# Myocardial Ischemia Detection Algorithm (MIDA): Automated Echocardiography Sequence Analysis for Diagnosis of Heart Muscle Damage

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## Abstract

A Myocardial Ischemia Detection Algorithm (MIDA) is presented that analyses echocardiography sequences automatically in order to detect the presence of heart muscle damage. MIDA involves an image enhancement, fuzzy multi resolution edge detection to obtain the heart wall boundaries, composite motion image creation using the heart wall boundaries, followed by statistical pattern recognition and classification to identify the heart wall abnormality. The performance of MIDA is assessed using 62 real patient data with both normal and abnormal conditions. The results indicate that MIDA can be used as an effective tool for automatically diagnosing Myocardial Ischemia.

## 1. Introduction

Cardiovascular disease such as myocardial ischemia is the leading cause of death worldwide [1]. Myocardial Ischemia is a heart condition where the heart muscle is damaged due to insufficient blood flow to the heart muscle via the coronary arteries. It leads to complications such as heart failure or heart attack. This damaged heart muscle does not contract as much as the healthy heart muscle leading to abnormal heart wall movement. Echocardiography (Echo) is one of the widely used cardiac imaging modalities to visualise and assess the heart anatomy and function. When compared to the other modalities, an Echo scan is considered to be a safe imaging tool, with no known negative effects for patients. It is low-cost, non-invasive, real-time, portable, versatile and flexible to use.

The drawbacks of Echo images (such as speckle noise, artifacts due to gain setting problems during recording, dropouts, shadowing, scan sector limitations and limited echo windows) have hindering effects on analysis of heart function and its wall motion. There is significant inter and intra- observer variability in analysing heart wall motion using Echo scans.

This paper presents a Myocardial Ischemia Detection Algorithm (MIDA), an algorithm developed to automatically analyze the Echo to identify heart muscle damage. A detailed description of the various stages involved the algorithm is described in section 2. The experimental results are discussed in section 3, and section 4 contains concluding remarks.

## 2. Methodology

An overview of MIDA is shown in Figure 1. When a patient Echo data is obtained, the image pre-processing is performed and the LV boundary edges are obtained. The global LV parameters that describe the health of the heart such as LV ejection fraction and cavity area are extracted from the boundary. The boundary edges obtained for the entire echo image is also used to create a composite motion (CM) image. Then, the automated diagnosis can be performed on the CM images in two different approaches. In the first approach, Principal Component Analysis (PCA) is applied on the composite motion (CM) image to reduce the dataset and extract the features which are processed by a classifier to identify the abnormality. In the second approach, PCA is applied on the CM image to reduce the dimension of the dataset, followed by feature extraction using Independent Component Analysis (ICA). These features are subsequently used to classify the heart wall abnormality. These stages are detailed in the following sections.

### 2.1. Image pre-processing

In MIDA, undecimated wavelets decomposition of the image (up to 4 levels) into approximation and details is performed as a speckle reduction preprocessing stage. An average filtering process is performed on the approximations. A mean based smoothing is performed to all the details, which is defined for an image I(x, y) as

$$I(x,y) = \begin{cases} I(x,y) & \text{if } |I(x,y)| \le N \\ N & \text{if } |I(x,y)| > N \end{cases} \quad (1)$$

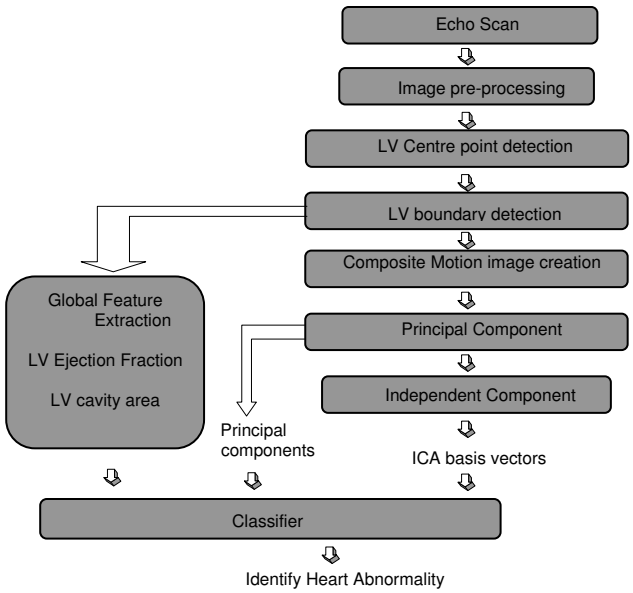



Figure1. Myocardial Ischemia Detection Algorithm (MIDA) overview

where N is the trimmed mean value of row of the pixel I(x, y) and x, y are the pixel coordinates. The trimmed mean of a data X with n values, is the mean calculated by excluding the highest and lowest k data values, where k=n*(p/100)/2 and where p is the percentage to be trimmed. Here 25 % of the outliers are trimmed from the data. However, if the data is all from the same probability distribution, then the trimmed mean is less efficient than the sample mean as an estimator of the location of the data. This operation is used to smooth the sudden changes of coefficient values. Then the image is reconstructed using all the modified sub bands to get the noise reduced image. Figure 2(a) shows the noisy image (speckle noise variance=0.5 is added to the image) and 2(b) shows the speckle noise reduced image.

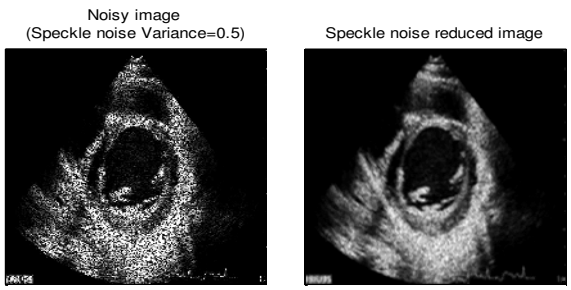
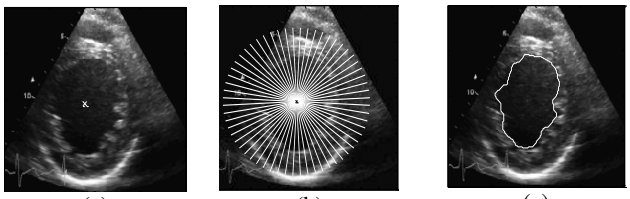



Figure 2. (a) Original image, (a) Speckle noise reduced image

## 2.2. LV boundary detection

A radial search based heart wall boundary detection (as shown in Figure 3) is performed on the speckle noise reduced image. This is carried out in two stages: LV centre point (LVCP) detection and the LV boundary detection. LVCP detection is performed by using the prior knowledge of the Short-Axis view images to set fuzzy rules. In other words, fuzzy membership functions are used to represent spatial (LVCP is in the center part of the image), structural (LVCP is close to the vertical diameter of the LV passing through the lowest point of the posterior epicardial boundary) and intensity (LVCP is a dark pixel) information. These membership functions are combined by fuzzy operators to obtain the potential centre point pixels. A template matching is performed to obtain the actual LVCP.

Once the LVCP is identified, the endocardium edges are searched along 60 radial lines originating from the LVCP (as the LV wall has a radial oriented motion). The endocardial edge is obtained in the region of interest which is determined by the estimated epicardial boundary and the wall thickness. The edge detection is done by fuzzy multiscale edge detection [2], where the different scale information in the wavelet decomposition is combined in a fuzzy manner using the fuzzy set theory.



(a) (b) (c)

Figure 3. (a) Fuzzy logic based LV centre point detection, (b) radial search and (c) LV boundary determined by Fuzzy multi resolution edge detection

## 2.3. Global LV Parameters

The global features extracted from the heart wall boundaries include ejection fraction and LV cavity area. These features are based on the average radius of the LV boundary.

**Ejection fraction:** Ejection fraction is obtained for one cycle to determine the volume of blood ejected during that heart beat. Left ventricle ejection fraction (LVEF), which is used for the decision making, is determined by

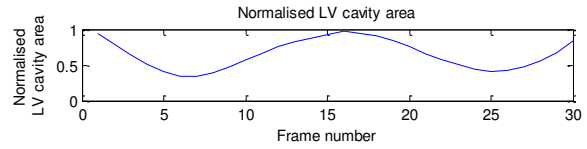
$$\mathrm{LVEF} = \frac{\mathrm{EDV} - \mathrm{ESV}}{\mathrm{EDV}} \quad (2)$$

where EDV is the End-Diastolic Volume and ESV is the End-Systolic volume. The Volume of the LV can be determined by the following equation [3]

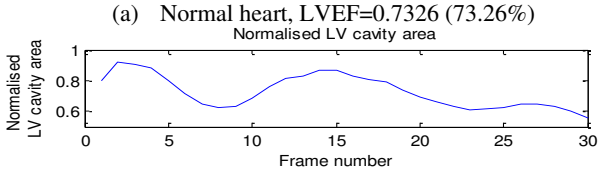
$$\mathrm{Volume} = \left(\frac{7.0}{2.4 + \mathrm{D}}\right)\mathrm{D}^3 \quad (3)$$

where D is the average endocardial diameter from the SA view. In healthy individuals, the LVEF is typically greater than 0.5 (50%) [4].

**LV cavity area:** LV cavity area is determined by using the average endocardial radius in a frame. The LV cavity




(a) Normal heart, LVEF=0.7326 (73.26%)




(b) Abnormal heart, LVEF=0.407 (40.7%)

Figure 4. Normalized LV cavity area along the echo movie

area in a complete cycle is normalized by dividing it by the end-diastole cavity area. It has a maximum value at the end-diastole and has a minimum value at the end-systole. Figure 4 shows the LV cavity area along the complete cardiac cycle for both normal and abnormal heart. It can be seen that the normalized systolic LV cavity area is around 0.3 for a sample healthy heart with an ejection fraction of 73.26%. The normalized systolic LV cavity area is around 0.6 for the sample heart with abnormality, which has an ejection fraction of 40.7%.

## 2.4. Composite image creation

The wall position at contracted phase and relaxed phase of the LV chamber is significant in estimating information on the contractility of the heart wall. The movement of the inner heart wall is used by experts to identify the wall motion abnormality. Hence, the LV wall boundaries are detected for each frame and the edges obtained for all the frames between the end-systole and the end-diastole are used to create a composite motion image. The extracted inner wall boundaries for all the frames are placed into a composite image to show the movement of the heart wall from the contracted phase to the relaxed phase. This image is referred as the composite motion image. As the location of the LV is different in different echo movies, to eliminate errors, the image is suitably cropped with 2 pixels on either side of the edge and resized to 50x50 for consistency through the image database information (as shown in Figure 5).

(a) Sample normal heart wall motion

(b) Sample abnormal heart wall motion

Figure 5. CM images showing inner wall motion

## 2.5. Principal component approach

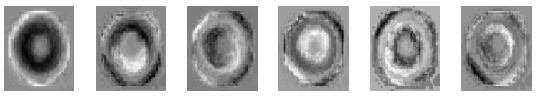
Principal component analysis (PCA) is widely used for pattern identification in fields such as face recognition (eigenfaces) [5]. In this approach, PCA is applied to extract features from the CM image dataset. Eigenvectors and eigenvalues of the covariance matrix of the mean adjusted CM image dataset are calculated [6]. These vectors are arranged in order of significance, based on their eigenvalues. Any heart image can be described and classified using the top few PCA vectors (more significant), while the less significant ones (which typically represent minor features within the images or noise) can be ignored to reduce computation.

## 2.6. Independent component approach

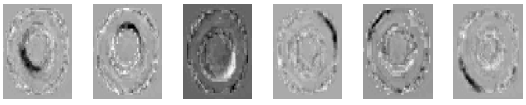
In this approach, PCA is applied to reduce the dimensionality in the datasets, followed by applying ICA to extract the underlying features or components from the data [7]. The ICA is implemented using the infomax algorithm [8], by applying it to the top 'm' PC vectors to obtain 'm' statistically independent basis vectors or independent components (IC). For any new image, the IC representation can be obtained and used for classification.

## 3. Results and discussion

When a short axis mid-cavity view Echo scan of a patient is obtained, the composite motion image is formed and stored in a database. Our real patient dataset consists of 62 images in total with 27 normal hearts and 35 abnormal hearts, which were annotated by medical experts. The abnormal hearts used in the database had varied levels of wall damage. Sample CM images in the real dataset which shows normal heart wall motion and abnormal heart wall motion is shown in Figure 5. Then the PC vectors (as shown in Figure 6 (a)) and the IC vectors (as shown in Figure 6 (b)) are determined and used for classification. A k- nearest neighbour (k-NN) classifier with Euclidean, City-block and Cosine distance metric is used for classification. The classifier outputs can be combined by various rules such as sum, product rule,



(a) Sample PC vectors obtained from the dataset (Top 6)



(b) ICA basis vectors obtained from the dataset (Top 6)

Figure 6. Sample features

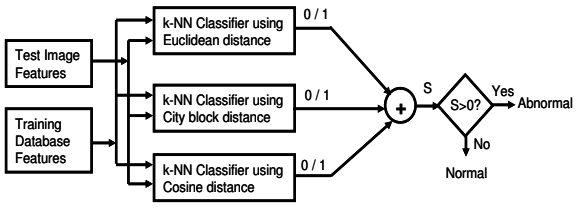



Figure 7. Combined k-NN Classifier

max rule, min rule [9]. The three classifier outputs are combined to form a combined k-NN classifier as shown in Figure 7, that is, if any one of the output suggest that the heart is abnormal, then it is classified as abnormal heart.

The performance of the various features along with different classifiers in identifying the heart abnormality is given in Table 1. The identification of the abnormality based on the PCA and ICA components from the composite motion image as the feature, using the combined k-NN classifier classification gave a highest accuracy of 83.87%. Though the overall classification was the same for both cases, the sensitivity was greater for PCA vectors. The heart function can also be classified based on the global features such as normalised systolic LV cavity area and ejection fraction. While using the systolic LV cavity area as a feature, a correct classification of 79.03 % was obtained. When the ejection fraction was used as a feature for classification, a correct classification of 75.81% was obtained. A combined k-nearest neighbour classifier provided better classification results when compared to Bayes classifier, linear classifier and support vector machines.

Table 1. Classification result in identifying heart abnormality

| Feature+ Classifier | % Correct Recognition | Specificity (%) | Sensitivity (%) |
|---|---|---|---|
| PCA + Comb. kNN | **83.87** | 85.18 | **82.86** |
| ICA+ Comb.kNN | 83.87 | 96.3 | 74.29 |
| ICA+SVM | 82.26 | 100 | 68.57 |
| PCA+SVM | 80.65 | 96.3 | 68.57 |
| ICA+Linea | 80.65 | 96.3 | 68.57 |
| PCA+Linea | 79.03 | 96.3 | 65.71 |
| LVCA | 79.03 | 88.57 | 66.67 |
| PCA+Baye | 75.81 | 81.48 | 71.43 |
| LVEF | 75.81 | 85.71 | 62.96 |

## 4. Conclusion

A new Myocardial Ischemia Detection Algorithm (MIDA) was presented in this paper. The heart wall boundaries extracted to using FMED edge detection were used to analyse the heart wall to identify the heart wall abnormality. The results indicate that the MIDA can be effective in diagnosing Myocardial Ischemia. Further analysis on larger and varied dataset has to be performed. Performing segmental analysis on the heart wall will provide information on the location of the tissue damage. This should help identify the possible source of the damage.

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