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# SEGMENTATION OF 2D MYOCARDIAL PERFUSION SPECT IMAGES

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## ABSTRACT

Myocardial perfusion imaging (MPI) is a widely used and non-invasive diagnostic method for the detection of patients with suspected or known ischemic heart disease. MPI test is commonly realized by single photon emission computed tomography (SPECT). This test provides several images illustrating the function of the heart muscle. Appropriate segmentation of those images play a crucial role for the diagnosis of heart disease. Consequently, this paper proposes a segmentation method for 2D myocardial perfusion SPECT images acquired in both stress and rest cases. In this way, an expert can make visual assessment of the changes in the stress and rest images easily. Hence, possible heart diseases would be identified based on those changes without a need of using polar maps or reference databases.

**Keywords:** Myocardial perfusion imaging; SPECT; Coronary artery disease; Segmentation; Image processing

## 1. INTRODUCTION

Cardiovascular disease (CVD) is one of the most widespread health problems and the leading causes of death worldwide [1-2]. Almost one third of all deaths are caused by CVDs, mainly by coronary artery disease (CAD). Consequently, accurate detection of CVD has been of great interest in biomedical image analysis [3].

Nuclear cardiology is a well-established technique to detect CAD and to assess ventricular function. One of the most commonly used techniques in nuclear cardiology for detecting and determining the severity of CAD is myocardial perfusion imaging (MPI) test using single photon emission computed tomography (SPECT), which provides three-dimensional information on the distribution of a radioactive compound within the heart. The metabolic/functional/molecular activities, which are not visible to the naked eye, can be seen by this non-invasive method. There are two approaches used to inspect SPECT MPI: visual and automated [4]. The use of visual inspection alone may introduce considerable observer variability [4]. In nuclear cardiology, interpretation of MPI is dependent on the knowledge of the physician and is subject to inter and intra observer variability [4-6]. It is crucial to develop and implement decision support tools for assisting physicians in interpreting studies at a faster rate and highest level of up to date expertise. Such tools would minimize subjectivity and intra/inter observer variation in image interpretation, help to achieve a standardized high-level performance, and reduce healthcare costs [7]. Automated interpretation of quantitative information would help to train rookie nuclear cardiologists, aid in analysis of complex cases, or act as a second opinion [7]. In order to improve the reliability, accuracy and confidence, automated techniques are needed for the interpretation of MPI tests.

The main goal of MPI is the detection of CAD. The SPECT MPI is used for the assessment of the presence, localization, prevalence and severity of myocardial ischemia or infarction and the evaluation of myocardial viability and the prediction of functional recovery after revascularization. A sample MPI SPECT image presenting short axis (SA), vertical long axis (VLA) and horizontal long axis (HLA) of myocardium as the counterparts of the coronal, sagittal and transaxial sections is given in Figure 1.

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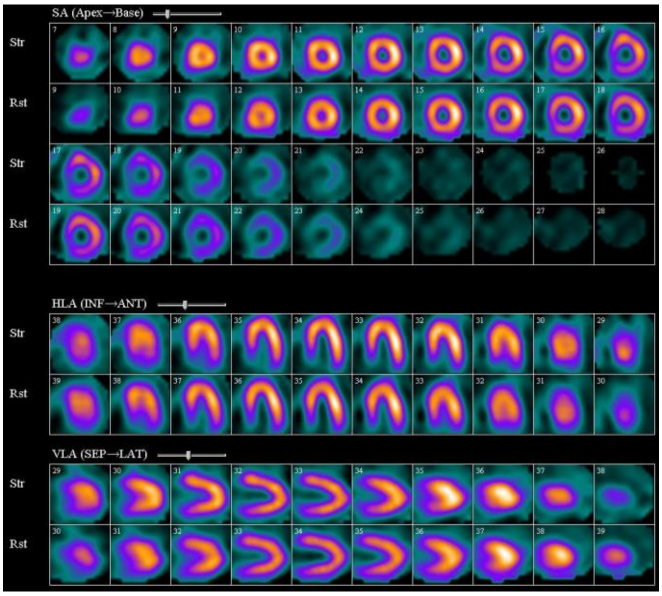


**Figure 1.** Sample SPECT image belonging to a healthy heart

In SPECT MPI, the disease is typically quantified as the difference between stress and rest defect sizes obtained by separate comparisons with stress and rest normal limits [8]. In typical quantification protocols, the stress and rest data are fitted separately to a geometric polar map model. Subsequently, polar map samples of stress and rest patient data are compared to normal limit polar map samples. Using a standard database approach, a change on stress might not be significant in comparison to the stress scans of healthy population, but there still may be a detectable stress-rest count change for a given patient [8].

The most widely used commercial software packages are 4D-MSPECT [9], Emory Cardiac Toolbox [10], Quantitative Perfusion SPECT (Cedars-Sinai Approach) [11] and Yale-CQ approach [12]. The comparison of diagnostic performances of those software packages are published in some studies using different radionuclide [13-14]. There are several efforts to diagnose CAD from SPECT MPI using artificial neural network [5-6, 15], boosted ensemble machine learning algorithm (Logit-Boost) [16], and support vector machine [17].

This paper proposes a method, which would serve as a computer aided diagnosis tool, for detecting actual edge segments of left ventricle (LV) in stress and rest images. To the best of our knowledge, such an approach has not been previously reported for SPECT MPI analysis in this way. With the help of the proposed method, an operator can make visual assessment on the changes of stress and rest images easily. In this way, the diseases can be classified based on the detection of changes without need for polar maps or reference databases. In other words, the main goal of this work is to help to improve the diagnostic performance of MPI interpretation analysis.

The rest of the paper is organized as follows: Section 2 explains the materials and methods used for the detection of actual edge segments of LV. Section 3 introduces the proposed segmentation method. Section 4 briefly presents the experimental results. Finally, some concluding remarks and future directions are provided in Section 5.

## 2. MATERIALS AND METHODS

### 2.1. Patient Profile

A total of 26 patients, who were referred to the Department of Nuclear Medicine, Eskişehir Osmangazi University, Eskişehir, Turkiye for rest and stress Tc-99m MPI, are considered for inclusion. One of those patients suffer from both infarct and ischemia, 17 patients suffer from ischemia and the others are evaluated as healthy. All patients were instructed not to consume beta-blockers and calcium channel blockers for 48-72 hours, nitrates for 12 hours before the study and warned not to eat anything 3 to 4 hours before the study.

This retrospective work has been approved by the Ethics Committee of Eskişehir Osmangazi University.

### 2.2. Exercise and Imaging Protocol

Imaging is performed in two stages in Nuclear Medicine Department: stress and rest. In this department, the resting myocardial SPECT images of the same day are acquired according to the 1-day protocol and imaging is performed 30 min after injection of 30 mCi Technetium-99m methoxyisobutylisonitrile (Tc-99m MIBI). Stress myocardial SPECT images are acquired 30 min after injection of 10 mCi Tc-99m MIBI as a result of effort test (exercise is performed using treadmill test (Modified Bruce protocol is applied and Tc-99m MIBI is injected after at least 85% of the age-predicted maximum heart rate is reached. Exercise treadmill test is ended 1 minute after Tc-99m MIBI injection)) or pharmacological stress with adenosine or dobutamine.

### 2.3. Acquisition Protocol

Rest and stress studies are acquired after Tc-99m MIBI injection using a dual-headed SPECT scintillation gamma camera (Siemens Medical Systems, Symbia-S) equipped with a low-energy high resolution, parallel-hole collimator. Data are obtained from 64 projections of 30 seconds for stress, 25 seconds for resting study in the 140 keV photo peak over a 180 degrees' arc in a 64x64 matrix. Stress and rest studies were performed at 180 degrees SPECT imaging; starting from 45 degrees right anterior-oblique and completed at 45 degrees left posterior-oblique. Patients are imaged at supine position. SA, HLA and VLA are reconstructed from the raw data by filtered back projection with a Butterworth filter, with a cut-off frequency of 0.5 Hz and order of 10 in the rest and stress studies.

### 2.4. Reference Standard – Visual Analysis

An expert nuclear medicine specialist use the cine display of the rotating planar projections to evaluate sub-diaphragmatic activities, attenuations, and patient motion to optimize the quality of the images. The segments (SA, HLA, VLA) of LV images are automatically generated. All edge segments in given SPECT images are manually tagged independently by two expert readers (both readers have more than 10 years of clinical experience in nuclear cardiology).

## 3. THE PROPOSED SEGMENTATION ALGORITHM

During the interpretation phase, the presence of ischemia or infarction is investigated. Ischemia is detected if perfusion defect in the stress image has improved on the resting image. Infarction is detected by a constant perfusion defect in both stress and rest images. In order to detect ischemia or infarct, the perfusion defects in stress and resting images are determined accurately. This can be realized by the detection of actual edge segments of LV sections. If the actual edge segments are obtained accurately, for further processing; SPECT images can be automatically classified as accurately as possible. SPECT images are evaluated and the patients are classified independently by two expert readers using three different class labels (1: healthy, 2: ischemia, 3: infarct) for further processing.

In this work, the preprocessed SPECT images including SA, HLA, VLA segments of myocardium are used. The operator uses a computer program extracting the segments of LV. The extracted images of the segments are fed into the edge segmentation algorithm for detection of actual edge segments of 3 LV sections so that the interpretation of CAD presence and severity become easier. In other words, the proposed work is used as a decision support tool by the experts.

The proposed segmentation algorithm works with grayscale images and follow several steps in a given image. General outline of the algorithms is presented below:

i) The region of interest (ROI) is obtained from the image using the Lab-based color thresholding algorithm. Then, binary image is obtained using this thresholded image.
ii) The edge segments in the ROI are extracted by Edge Drawing (ED) [18] and Edge Drawing Parameter Free (EDPF) method [19].
iii) Edge segments are converted into line segments using EDLines [20] algorithm.
iv) Closed edge segments (actual edge segments) are detected for all axes.
v) The actual edge segments in the given image are highlighted.

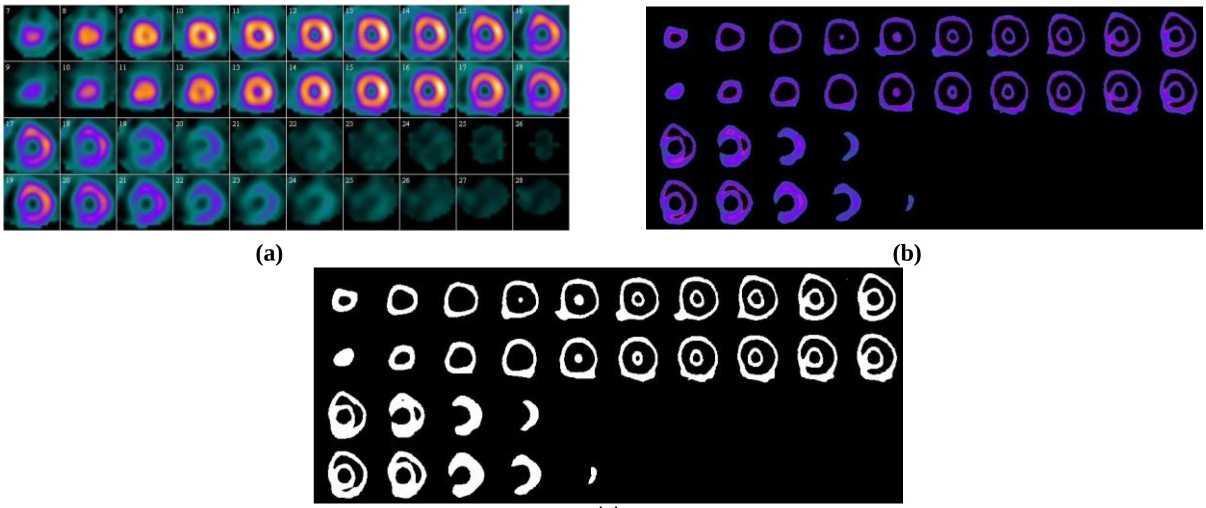
Each step of the algorithm above is described in detail within the following subsections.

### 3.1. Color Thresholding and Segmentation

Lab-based color thresholding algorithm aims to eliminate the red parts (hot spots which indicate the areas where blood passes through the vessel) of the image. In order to achieve this goal, analysis is performed on the images of patients with infarct disease. Infarction can be defined as the death of cells in that region due to lack of blood passing through the vessel. The threshold value is obtained by determining the last boundary of blood passing according to the result obtained from this analysis. The mask equation for non-red colors is defined as follows:

$$\mathrm{NonRed}(i,j)=\begin{cases}\mathrm{True}, & \text{if } \mathrm{b}(i,j)\le -60\\ \mathrm{False}, & \text{otherwise}\end{cases} \tag{1}$$

After color thresholding, binary image is obtained. This binary image is divided into 3 sections as SA, HLA, VLA by using the start and end pixel coordinates of each section. The image size is determined as 900x360 for SA and 900x180 for HLA and VLA by using these coordinates. Figure 2a shows a 900×360 SPECT image presenting short axis of myocardium. The resulting image after applying the proposed red thresholding algorithm is shown in Figure 2b. Clearly, the red and green parts of the image are wiped out and all the other sections of the image are preserved for further processing. Following the red thresholding, a binarization is performed to reduce noise and highlight the boundaries of LV segments (Figure 2c).



**(a)** **(b)** (c)

**Figure 2.** (a) A sample stress-rest SA image; (b) Lab-based color thresholding; (c) Binarization

### 3.2. Edge Segment Detection by EDPF

Lab-based color thresholding algorithm is followed by the high-speed parameter free edge segment detection algorithm, i.e., EDPF. ED [18], a real-time edge/edge segment detector outputs the result as a set of edge segments each of which is a connected pixel chain [21].

The validation mechanism based on the Helmholtz principle was added to the ED to obtain a real-time parameter-free edge segment detector, which named EDPF [19]. EDPF works by running ED with all ED's parameters at their extremes, which detects all possible edge segments in a given image with many false positives. Then the extracted edge segments are validated by the Helmholtz principle, which eliminates false detections leaving only perceptually meaningful edge segments [21].

## 4. EXPERIMENTAL RESULTS

When the resulting images given in Figure 2b and Figure 2c are fed into EDPF, the edge segments shown in Figure 3a and Figure 3b are obtained, respectively. One can easily see from those figures that the edge segments detected after binarization process represent the closed edge segments much better.
During the interpretation phase, while the presence of ischemia or infarction is investigated, the operator looks for an abnormality in each of the LV segments in the given image. If an abnormality is detected in two of these 3 segments (SA, HLA, VLA), suspicion of the presence of a disease arises.
Each segment must be visually assessed separately. The total number of images in each section are 40, 20 and 20 for the SA, HLA and VLA images, respectively. In particular, the evaluation is carried out by prioritizing the images 5 to 12 in the corresponding stress-rest SA image and 3 to 8 in the corresponding stress-rest HLA and VLA images.

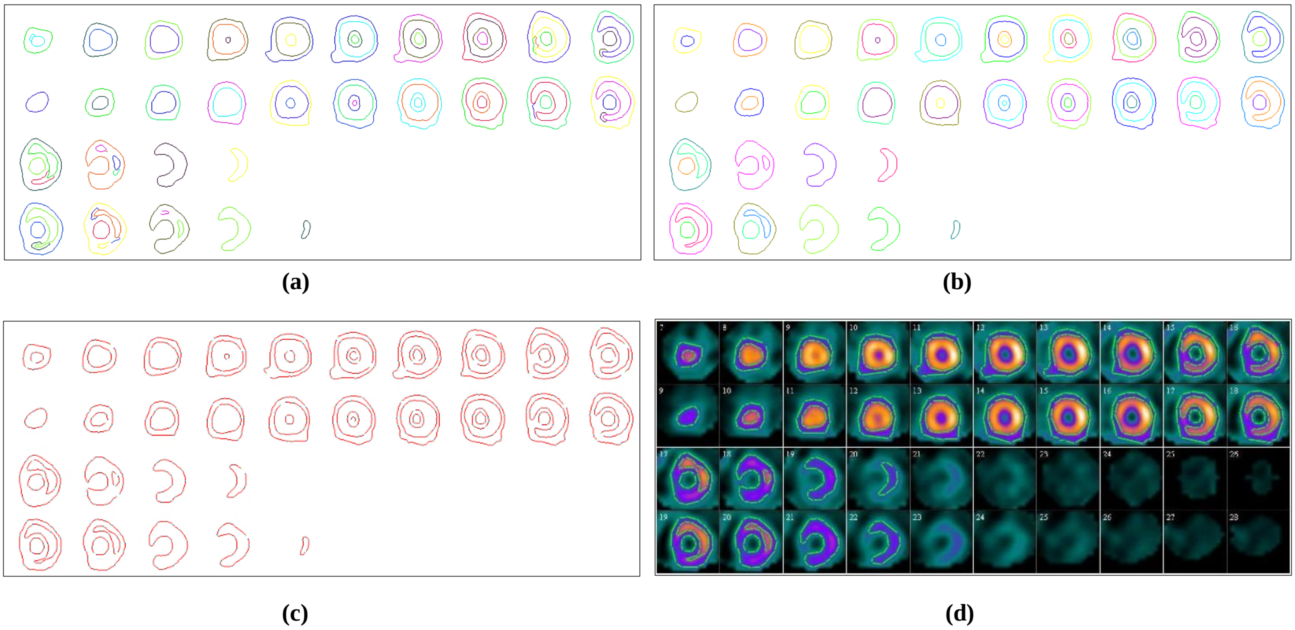
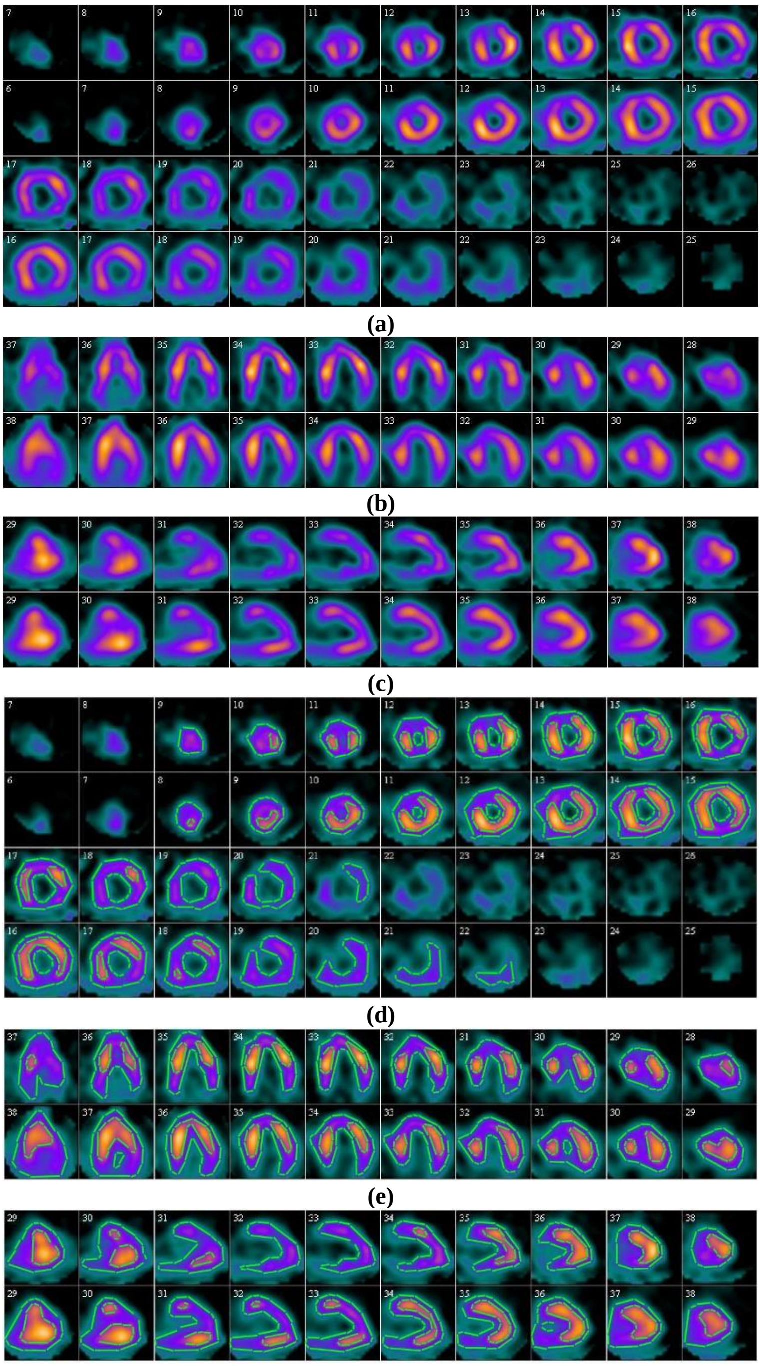



**Figure 3.** The results of the segmentation algorithm: (a) EDPF followed by red thresholding on Figure 2a; (b) EDPF followed by binarization on Figure 2a; (c) Line segments approximating the edge segments given in (b); (d) Final lines belonging to the detected closed edge segments (overlapped on top of the image with green color).

In summed stress-rest image, 10 images in the first and third rows belong to the stress study and remaining images in the second and fourth rows belong to the resting study (20 images belong to stress study and the remaining 20 images belong to resting study) for SA image. In HLA and VLA stress-rest images, 10 images in the first row belong to the stress study and remaining images in the second row belong to the resting study. Possible disease is diagnosed by detecting changes between these two images. Some possible abnormalities can easily be overlooked during this evaluation.

The aim of the proposed method is to minimize this type of overlooking. As an example, all three segments of LV and the results of the proposed method for a patient, who is interpreted as ischemia, are illustrated in Figure 4. It is verified that each closed edge segment has been successfully detected by the proposed method for all images.




(f)

**Figure 4.** (a-c) Sample summed stress-rest SA, HLA, VLA SPECT images belonging to a patient interpreted as ischemia, respectively; (d-f) Final lines belonging to the detected closed edge segments in SA, HLA, VLA SPECT images, respectively (overlapped on top of the images with green color).

## 5. CONCLUSIONS

Main goal of computer-aided diagnosis in biomedical imaging is to design and develop particular software to be able to assist in detection and evaluation of abnormalities, to alert physicians to cognitive biases, to reduce intra and inter-observer variability and to allow physicians to interpret studies at a faster rate and with a higher level of accuracy. In this work, an automatic segmentation method, which is utilized as a computer aided diagnosis tool, is proposed for detecting actual edge segments of left ventricle in automatically generated stress and rest images. The experimental results show that the detection of actual LV boundaries would help physicians in visual assessment of disease detection and provide more accurate results.

The design and development of automatic classification framework for the segmented myocardial perfusion SPECT images using pattern recognition techniques remain as an interesting and challenging future work.

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