and apical septal. Fig. 4 is the image redrawn from slice D105 with the LV apical segments were sketched by hand. Based on the figure, the apical myocardium tissue RoIs were selected on the area of apical lateral segment. Each apical myocardium tissue RoI is having same size of 12 x12 pixels. The inclusion criteria for the RoIs selection strictly cover only the area of LV myocardium on the apical lateral region. The exclusion criteria for the RoIs selection are the lungs, LV cavity, middle and basal myocardium.

B. Edge Detection Methods

Edge detection methods were applied to the RoIs with the objective to change the representation of the small size RoIs into something easier to be analyzed. Edge detection works by transforming the grayscale input image into binary image that indicates the presence or the absence of an edge. In this study, three edge detection operators were applied in MATLAB R2023a software platform. It is consisting of Sobel, Canny, and Laplacian of Gaussian (LoG) operators. As result, each method returns a binary image of the same size as original image with '1' where edges are detected and '0' (zero) for elsewhere.

Sobel operator is technically a discrete differentiation operator which computes an approximation for the gradient of the image intensity (Sobel, 2014). Basically, it returns edges at those points where the gradient of the image is maximum (Gupta and Mazumdar, 2013). Canny edge detection method operates based on multistage algorithm to detect a wide range of edges in images (Canny, 1986). Canny edge detection method uses double thresholding to detect strong and weak edges, and then includes the weak edges in the output only if they are connected to the strong edges. LoG method works by finding the zero crossings after LoG filtering. This method involves with three main operations: filtering, enhancement, and detection (Juneja and Sandhu, 2009). The filtering step used the Gaussians smoothing prior to the effect of noise. Then, Laplacian as a second order derivative mask uses highlight gray level discontinuities in the filtered image and try to deemphasize regions with slowly varying gray levels.

C. Texture Analysis

Features extraction step was performed using statistical texture analysis. The analysis represents the texture indirectly on how the gray levels are distributed over the pixels in the image. In this study, three type of statistical texture analysis was applied consist of First, Second, and Higher order texture analyses. From each analysis, two selected texture features were extracted from every image. The First order statistical texture analysis is based on the intensity histogram texture measures that calculated from 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). The histogram is formed based on the frequency (how many times pixels) of each gray level in the image. Based on the histogram, several statistical features could be calculated. In this study, two features were calculated consist of mean and median.

Implementation of the Second order statistical texture analysis is based on gray level co-occurrence matrix (GLCM). GLCM of an image is computed using two important parameters; relative distance measured in pixel numbers (d) and their relative orientation angle (θ) (Haralick, 1979). This method is based on the joint probability distributions of pairs of pixels. It is used to estimate properties of two or more-pixel values occurring at specific locations relative to each other (Haralick et al., 1973). From the GLCM computation, Haralick et al. had identified fourteen GLCM texture features to extract the characteristics of an image (Haralick et al., 1973). In this study, two features were calculated consist of contrast and energy.

Higher-order statistical 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 direction and then count the occurrence of runs for each gray levels and length in this direction (Galloway, 1975). Based on the GLRLM computation, several statistical texture features could be obtained. In this study, two features were calculated consist of Gray Level Non-uniformity (GLN) and Run Length Non-uniformity (RLN).

D. Combination of Edge Detection and Texture Analysis

The binary images produced from edge detection method were manipulated to obtain more interesting representation. The pixels with value '1' were replaced with the original RoI pixel's value and pixels with value '0' were kept the same. The resulting images were then analyzed using First, Second, and Higher statistical texture analyses to investigate the structural characteristic based on the edge information.

III. RESULTS AND DISCUSSION

In this study, the proposed methodology was implemented using 10 selected slices of the ECG-gated cardiac CT datasets. 12x12 pixels apical myocardium tissue's RoIs for systole and diastole phases were defined and unique edge detection RoIs were obtained. In total, 10 original RoIs and 30 edge detection RoIs were used to test this study. Then, nine statistical texture features were extracted from each RoI image using First, Second, and Higher-order statistical texture analysis. The texture features result was analyzed and compared between systole and diastole phases RoI. The performance of the proposed methodology was evaluated by comparing the results for edge detection RoIs with original RoIs.

A. Edge Detection RoI

From Sobel, Canny, and LoG edge detection methods, 30 edge detection RoIs were obtained with unique representation. Fig. 5 and 6 shows the original apical myocardium RoIs with Sobel, Canny, and LoG edge detection RoIs for systole and diastole phase respectively. From the results, it was observed Sobel edge detection produced unique RoIs with fewer pixels that contain value different than zero (black). Canny and LoG edge detection methods at the other hand produced RoIs with more pixels that contain value different than zero (black). From this result, different edge detection methods produced different pattern of image information.

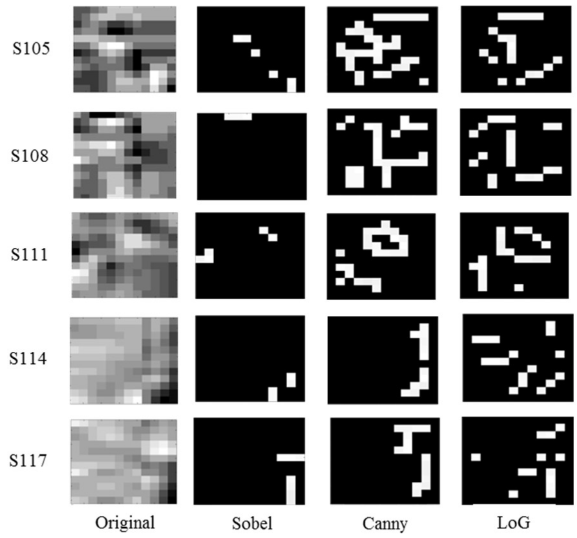

Fig. 5 Original and edge detection RoIs of apical myocardium region for systole phase

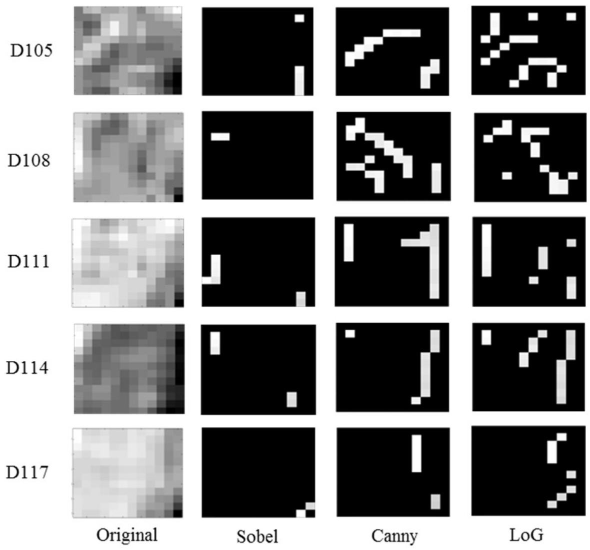

Fig. 6 Original and edge detection RoIs of apical myocardium region for diastole phase

B. First-order Statistical Texture Features

Fig. 7 shows the graphs of First-order statistical texture features result for original apical myocardium RoIs which did not involve with edge detection. From the mean and median feature graphs, it can be observed that their pattern is not consistent along the slices number. In certain slices, the systole phase RoI showed higher features value and in other slices it showed lower features value compared to the diastole phase RoI.

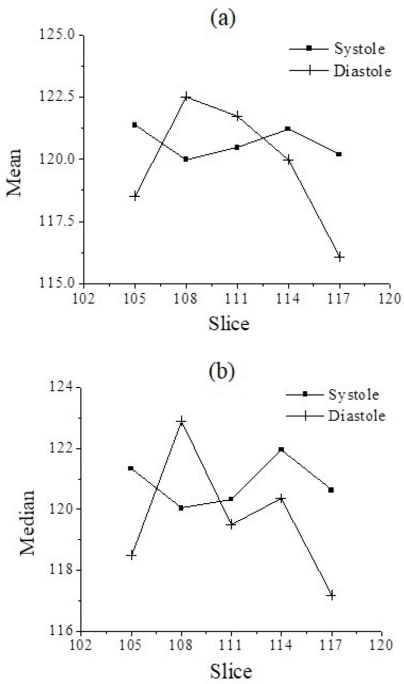

Fig. 7 (a) Mean and (b) median feature profile of First-order texture analysis for original apical myocardium tissue RoIs (without edge detection)

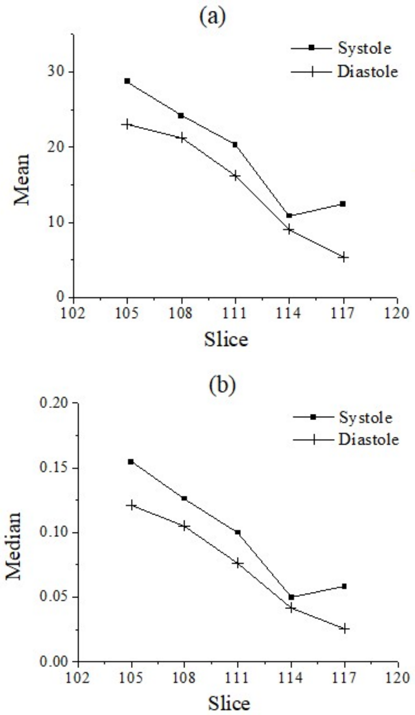

Fig. 8 (a) Mean and (b) median feature profile of First-order texture analysis for apical myocardium tissue RoIs from Sobel edge detection

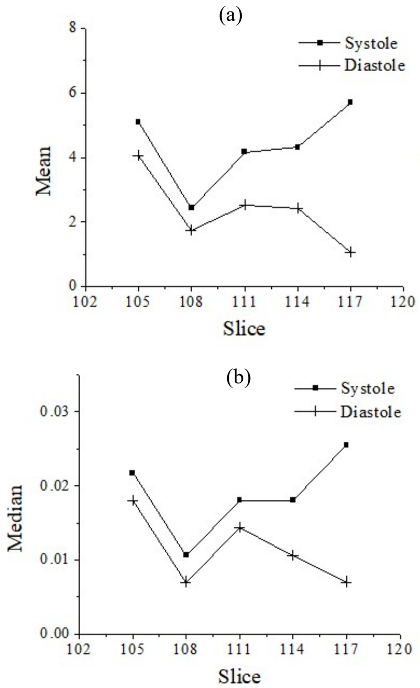

Fig.9 (a) Mean and (b) median feature profile of First-order texture analysis for apical myocardium tissue RoIs from Canny edge detection based

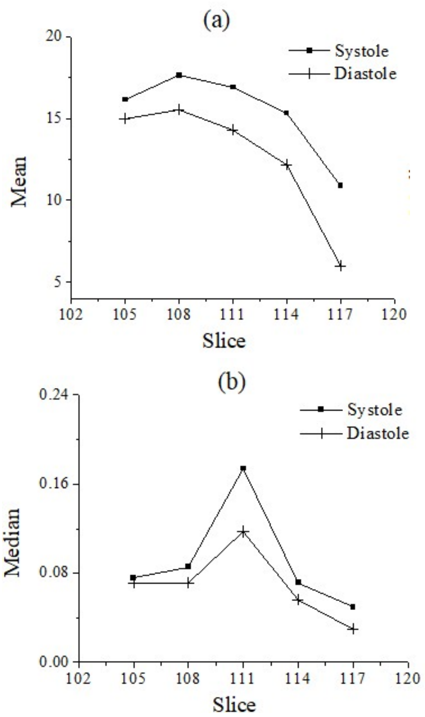

Fig. 10 (a) Mean and (a) median feature profile of First-order texture analysis for apical myocardium tissue RoIs from LoG edge detection

Fig. 8, 9, and 10 depicts the First-order statistical texture features result for the Sobel, Canny, and LoG edge detection RoIs. From the graphs in Fig. 8, 9, and 10, it can be observed that their differentiation pattern is similar along the slices number. All graphs show that systole phase RoIs produced higher mean and median features value compared to diastole phase RoIs. From this result, it can be described that the edge detection RoIs produced better First-order statistical texture features information compared to the original RoIs.

C. Second-order Statistical Texture Features

Fig. 11 shows the graphs of Second-order statistical texture features result for original apical myocardium tissue RoIs which did not involve with edge detection. From the contrast and energy feature graphs, it can be observed that their pattern is not consistent along the slices number. In certain slices, the diastole phase RoI showed higher features value and in other slices it showed lower or same features value with the systole phase RoI.

Fig. 12, 13, and 14 depicts the Second-order statistical texture features result for the apical myocardium tissue RoIs based on Sobel, Canny, and LoG edge detection methods. From the contrast and energy feature graphs in Fig.12, 13, and 14, it can be observed that their differentiation pattern is similar along the slices number. All contrast feature graphs show that systole phase RoIs produced higher value compared to diastole phase RoIs. Energy feature graphs at the other hand show that diastole phase RoIs produced higher value compared to systole phase RoIs. From this result, it can be described that the edge detection RoIs produced better Second-order statistical texture features information compared to the original RoIs.

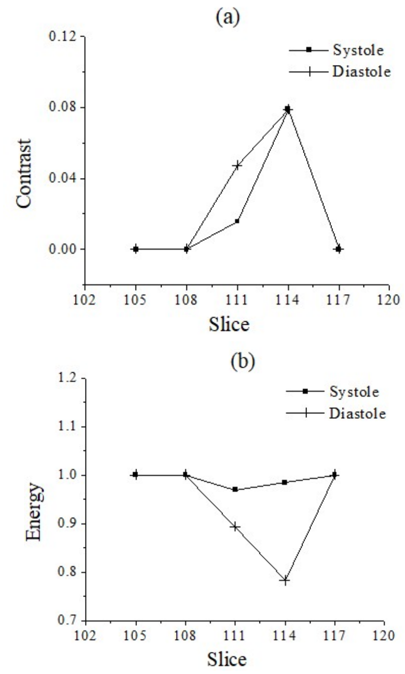

Fig. 11 (a) Contrast and (b) energy feature profile of Second-order texture analysis for original apical myocardium tissue RoIs (without edge detection)

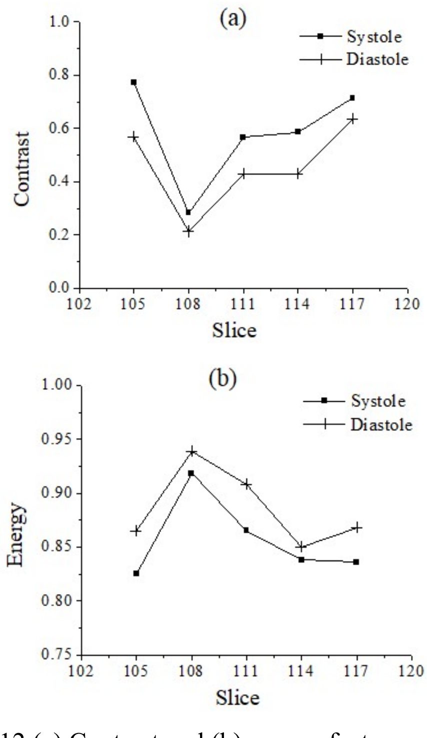

Fig.12 (a) Contrast and (b) energy feature profile of Second-order texture analysis for apical myocardium tissue RoIs from Sobel edge detection

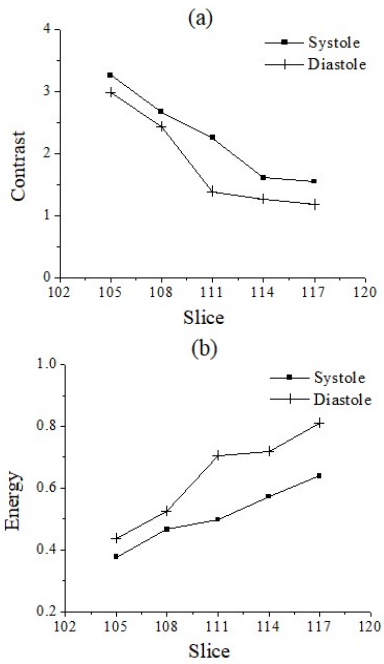

Fig. 13 (a) Contrast and (b) energy feature profile of Second-order texture analysis for apical myocardium tissue RoIs from Canny edge detection

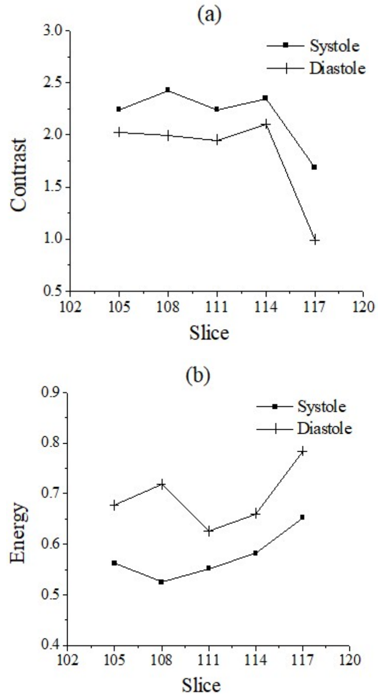

Fig.14 (a) Contrast and (b) energy feature profile of Second-order texture analysis for apical myocardium tissue RoIs from LoG edge detection

D. Higher-order Statistical Texture Features

Fig. 15 shows the graphs of Higher-order statistical texture features result for original apical myocardium tissue RoIs which did not involve with edge detection. From the GLN and RLN feature graphs, it can be observed that their pattern is not consistent along the slices number. In certain slices, the systole phase RoI showed higher features value and in other slices it showed lower features value compared to the diastole phase RoI.

Fig. 16, 17, and 18 depicts the Higher-order statistical texture features result for the apical myocardium tissue RoIs based on Sobel, Canny, and LoG edge detection methods. From the GLN and RLN feature graphs, it can be observed that their differentiation pattern is similar along the slices number except for GLN feature graph for Sobel edge detection RoIs. GLN and RLN feature graphs for Canny edge detection RoIs and GLN feature graph for LoG edge detection RoIs howed that systole phase produced higher value compared to diastole phase.

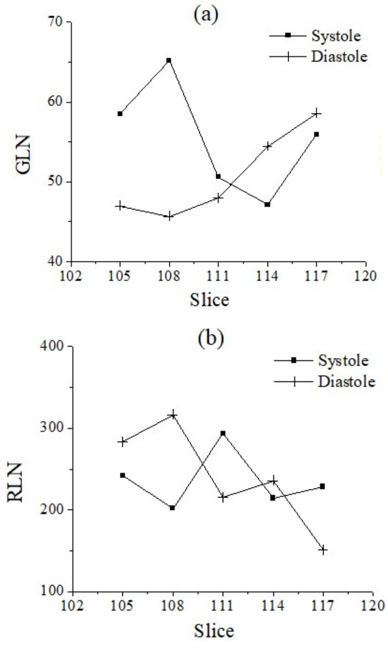

Fig. 15 (a) GLN and (b) RLN feature profile of Higher-order texture analysis for original apical myocardium tissue RoIs (without edge detection)

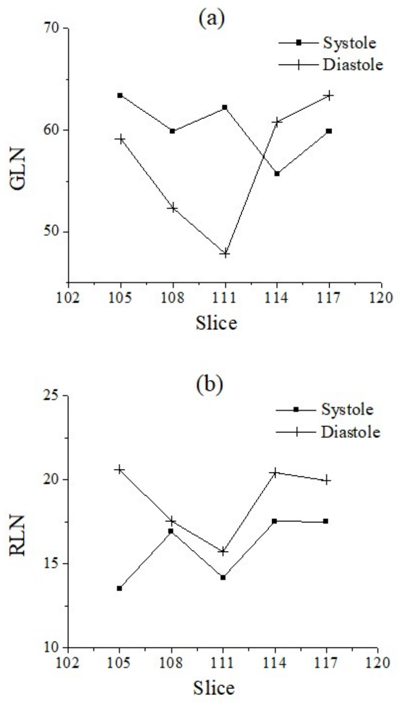

Fig. 16 (a) GLN and (b) RLN feature profile of Higher-order texture analysis for apical myocardium tissue RoIs from Sobel edge detection

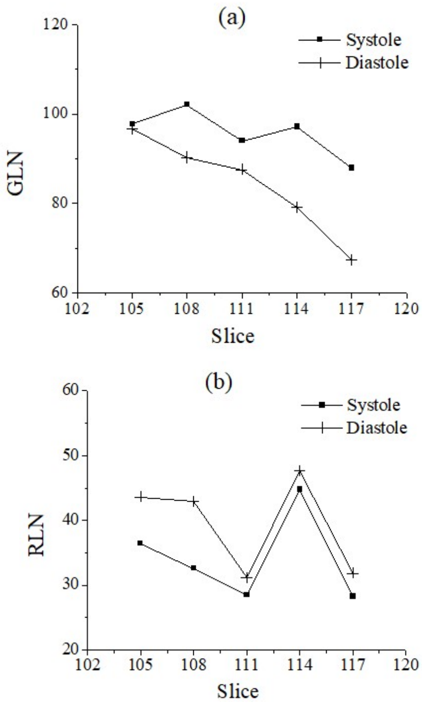

Fig. 18 (a) GLN and (b) RLN feature profile of Higher-order texture analysis for apical myocardium tissue RoIs from LoG edge detection

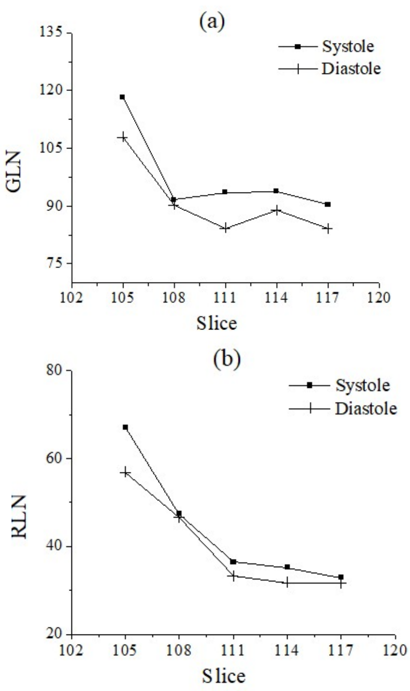

Fig. 17 (a) GLN and (b) RLN feature profile of Higher-order texture analysis for apical myocardium tissue RoIs from Canny edge detection

The RLN feature graph for Sobel and LoG edge detection RoIs showed that diastole phase produced higher value compared to systole phase. From this result, it can be described that the edge detection RoIs produced better Higher-order statistical texture features information compared to the original RoIs.

In this study, texture is represented by the irregular or regular patterns of the cardiac tissues in the CT image. Due to some limitations, texture analysis performance can be affected by region size, image resolution, and noise. From the texture analyses results, it can be discussed that the original apical myocardium RoIs from the CT images failed to provide strong structural characterization for systole and diastole phases as the texture features value is not consistent throughout the slices. The analyses could be affected from the small RoI size, blurring, and noise in the CT images. It was reported that the accuracy of texture analysis on small RoI size in a medical image could be adversely affected by noise and can cause errors in the reported diagnosis (Osicka et al., 2007).

From the texture analysis results, it can be described that the edge detection RoIs produced stronger structural characterization of apical myocardium tissue in differentiating systole and diastole phases. In theory, the shape and position of cardiac tissue layers should be different for systole and diastole phases due to contraction and relaxation of the cardiac muscle (Rodriguez et al., 2006). The ability of edge detection to identify the boundaries and tissue layers had contributed to extracting useful structural information of the apical myocardium image and produced better texture analysis result to differentiate between for systole and diastole phases. Canny and LoG edge detection RoIs had produced clear characterization of systole and diastole phases for all calculated statistical texture features. Sobel edge detection RoIs at the other hand had produced clear characterization for all calculated statistical texture features except the GLN feature from Higher-oder texture analysis.

The result from this study may serve as the baseline information for normal condition. In the future, it is expected that the proposed methodology could be used to extract more valuable information for abnormal condition and provide biomarker for cardiac disorders involving LV apical myocardium tissue.

IV. CONCLUSIONS

In this paper, an improved methodology was proposed to characterize the structural properties of LV apical myocardium from ECG-gated cardiac CT image and differentiating between systole and diastole phases. The study particularly focuses on the edge detection method that improved the performance of statistical texture analysis on small LV apical myocardium RoI. The proposed methodology had point out stronger structural characterization for LV apical myocardium RoI and more consistent differentiation between systole and diastole phases. This paper is a proof of concept of the proposed methodology on normal structure in cardiac CT image which may serve as baseline information for future potential biomarker. As future work, the study will be extended with more data of the ECG-gated cardiac CT image. Furthermore, it is in future planning to implement the proposed methodology on abnormal LV apical myocardium.

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