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Automatic classification of Cardiac Views in Echocardiogram using Histogram and Statistical Features

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Abstract

Automatic classification cardiac views is the first step to automate wall motion analysis, computer aided disease diagnosis, measurement computation etc. In this paper a fully automatic classification of cardiac view in echocardiogram is proposed. The system is built based on a machine learning approach which characterizes two features 1) Histogram features and 2) Statistical features. In this system four standard views parasternal short axis (PSAX), parasternal long axis (PLAX), apical two chamber (A2C) and apical four chamber (A4C) views are classified. Experiments over 200 echocardiogram images show that the proposed method with an accuracy of 87.5% can be effectively used in cardiac view classification.

Keywords: parasternal short axis (PSAX);parasternal long axis (PLAX); apical two chamber (A2C) and apical four chamber (A4C).

1. Introduction

The human heart consists of four chambers the two upper chambers are known as atrium and the two lower chambers are known as ventricles [1]. Echocardiogram is one of the easiest widely employed methods which uses ultrasound to visualize and heart related diseases. The two major types of echocardiogram are 1) Transthoracic Echocardiogram and 2) Transesophageal Echocardiogram. In Transthoracic Echocardiogram, The sound waves are sent through a device called a transducer and are reflected as different heart structures. In Transesophageal

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Echocardiogram the sound waves are sent through a hose into the esophagus. The echos obtained are converted to images or video which can be seen on the monitor. Various heart diseases such as heart muscle damage, heart valve diseases etc., can be diagnosed using echocardiogram [2]. The appearance of images captured in the same view of heart will vary for different patients because of two reasons i) Heart structure of the patients slightly varies depending on their physical characteristics. ii) There is no specific marker area to place the transducer on the patient body. Therefore, the appearance based methods cannot be applied for view classification problem.

Various echocardiogram views are automatically classified in this work. The standard views taken up for this study are parasternal short axis, parasternal long axis, apical two chamber and apical four chamber and is shown in Fig.1.

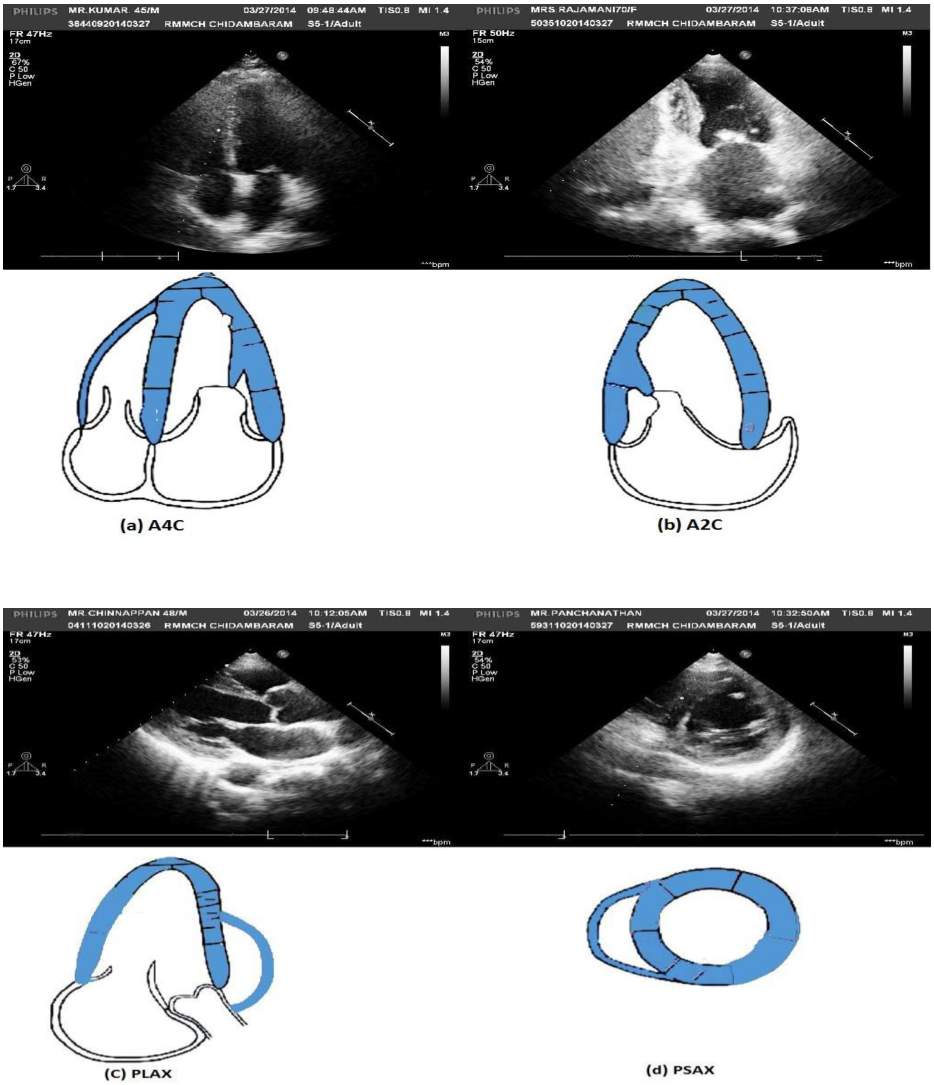

Fig. 1 Standard echocardiogram views and their corresponding heart structures

The apical four-chamber view is usually the easiest one to produce. This view is achieved by letting the patient lie on the back, about 45 degrees to the left side. Fig. 1 (a) shows a typical four-chamber view. According to current standard, the left half of the heart is in the right side of the image.

The apical two-chamber view can be found halfway between the apical four chamber view and the apical long axis view. That is, the transducer should be rotated clockwise 60 degrees from the long axis view. This is the hardest of the three apical projections, because the image plane contains no evident landmarks, Fig.1 (b) shows a typical two chamber view. What can be seen in the two-chamber view are the walls of the left ventricle, the mitral valve in the middle, and the left atrium at the bottom. By making the patient lie on his or her side placing the transducer close to sternum produces the parasternal long axis view. The scanning plane is identical to the apical long axis plane, and therefore aslant to the patient's body. But the viewpoint of the transducer is not identical to that of the apical views. Fig.1 (c) shows a typical parasternal long axis view. The aorta and the left atrium can be seen in the right part of the image. The mitral valve is in the middle, and in the left bottom part the two ventricles are divided by the septum. The parasternal short axis view is imaged with the transducer in the same position as that of the parasternal long axis view, but has to be rotated 90 degree clockwise. Fig.1 (d) shows a typical parasternal short axis view.

2. Previous Work

Cavity detection algorithm is used for detecting the heart chambers in echocardiogram images in [3]. Cardiac chamber detection using Gray Level Symmetric Axis Transform and Markov Random Fields for modeling the constellation of chambers is proposed in [4]. Automatic segmentation of left ventricle (chamber) is proposed in our previous work [5]. There are two main trends used for view classification and object recognition namely model based approach and appearance based approach. For representing an echocardiogram video a hierarchical state-based model is proposed in [6]. Automatic classification of CC view and MLO view in digital mammogram is proposed in [7]. Tracking of left ventricular border using gesture features and hidden Markov model is proposed in [8].

View classification is carried out in [9] which uses images were the LV is manually identified by human experts. The authors were successful only in differentiating between the a2c and a4c views, and they achieved an accuracy of up to 90% for this problem. Edges and corners are properties that can be detected and analyzed in an image. The work in [10] attempted to recognize the various views by image matching which uses a set of local key points as features. A voting scheme was proposed by authors in [11] to study the condition between the model and scene. The performance of the system was measured in the presence of various distortions such as occlusion and clutter influences the performance of the proposed work. Where the recognition rate highly depends object model similarity. Template matching is used to recognize object by matching the histograms of the image with that of model images. This is invariant to object orientation, scaling and occlusion, however fails in case where the objects cannot be recognized based on color alone. A generalized approach to histogram matching is given in [12]. For accurate object recognition the appearance-based methods require isolation of the region of interest from the background. This means that they are sensitive to occlusion and therefore require good segmentation. This is a major limitation and the work in [13] addresses this problem. Segmentation of cardiac views of echocardiogram using morphological operations is proposed in [14].

3. Methodology

The block diagram of proposed system is shown in Fig.2. The Echocardiogram image is given as input to the system. The processing echocardiogram images is difficult because of the presence of noise. The salt and pepper noise present in the echocardiogram image will make the view classification process difficult. Firstly the input echocardiogram image is smoothened by median filtering in order to remove the noise. The artifacts are labels and wedges present in the boundaries of Echocardiogram image. Since the artifact present in the images affects the feature extraction the region of interest ie the triangular region containing the heart alone is selected and cropped before extracting the features.

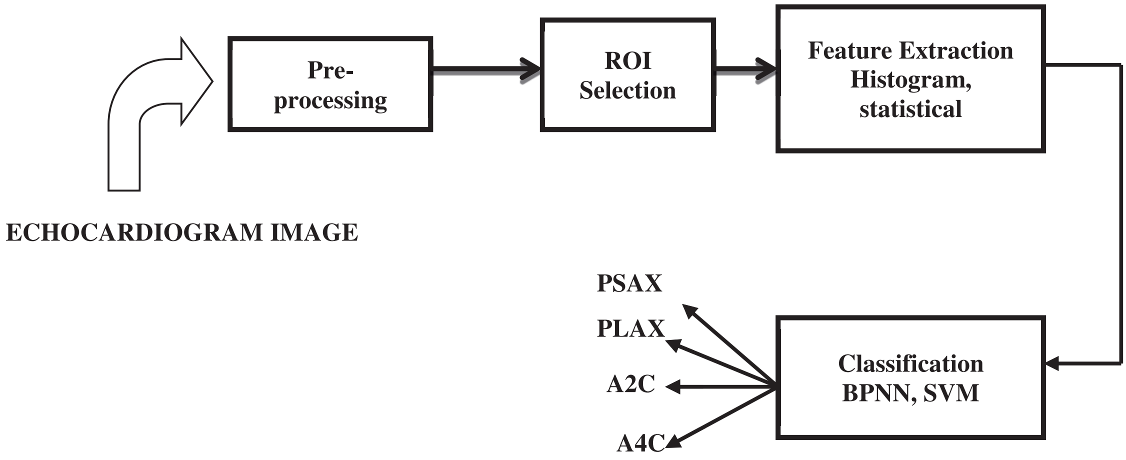

Fig.2. Block diagram of proposed system

Two different texture features namely 32 bin gray scale histogram and statistical features such as entropy, kurtosis, skewness, mean and standard deviation were extracted from the region of interest. The Histogram gives an idea about the contrast of the image and distribution of the gray values. For gray level histograms the tonal distribution is from 0 to 255 while 0 represents black and 255 represents white. The statistical texture characteristics provide information about the properties of the level of the intensity distribution in the image like the smoothness, contrast, uniformity, flatness, and brightness. The usages of these features in correctly classifying the four different cardiac views were tested with BPNN and SVM classifiers. The Back Propagation Neural Network (BPNN) was chosen as a classifier because of its ability to generate complex decision boundaries in the feature space. Furthermore, there are several parameters of the BPNN that must be chosen, including the number of training samples, the number of hidden nodes, and the learning rate. Support Vector Machine is a supervised machine learning algorithm that uses kernel function to map linearly inseparable data to linearly separable data by mapping given data in higher dimension. A hyperplane is constructed in such a way that the margin between the two classes is maximum. The data vectors lying near the hyperplane are called support vectors which are alone then classified rather than considering all data points unlike clustering algorithms.

4. Data Source

A dataset of 200 patients consisting of 55 PSAX, 45 PLAX, 40 A2C and 60 A4C were collected in Cardiology department of The Raja Muthaiah Medical College Hospital, Annamalai University, taken with the new iE33 xMATRIX echo system. The resolution of the images is 1024 x 768 pixels.

5. Results And Discussion

The preprocessing is the first step which removes the noise present in the echo image. The median filter is applied to reduce variation of histogram due to the presence of noise. Fig. 3 shows the images after applying median filter.

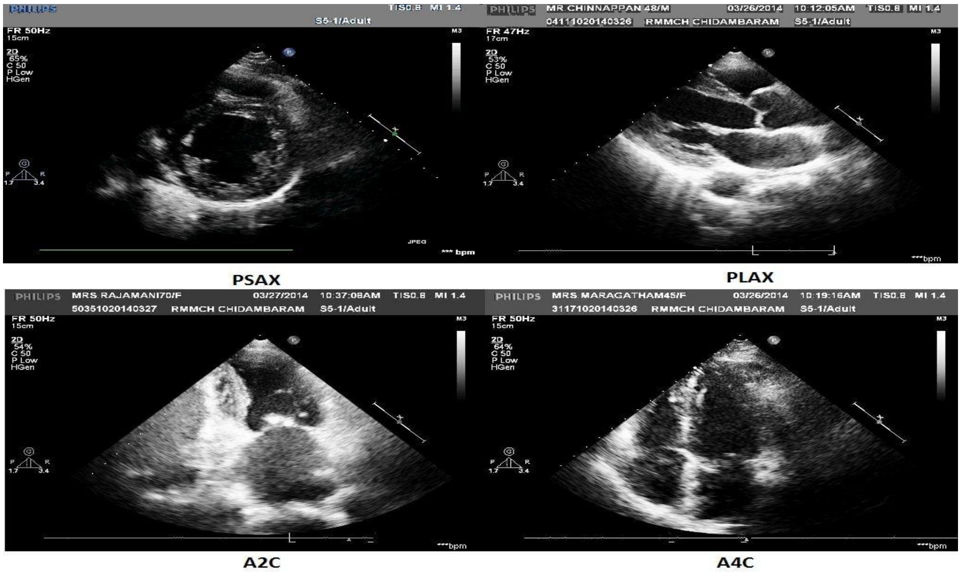

Fig. 3 After applying median filter

Raw Echocardiogram image contains wedges and labels known as artifacts which will produce unnecessary disturbances like histogram variation during view classification process. Hence, it should be removed. Empirically after analyzing a number of Echo images the rectangular ROI is selected by cropping the image using the [135 105 775 575] where (135,105) represent the top left (x,y) coordinates of the ROI triangle and 775 is the height and 575 is the width of the rectangle. The image outside the region contains artifacts which are not subjected to further processing as shown in Fig. 4.

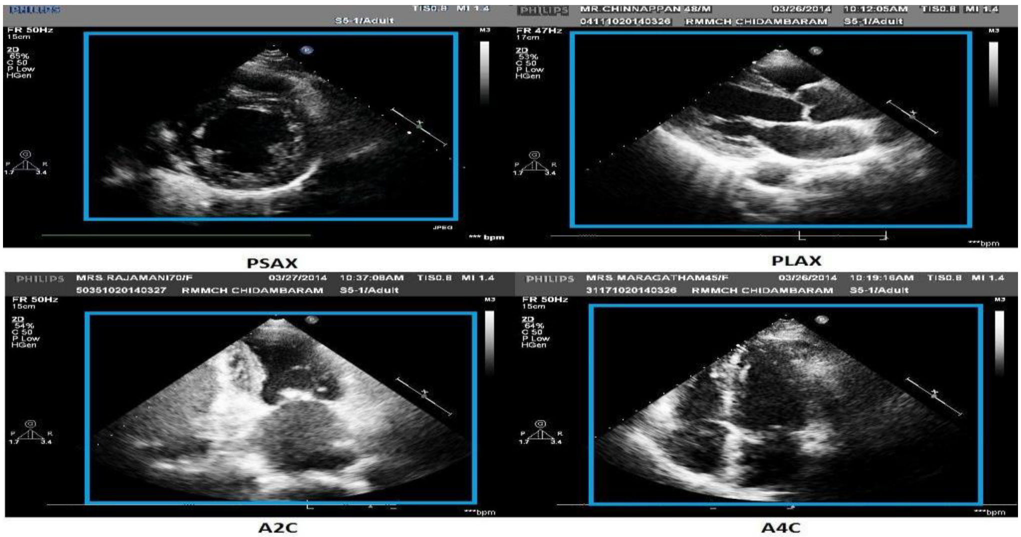

Fig. 4 ROI selection in sample images

From the 200 echocardiogram images collected 120 echo images ie., 35 PSAX, 25 PLAX , 20 A2C and 40 A4C were used for training and remaining 80 echo images (20 in each view) were used for testing the classifiers.

6. Classification Of Cardiac Views Using Histogram Features

The histogram features are extracted since the histogram pattern varies according to the arrangement of chambers which will make the classification easier. The gray level histogram using 32 bins of the sample is shown in Fig. 5 and it can be seen that the histogram pattern of each view varies.

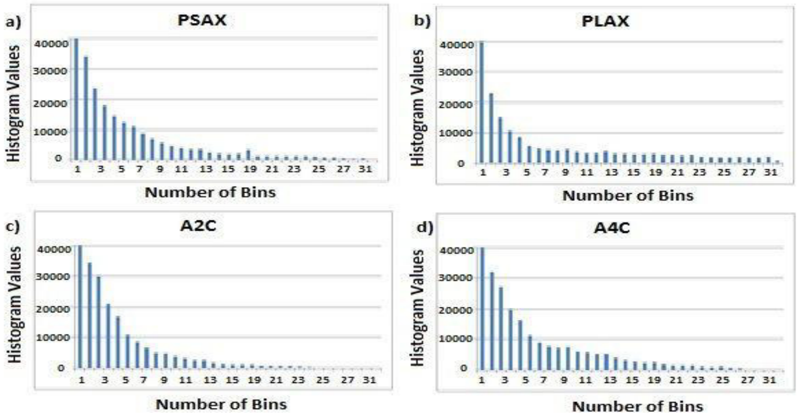

Fig.5 Gray level histogram of each view

Since 32bin histogram features are used for classification the BPNN is trained with 32 input layers the number of o/p layer is4 which corresponds to the four different cardiac views (PSAX, PLAX, A2C and A4C). The number of hidden layer is taken as 17 which was chosen empirically. From Table 1 (a) it can be seen that the accuracy of histogram features with BPNN classifier is 87.5%.

Table 1 (a) Confusion matrix of histogram features with BPNN classifiers

Test Image	PSAX	PLAX	A2C	A4C	Correct classification (%)
PSAX (20)	19	0	1	0	95
PLAX(20)	0	18	0	2	90
A2C (20)	1	1	16	2	80
A4C (20)	0	1	2	17	85
	Overall Accuracy				**87.5**

Table 1 (b) shows the confusion matrix of histogram features with SVM classifiers and it can be seen that the accuracy of SVM is 85%.

Table 1 (b) Confusion matrix of histogram features with SVM classifiers

Test Image	PSAX	PLAX	A2C	A4C	Correct classification (%)
PSAX (20)	18	0	2	0	90
PLAX(20)	1	17	2	0	85
A2C (20)	1	0	16	3	80
A4C (20)	0	0	3	17	85
		Overall Accuracy			**85**

7. Classification Of Cardiac Views Using Statistical Features

The statistical features like mean, standard deviation, entropy, skewness and kurtosis are extracted from the ROI. Mean returns the average value of the extracted region of interest. The standard deviation gives the information regarding how the data is dispersed from the mean. Entropy is a statistical measure of randomless that can be used to characterize the texture of the input image. Kurtosis gives an idea about the shape of the probability distribution. Skewness is a measure which tells how the data are symmetrically arranged about its mean.

Table 2(a) Confusion Matrix of statistical features with BPNN classifiers

Test Image	PSAX	PLAX	A2C	A4C	Correct classification (%)
PSAX (20)	17	0	2	1	85
PLAX (20)	0	20	0	0	100
A2C (20)	1	1	15	3	75
A4C (20)	0	1	2	17	85
		Overall Accuracy			**86.25**

From Table 2 (a) it can be seen that the statistical features with BPNN gives the accuracy of 86.25%. From Table 2 (b) it can be seen that the statistical features with SVM gives the accuracy of 77.5%.

Table 2 (b) Confusion Matrix of Statistical features with SVM classifiers

Test Image	PSAX	PLAX	A2C	A4C	Correct classification (%)
PSAX (20)	17	0	2	1	85
PLAX (20)	0	16	2	2	80
A2C (20)	1	2	14	3	70
A4C (20)	0	2	3	15	75
		Overall Accuracy			**77.5**

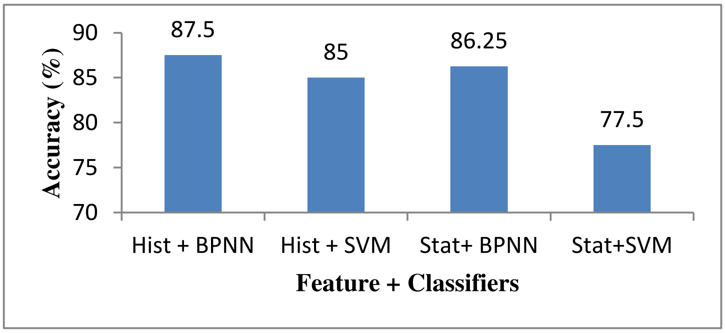

Fig.6 Comparison graph of SVM and BPNN for histogram and statistical features.

From Fig.6 it can be seen that the histogram features with BPNN gives the better performance of 87.5% among the combinations of features and classifiers used.

8. Conclusion

In this paper cardiac view classification of echocardiogram is automated by extracting histogram features and statistical features. SVM and BPNN were used to test the usefulness of these features in correctly classifying the cardiac views. The back propagation neural network with histogram features gives the better performance of 87.5%. The proposed method performs well for all four standard views namely PSAX, PLAX, A2C and A4C. The work could be extended to include other views such as subcostal view, Doppler view etc.

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