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Title: **Texture Spectrum coupled with Entropy and Homogeneity Image Features for Myocardium Muscle Characterization**

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Abstract: People in middle/later age often suffer from heart muscle damage due to coronary artery disease associated to myocardial infarction. In young people, the genetic forms of cardiomyopathies (heart muscle disease) are the utmost protuberant cause of myocardial disease. Accurate early detected information regarding the myocardial tissue structure is a key answer for tracking the progress of several myocardial diseases. The present work proposes a new method for myocardium muscle texture classification based on entropy, homogeneity and on the texture unit-based texture spectrum approaches. Entropy and homogeneity are generated in moving windows of size 3x3 and 5x5 to enhance the texture features and to create the premise of differentiation of the myocardium structures. Texture is then statistically analyzed using the texture spectrum approach. Texture classification is achieved based on a fuzzy c–means descriptive classifier. The noise sensitivity of the fuzzy c–means classifier is overcome by using the image features. The proposed method is tested on a dataset of 80 echocardiographic ultrasound images in both short-axis and long-axis in apical two chamber view representations, for normal and infarct pathologies. The results established that the entropy-based features provided superior clustering results compared to homogeneity.

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1. INTRODUCTION

Public health services aim to prevent the myocardial diseases and to minimize adult death by using a fast and inexpensive tool, such as echocardiography imaging for screening cardiac anatomy. An accurate interpretation of 2D (two-dimensional) echocardiography images is highly claimed for early diagnoses. Typically, the infarct size of the ischemic muscle and its localization are strongly affecting the physicians' ability to correctly identify the myocardial tissue injuries as well as the patients' survival. In addition, the duration of ischemia is another controlling mortality factor. Consequently, it is essential to consider two main issues, namely (i) the several artifacts and alterations of the 2D echocardiography images that can induce significant misinterpretation that consecutively affect the diagnostic correctness, and (ii) the subtle changes of texture, which are problematic to the human eye.

Two-dimensional echocardiography displays a cross-sectional view of the beating heart, the chambers of the heart, valves and the blood vessels. It is considered an important tool for myocardial tissue visualization, which is useful in the diagnosis of the onset and the monitoring of the progress of several myocardial diseases.

Distinctive echocardiographic features of myocardial pathologies related to the texture appearance have been discussed in several studies [1-3]. Bibicu and Moraru [1] proposed a hybrid approach to estimate the cardiac cycle phases in 2D echocardiographic images based on geometrical position of the mitral valve and on a set of three image features. The Artificial Neural Networks (ANN) method has been used as a classifier to select the requested anatomical information. Based on quantitative texture analysis, Amichi and Laugier [2] searched for an increase in thickness of the myocardium at the end of the diastole and an increase in the reflectivity of the echoes coming from the affected area of the myocardium muscle. It was found that none of the first order parameters has been able to discriminate between normal and contused myocardium, instead, the second order parameters were capable to discriminate contused myocardium. Gerber *et al*. [3] used a neural network-based algorithm and statistical descriptors of the apparent echocardiographic texture to differentiate between intracardiac tumours and trombi. Several statistical descriptors have been used, namely homogeneity (or inverse difference moment), sum average, and product moment.

To date, various fuzzy clustering algorithms had been proposed for image clustering [4-10]. Fuzzy ISODATA, fuzzy C-means (FCM), fuzzy K-nearest neighborhood algorithm and potential-based clustering are the most used. FCM is able to determine the membership values of a data point with the pre-defined number of clusters. Despite of the fact that FMC is sensitive to the initial conditions, it provides satisfactory results for clustering accuracy. Abonyi *et al.* [4] developed a clustering algorithm used for the clustering and the visualization of high-dimensional data. This algorithm arranged the clusters on a low dimensional grid for visualization. Krinidis and Chatzis [5] employed a FCM based on both spatial and gray level similarity measure algorithm for image clustering to achieve noise insensitiveness and image detail preservation. Park [6] introduced a model called intuitive fuzzy c-means, which was based on an 'intuition level' in order to alleviate the effect of noise. This model showed good results for data clustering and image segmentation problems.

In the current work, we extended the standard FCM algorithm applicability by employing an image feature extraction. This approach provides measurable variables (i.e. pixels) that can be better grouped or clustered by using mathematical similarity, geometrical shapes or densities of the individual pixels. Texture analysis for echocardiography image inspection requires a set of features that accurately and effectively describe the textured myocardium. Image processing and intelligent pattern recognition for complex application problems have a relatively high rate of classification confusion due the high degree of similarity between the gray level distributions of the digital medical images. Thus, pixel-based analysis methods are insufficient to satisfy the needs of efficient and accurate classification. Since texture features characterize statistical or structural relationships between pixels, then texture analysis is considered an alternative solution to this problem [11-13].

The first order textural features are computed in a moving window or kernel based on the image histogram that determines the frequency of occurrence of the pixels' values within the kernel. It is denoted as $P(i, j)$ and indicates the probability of appearance of each pixel value placed at the coordinates (i, j). It is also correlated to the number of distinct gray levels in the image and does not consider the spatial interdependencies [14]. When the analysis is devoted to the relationship between pixel pairs, the texture is investigated by using the co-occurrence matrix. The most popular statistical method (such as the grey-level co-occurrence matrix) used in practice to measure the textural information of images has few drawbacks. Thus, He and Wang [15, 16] mentioned that the co-occurrence matrix elements depend on both the spatial relationships of the grey levels and on the intensity background variation into the image. Also, the displacement vector choice depends on experimental conditions. These works proposed the concept of texture unit to characterize some local texture aspects in one small pixel neighborhood (usually 3 x 3 pixels) and in eight directions. Furthermore, the distribution of the texture units extracted from an image allows building the texture spectrum. The texture spectrum is used for image classification [17].

The present work is interested in both spatial pixel distribution and their relative intensity relations in a small neighborhood. The used measurements in the proposed analysis are the entropy that measures the randomness of gray-level distribution and homogeneity that is a measure of homogeneity of an image. By definition, a homogeneous image area will contain only a few gray levels and a few but relatively high values of intensity. In texture analysis, the entropy and homogeneity are defined as the first-order textural features and the second-order textural features respectively, based on the relationship between pixel pairs [18-20]. In previous studies [1, 21], textural image features have been used for segmentation or classification. Thus, the standard deviation image features computed in k × k (k = 3, 5, 7) masks are combined with the gray-level information to extract the shapes of breast and liver cysts from ultrasound images. Statistical texture information of images, such as mean, standard deviation, skewness, kurtosis and entropy and four n × n kernels (n = 3, 5, 7, 9) have been used for semi-automatic detection of breast lesion boundaries [21]. The standard deviation, skewness and entropy image features are found being the most relevant image features.

Motivated by the main declared goal of noise effect minimization and to get high accuracy of clustering, the present work proposed a classification method based on texture spectrum of image features and FCM clustering. The proposed study is driven by the idea to embed the new tool based on textural features for a fast and easier detection of abnormal anatomy of myocardium structures. The proposed work aims to induce a low-dimensionality approach based on the texture spectrum in new created statistical image features for an accurate classification of echocardiographic images. Based on our previous findings, entropy and homogeneity are selected as statistics descriptors used to characterize the gray-level distribution into the images and to extract the meaningful information for texture classification. The proposed method is robust against ambiguity as it retains much more information. The drawback of FCM noise sensitivity is overcome by using the entropy and homogeneity image features, where the important image details, such as boundaries or edges are preserved.

The remaining sections are organized as follows. Section 2 presents the employed methodology. The results and discussion are given in Section 3, and the conclusions are drawn in Section 4.

2. METHODS

2.1 Texture spectrum

A promising method for texture characterization and discrimination based on the statistical approach considers the concept of texture unit and texture spectrum. The Texture Unit (TU) extracts the local texture information from a neighborhood of 3 × 3 and 5 × 5 pixels of a square raster. This window represents the smallest complete unit that surrounds the central pixel in all eight directions. He and Wang [15, 16] showed that any central pixel having an intensity value I_0 is surrounded in a 3 × 3 neighborhood by eight pixels having the intensities $\{I_1,I_2,\ldots,I_8\}$. The TU is defined as an eight elements set $\{E_1, E_2,\ldots,E_8\}$ given as:

$$E_i = \begin{cases} 0 & if \quad I_i < I_0 \\ 1 & if \quad I_i = I_0, i = 1,\ldots,8 \\ 2 & if \quad I_i > I_0 \end{cases} \qquad (1)$$

where $I(i)$ is the intensity of the pixel gray levels at the coordinates $i = 1,\ldots,8$ inside the matrix of the Region of Interest (ROI). It should be noted that the element E_i is placed in the same position as the pixel *i*. The number of the all possible texture units is, in this case, $3^8 = 6,561$, which is far less than the co-occurrence approach (namely, for an image with 8 bits per pixel and a gray level resolution of 256 and only two pixels considered: 256^2 = 65,536). These sets of 6,561 TUs are considered the local-texture attribute based on the relative grey-level relationships of a given pixel in relation to its neighbors. The texture information is provided by the statistics of the frequency of occurrence of all the TUs over a large region of an image. The similarity with image histogram exists in the sense that the abscissa indicates the texture unit number TUs and the ordinate represents the occurrence frequency.

Textures have two components, namely texture elements (both periodic and random components) and random noise or background. Texture spectrum is constructed in a way that is similar to the white noise construction. For a completely random texture signal that contains some amount of the salt-and-pepper noise (the pixels in the image are either black or white), the texture spectrum shows a constant power spectral density. In the image, when the percentage of the texture components increases, the spectral density changes by forming a particular distribution of peaks. Moreover, different textures are characterized by distinct TUs, which, in turn, show different distributions in their texture spectra. In this framework, entropy images displays the whole gray-level distribution while the homogeneity images only retain a few gray levels having relatively high values of intensity. This is the premise of the highly different texture spectrum appearance in image features approach. In the current work, the entropy and homogeneity image features are very power tools used to enhance the texture characteristic into images and, texture spectrum is a proper approach for texture analysis and characterization.

2.2. Textural image features

The entropy indicates the randomness in an image that has low values for smooth images and large values when the image is not texturally uniform. It is defined as a measurement of the level of disorder inside the gray level distribution, which can be expressed as [22]:

$$Entropy = -\sum_{i,j=2}^{N} P(i,j) \log P(i,j) \qquad (2)$$

where, the first-order histogram *P(i, j)* is defined as:

$$P(i,j) = \frac{number\ of\ \ pixels\ with\ gray\ level\ I(i,j)}{total\ number\ of\ pixels\ in\ the\ region} \qquad (3)$$

Based on the gray-level distribution of the image and on the information provided by the co-occurrence matrix that measures second-order image statistics, homogeneity is given by [18]:

$$Homogeneity = \sum_{I_1,I_2} \frac{P(I_1,I_2)}{1+|I_1-I_2|^2} \qquad (4)$$

here, the matrix element $P(I_1,I_2)$ describes the joint probability that a pair of pixels in a relative distance inside the ROI have the pair of gray levels I_1, I_2. The weighting factor in equation $1+|I_1-I_2|^2$ indicates small contributions from inhomogeneous areas where $I_1 \neq I_2$ to homogeneity. Homogeneity takes high values for low-contrast images (or for smaller gray tone differences in pixel pairs' population).

The Algorithm 1 reported the pseudo code for both entropy and homogeneity image features creation.

Algorithm 1: Pseudo-code of the image features creation

Inputs: ROIs cropped from myocardium echocardiography ultrasound images
Output: Entropy/ homogeneity feature image

Start
 Read the input images
 Establish the size of original image
 Set the window size of the mask (w=3, h=3 and w=5, h=5)
  for each pixel i=1 to row-w **do**
   for each pixel j=1 to col-h **do**
    Crop the original image
    Create entropy image features
    Create homogeneity image features
     endfor
 endfor
Stop

In order to avoid losing the details of the original image, the processed image features should have some special characteristics, namely (i) to encompass both local spatial and local gray level information in order to maintain the noise insensitiveness; (ii) to control the impact of the neighborhood pixels based on their distance from the central pixel. Thus, the effect is inversely proportional to their distance to the center pixel and leads to a small influence of noisy pixels but has a potential effect to blur some details for large distances into image.

The texture spectrum approach is performed on the image features of the images under concern. The texture spectra are obtained using a 3 x 3 sliding window. This size has been chosen taken into account that myocardium has a fine texture. From the outcomes of texture unit algorithm, a histogram is first generated to provide the average of the pixel values intensity (APV) of the texture spectrum, whose range lies within the unit interval. Generally, as expected, different texture images have different texture spectra. Also, in the present work, the filtering operation is unnecessary because the image features minimize the textural noise effect [21].

2.3. Texture classification

The data provided by the texture spectra of the created features image is then classified to normal and infarct pathologies using clustering procedure. Clustering is carried out mainly to partition the set of *n* observations or data set into *c* clusters. Fuzzy clustering methods handle fuzzy datasets to categorize a piece of data into several clusters simultaneously with partial membership. Since the FCM is fast technique as it requires a small number of iterations to achieve the expected results of the clustering exercise and for an expected accuracy, it is used in the present work. FCM produces an optimal partition by minimizing the weighted within group sum of squared error objective function J_m [23-25]:

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} d^2\left(x_i, v_j\right) \tag{5}$$

where, n is the number of data to be clustered, c is the number of clusters to be created, $2 \le c < n$, $x_i \subseteq \Re^m$ is the data set in the m-dimensional vector space, and u_{ii} represents the degree of membership of the observation x_i in the jth cluster. In addition, $m \in [1, \infty)$ is a weighting exponent that determines the fuzziness of the resulting clusters and, usually, is chosen as m = 2. v_i is the prototype of the center of cluster j, which have to be determined, and $d^2\left(x_i, v_j\right)$ is a squared inner-product distance norm and can be determined by any appropriate distance measure between object or data set x_i and cluster center v_j. The fuzzy partition of membership of the observation has to satisfy certain condition, namely $\sum_{j=1}^{c} \mu_{ij} = 1, \forall i$; the cluster centers are computed using,

$$v_j^{(b)} = \frac{\sum_{i=1}^{n} \left(u_{ji}^{(b)}\right)^m x_i}{\sum_{i=1}^{n} \left(u_{ji}^{(b)}\right)^m} \tag{6}$$

where the membership matrix elements that minimize the cost-function (5) are,

$$u_{ji}^{(b+1)} = \frac{1}{\sum_{k=1}^{c} \left(\dfrac{d_{ji}}{d_{ki}}\right)^{\frac{2}{m-1}}} \tag{7}$$

and ε is the minimum difference imposed between iterations.

Consequently, in order to find the solution of the object function, algorithm 2 presents the proposed pseudo code.

Algorithm 2: Pseudo-code for finding the solution of the object function J_m

Inputs: ROIs cropped from healthy and myocardial infarction images
Output: Hierarchical clustering

Execute the following steps for each cropped ROI **do**
for each SAX and LAX view representations **do**
Count the pixels from spectrum
Compute the average of the pixels from spectrum
Cluster the average values
for *c*=1,2
Set values for *m*=2, and $\varepsilon \in (0,1)$
Initialize the fuzzy partition matrix $U^{(0)}$
Set the loop counter *b*=0
Calculate the distance $d^2(x_i, v_j)$, $2 \le c < n$
Calculate the c cluster centers $v_j^{(b)}$ with $U^{(b)}$
Calculate the membership matrix $U^{(b+1)}$
If $\max\left|U^{(b+1)} - U^{(b)}\right| < \varepsilon$ **then** stop,
else *b*=*b*+1 and repeat the previous steps from the start
endfor
endfor
Endfor
Stop

The error norm in the termination criterion is usually chosen as $\max_{ik}\left\{\left|u_{ji}^{(b+1)} - u_{ji}^{(b)}\right|\right\}$. The usual choice is ε =0.001.

This clustering procedure is applied to classify the dataset under concern into healthy and myocardium infarction classes. The block diagram of the whole method is presented in figure 1.

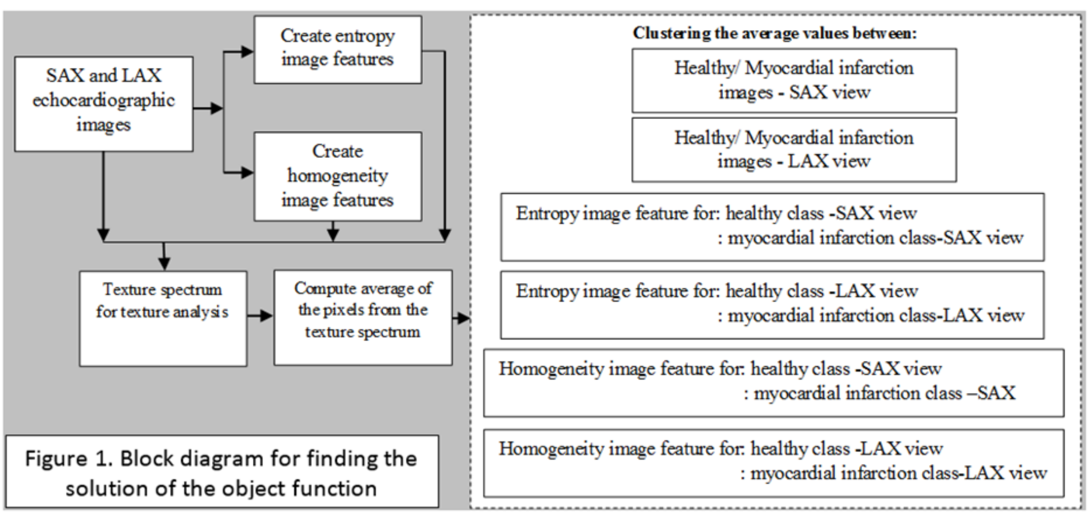

Fig. 1. Block diagram for finding the solution of the object function

2.4. Image database

An ultrasound images dataset encompassing both normal and infarct pathologies of 80 echocardiographic images representing short-axis (SAX, 40 images, distributed 20 for healthy and 20 for infarcted) and long-axis (LAX, 40 images, distributed 20 for healthy and 20 for infarcted) in apical two chambers (A2C) views is used. The targeted anatomical part is the myocardium that belongs to the left ventricle and is composed of contractile cardiac muscle (fig. 2). Texture analysis is restricted to certain ROIs. The ROIs selection requires a good balance between the need to capture sufficient textural information for classification and the requirement to avoid objects that span various tissue categories. The ROI area cover 1000 pixels and these myocardium areas allow the textural parameters to be statistically significant and reliable. The image datasets belong to a collections of video recordings existing in the Laboratory of Cardiovascular Imaging and Dynamics, Catholic University of Leuven, Leuven, Belgium.

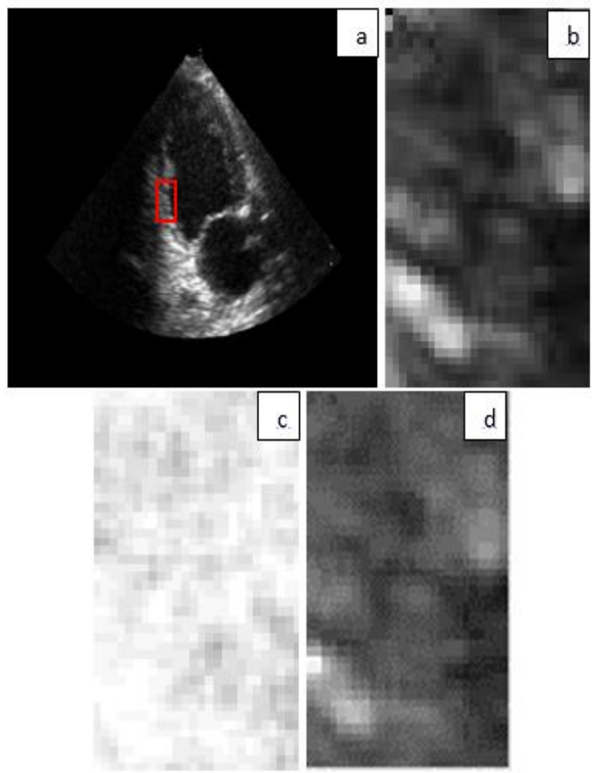

Figure 2. (a) Original echocardiography image, red square shows the chosen ROI; (b) ROI of the original echocardiography; (c) entropy feature image; (d) homogeneity entropy feature image.

3. RESULTS AND DISCUSSION

In order to enhance the robustness of the classification based on texture analysis, the feature images are constructed according to the content of the original image, when the value of each pixel is replaced by the local entropy and local homogeneity values computed in a 3 × 3 window. For a direct comparison between the efficacy of the mask size and in order to correlate to the clustering accuracy a second moving mask of 5 x 5 size is used. Typically, the widow size depends on the nature of the texture image. In the present work, using trial and error, it is found that a moving window of 3 x 3 size is the most adequate in order to achieve the declared goal of the current study. The texture spectrum approach has been applied to these image features (entropy feature image and homogeneity entropy feature image) of the healthy and myocardial infarction images. Texture spectra are obtained using a 3 x 3 sliding window. Afterward, a sparse histogram with 15 bins is generated from the texture unit algorithm output. This sparse histogram provides the APV of the texture spectrum, whose range lies within the unit interval. He and Wang [15, 16] proposed this sparse histogram representation as it drastically reduces the number of the texture units from 6,561 to 15 units without any loss of informative and discriminative ability of texture tool. The sparse histogram with 15 bins allows for a faster and less complex algorithm by discarding any redundancies in texture spectrum analysis. Sparse histogram representation allows to store only those bins whose content is not empty. It overcomes the current difficulty of regular histogram when the number of bins becomes excessively large with the number of dimensions of the data [26]. Some results of the texture spectra in a sparse histogram representation of four images LAX/SAX views, healthy and infarcted, are presented in figure 3.

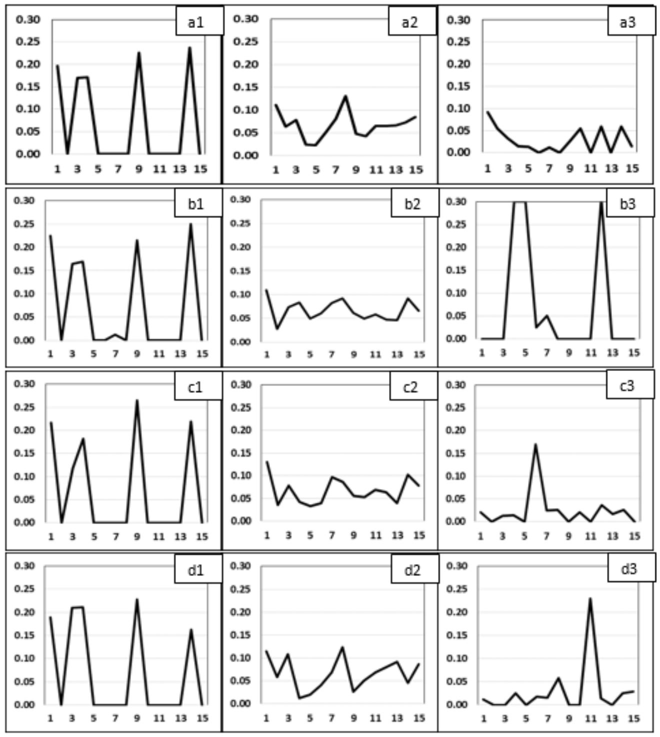

Figure 3. Texture spectra for healthy and infarcted myocardium. Index (1) indicates spectra of original image; Index (2) indicates spectra of entropy image feature; index (3) indicates spectra of homogeneity image feature. First row: healthy images in LAX view. Second row: myocardial infarction in LAX view. Third row: healthy images in SAX view. Forth row: myocardial infarction in SAX view.

The previously described algorithms and texture spectrum have been applied to the 80 raw echocardiographic images database. The images are classified using the above-described FCM algorithm. Figure 4 displays the fuzzy cluster analysis results for targeted images, namely SAX and LAX views for original/raw healthy and infarcted images and processed entropy and homogeneity image feature for the same SAX and LAX views/healthy and infarcted. Two different classes represent healthy and myocardium infarction.

Figure 4 depicts that the data in the same cluster are as similar as possible, while the data in different clusters are as different as possible. The center of gravity of the data set is the location that minimizes the distance between the members of the cluster and it is a clearly spatial separation between healthy and myocardial infarction.

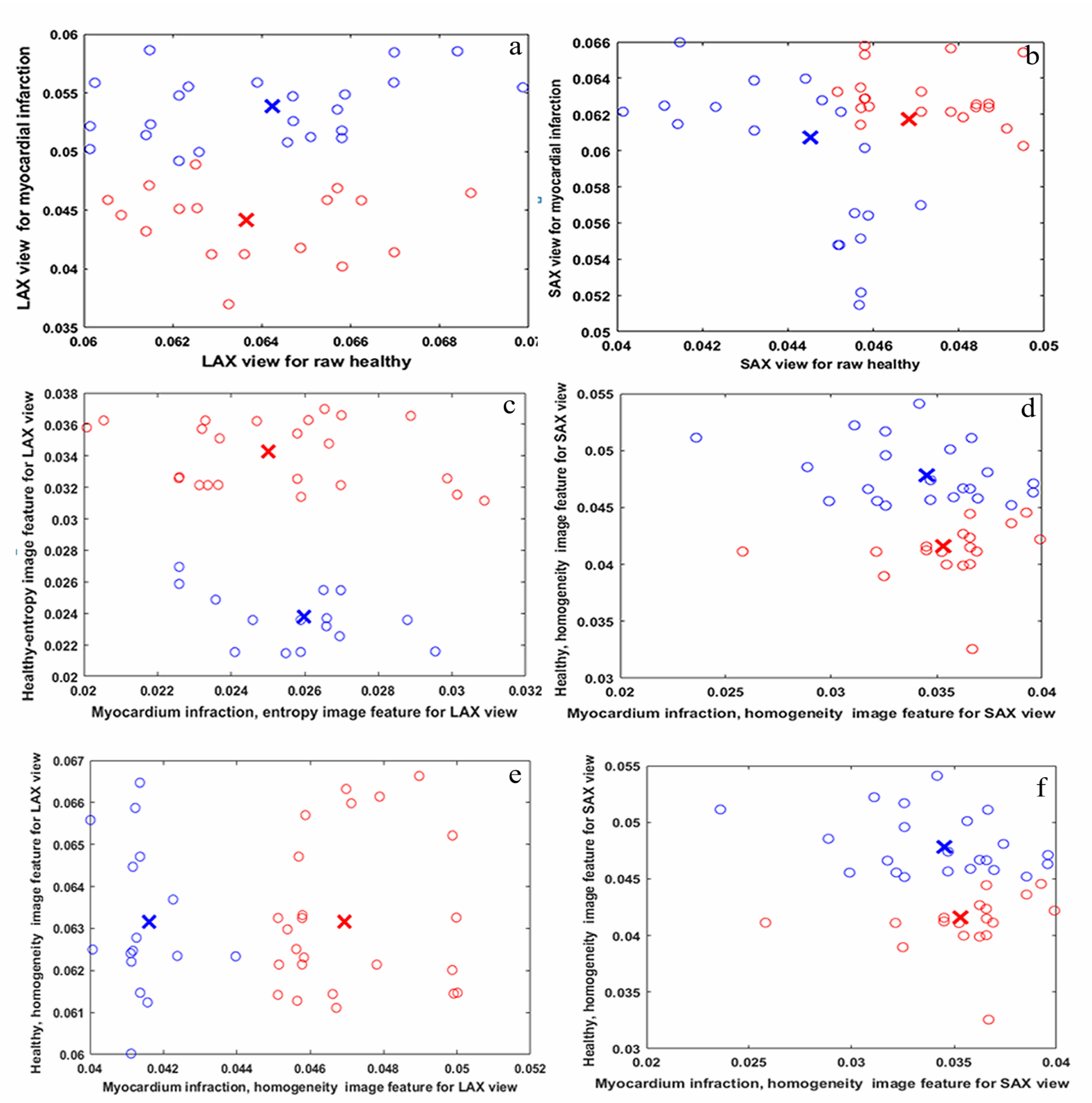

Figure 4. FCM classification output results, where blue color is assigned to the healthy patients and red to myocardial infarction. FCM algorithm clusters the average of the pixel intensity values (APV) of the texture spectrum for: (a) ROI cropped from LAX view for original/raw healthy and infarcted images; (b) ROI cropped from SAX view for original/raw healthy and infarcted images; (c) Entropy image feature of LAX view belonging to images (a); (d) Entropy image feature of SAX view belonging to images (b); (e) Homogeneity image feature of LAX view belonging to images (a); (f) Homogeneity image feature of SAX view belonging to images (b).

The Euclidean distance function between the centroids is of 0.009 for LAX view and of 0.007 for SAX view, when healthy vs. myocardial infarction are compared (fig. 4a and b). For entropy image feature, the Euclidean distance function between the centroids increases to 0.0105 for LAX view and of 0.0112 for SAX view (fig. 4c and d). In the case of homogeneity image feature, the Euclidean distance between the centroids is of 0.0115 for LAX view, but decreases to 0.0065 for SAX view (fig. 4e and f). When the Euclidian distance or squared inner-product distance norm is zero a singularity in FCM occurs. In this particular case, the algorithm will assign the memberships arbitrarily among the clusters. The obtained results are promising and show the success of both entropy and homogeneity image features in classification task. Moreover, it is established that the entropy-based FCM clustering provided more concentrated with far centroids of the two classes compared to the homogeneity-based FCM clustering, which has scattered clusters points with smaller distances between the clusters centroid compared to the entropy measurements.

The FCM algorithm allows an item (or data point) to belong to more than one class and the degree of membership (or likelihood) for each item is given by a probability distribution over the clusters. Due to the range values of the APV provided by the texture spectrum, the FCM algorithm is applied in the present study. The computed APV range from 0.012 to 0.075 for all studied images, either raw images or image features, and FCM is able to identify classes with almost similar APV. Also the number of clusters is 2 and this qualifies the FCM algorithm for the proposed analysis. In order to evaluate the accuracy of the clustering operation, an appropriate tolerance measure based on standard deviation is proposed. It is a measure of variation within a cluster. Ideally, for each class it is required to maximize the inclusion degree of the data into the cluster. In order to evaluate this, the standard deviation is computed for each APV vector of the analyzed data as reported in Table 1. The higher value of the standard deviation indicates the higher possibility that the cluster results to be inadequate.

Table 1 indicates that for the raw data (in both the LAX and SAX views), the spread (standard deviation) of the data tends to be maximal and the member of clusters tend to blend each other. In the case of entropy image feature, the spread of the data decreases with 77% for healthy subjects and with 38% for myocardial infarction. The homogeneity image feature indicates standard deviation values smaller than those of the raw data but higher than those of the entropy image feature. When the mask size has been increased to 5 x 5, the spread of the cluster’s members increased. Also, the texture spectrum became more flat because the larger window size generates a smoothing effect over the pixels. This finding clearly indicates that the increase of the mask size is not a solution to pick up changes in the echocardiography images.

Table 1. Standard deviation of the cluster member

Classes	**LAX**		**SAX**	
	3x3	5x5	3x3	5x5
Healthy /raw data	0.08806	0.0941	0.09763	0.09548
Myocardial infarction –/raw data	0.08891	0.0944	0.09104	0.09912
Entropy image feature/ healthy class	0.03652	0.05545	0.03626	0.05312
Entropy image feature/ myocardial infarction class	0.01921	0.03612	0.02901	0.04151
Homogeneity image feature/healthy class	0.08842	0.09681	0.07079	0.09121
Homogeneity image feature/myocardial infarction class	0.05894	0.07298	0.05623	0.06111

It should be noted that both the spread and distance between centroids are almost the same in the LAX and SAX views, for each analyzed classes. The homogeneity image feature shows an inconsistency behavior even if the spread of the data is smaller than for the case of the raw data. Entropy feature gives a measure of coarseness of the image and its value increases in correspondence of the decreases of the homogeneity. Accordingly, the present work established that the entropy image feature achieved superior classification of the healthy and myocardial infarction images regardless of the view mode.

The preceding results depicted that the achieved main findings are completely agree with other evaluations and applications. Ciulla *et al.* [14] reported results on the role of collagen in the left ventricular hypertrophy for hypertensive patients based on the first order statistical feature, such as average pixel intensity, skewness, kurtosis, and on the broad band of the echoes.

Significant differences between parameters have been found when they have been compared with the corresponding values obtained in control patients. Sudarshan *et al.* [22] proposed a computerized scheme based on second order statistics calculated from gray level co-occurrence matrix (GLCM), discrete wavelet transform and higher-order spectra texture descriptors in order to evaluate the echocardiography image features and to provide the cardiologists an objective interpretation of echocardiography. All the 16 second-order statistical parameters obtained using GLCM led to distinct differentiation between normal and myocardial infarction classes. Moldovanu *et al*. [27] reported the variation of entropy value from 6.23 ± 0.52 for control subjects to 9.95 ± 0.17 for myocardial infarction. The entropy has been found as a salient feature to clearly differentiate between pathologies.

Sudarshan *et al.* [28] used an algorithm for automated myocardial infarction characterization based on features extracted from parasternal short axis and apical four chambers cross-sectional view. The relative wavelet energy and entropy of the stationary wavelet transform have fed a Support Vector Machine (SVM) classifier to characterize the normal and myocardial infarction using a minimum number of features. It has been claimed that the proposed technique is able to identify the fine pixel variations in echocardiography images and the algorithm achieved an average accuracy of 96.8% with 16 features extracted.

4. CONCLUSIONS

From the hundreds of texture features that could be used to evaluate the heart tissue structure, the present work has focused on our previous experience of only using two features, namely the entropy and homogeneity. The key concept of the proposed method is to use the texture spectrum coupled with entropy and homogeneity image features for myocardium muscle characterization. The texture spectra of the myocardium tissue have been estimated, which differed significantly in the entropy image features. The texture classification experiments have been performed in the framework of fuzzy c-means algorithm. The classification results indicated that entropy image feature has the lower spread of the data in the clusters of healthy subjects and myocardial infarction. Also, the Euclidean distance function between the cluster centroids has the higher values for both LAX and SAX views for entropy images.

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