

Cardiac View Classification using Speed Up Robust Features

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Abstract

Objectives: Automating cardiac view classification is the first step for automating computer aided cardiac disease diagnosis. In this paper automatic cardiac view classification system is proposed. **Methods:** This system attempts to classify four standard cardiac views in echocardiogram namely Parasternal Long Axis (PLAX), Parasternal Short Axis (PSAX), Apical Four Chamber (A4C), and Apical Two Chamber (A2C) views automatically using Speed Up Robust Features (SURF). **Conclusion:** The Speed Up Robust Features is effective in collecting more class-specific information and robust in dealing with partial occlusion and viewpoint changes. To authenticate the generalizability and robustness, the proposed system is tested on a dataset of 200 echocardiogram images which achieve a classification rate of 90.7%.

Keywords: Apical Four Chamber (A4C), Apical Two Chamber (A2C), Echocardiogram, Parasternal Long Axis (PLAX), Parasternal Short Axis (PSAX), Speed Up Robust Features (SURF)

1. Introduction

In this paper we classify four standard cardiac views of Transthoracic echocardiogram namely Parasternal Long Axis (PLAX), Parasternal Short Axis (PSAX), Apical Four Chamber (A4C) and Apical Two Chamber (A2C) views. Figure 1 shows the standard echocardiogram views and their corresponding heart structures. 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 was not applied for view classification problem in¹. In echocardiogram images the presence of speckle noise is high which may lead to misclassification. Usually Harris corner detectors are used for image matching tasks but it fails for different resolutions, structural variations, and in the presence of noise. Scale Invariant Feature Transform (SIFT), Haar wavelets, and SURF are the local informative descriptors recently used

for object detection or recognition²⁻⁴. The appearance based methods cannot be used for the cardiac view classification of echocardiogram in⁵. There are two main trends used for view classification and object recognition namely model based approach and appearance based approach. Chamber detection using gray level symmetric axis transform and Markov random fields to model constellation of chambers for automatic indexing of echocardiogram videos is proposed in⁶. The cardiac view knowledge is required for heart wall motion analysis in⁷. The automatic placement of Doppler gate needs the cardiac view knowledge before-hand because each view shows different valves. Automatic cardiac view classification of echo cardiogram using part based representation is proposed in⁸. Echocardiogram video representation using hi-erarchical state-based model is proposed in⁹. View classification in¹⁰ uses manual segmentation of Left Ventricle (LV) and achieves an accuracy of 90% only in differentiating apical two chamber and four chamber views. Component based approach for bank note recognition using SURF features is proposed in¹¹.

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The performance of two robust feature detection algorithms namely Speeded up Robust Features (SURF) and Scale Invariant Feature Transform (SIFT) is summarized in¹². Keypoint detection and keypoint description are the two stages used by SURF¹³. 64D SURF feature descriptors are extracted by implementing OpenSURF¹⁴ and classification is performed. Combining Principal Component Analysis with SURF to extract features is proposed in¹⁵. Matching methods like Grid-Based, Maximal, and Grid-Based best matching, for feature matching is proposed in¹⁶. Telemonitoring System for High Risk Cardiac Patients is implemented in¹⁷. Classification of three basic cardiac views using morphological operations is proposed in¹⁸. In this paper we propose, a distance based approach for cardiac view classification of echocardiogram using SURF features to handle various conditions and to achieve high accuracy.

2. Methodology

The block diagram of the proposed system is shown in Figure 2. The echocardiogram image is given as an input to the proposed system. 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 i.e. the triangular region containing the heart alone is selected and cropped before extracting the features. 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.

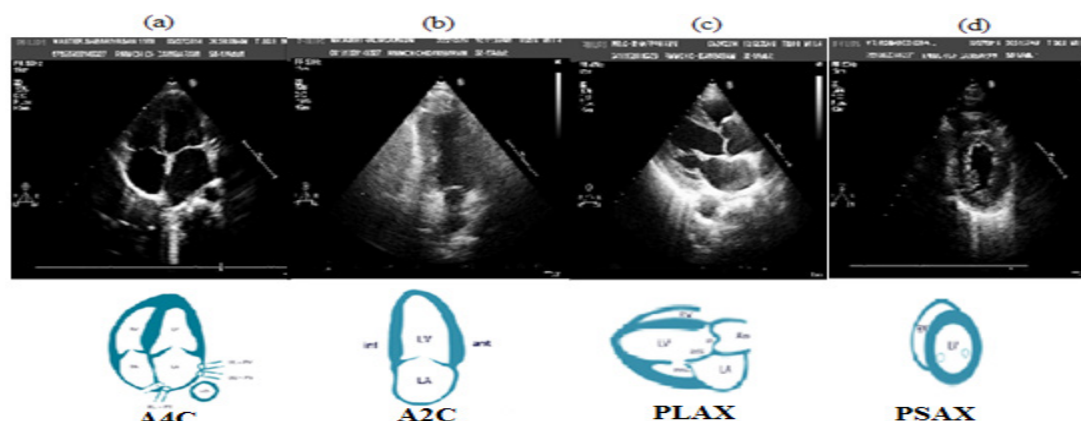


Figure 1. Standard echocardiogram views and their corresponding heart structures.

1.1 Speed Up Robust Features (SURF)

SURF³ is becoming one of the most popular feature detector and descriptor in computer vision field. It is able to generate scale-invariant and rotation-invariant interest points with descriptors. Evaluations show its superior performance in terms of repeatability, distinctiveness, and robustness. SURF is selected as the interest point detector and descriptor for the following reasons: 1) Echocardiogram image could be taken under the conditions of i) Within-view variation, ii) Between-view variation and iii) Structure localization. Interest points with descriptors generated by SURF are invariant to variation and location changes. 2) Computational cost of SURF is small, which enable fast interest point localization and matching.

The SURF detector is based on the Hessian matrix for its good performance in computational cost and accuracy. For a point (x,y) in an image I, The Hessian matrix $H(\sigma)$ with is defined as

$$H(X, \sigma) = \begin{bmatrix} L_{xx}(x, y, \sigma) & L_{xy}(x, y, \sigma) \\ L_{xy}(x, y, \sigma) & L_{yy}(x, y, \sigma) \end{bmatrix} \quad (1)$$

Modern feature extractors select prominent features by first searching for pixels that demonstrate rapid changes in intensity values in both the horizontal and vertical directions. Such pixels yield high Harris corner detection scores and are referred to as keypoints. Keypoints are searched over a subspace of $\{x, y, \sigma\} \in R^3$. The variable σ represents the Gaussian scale space at which the

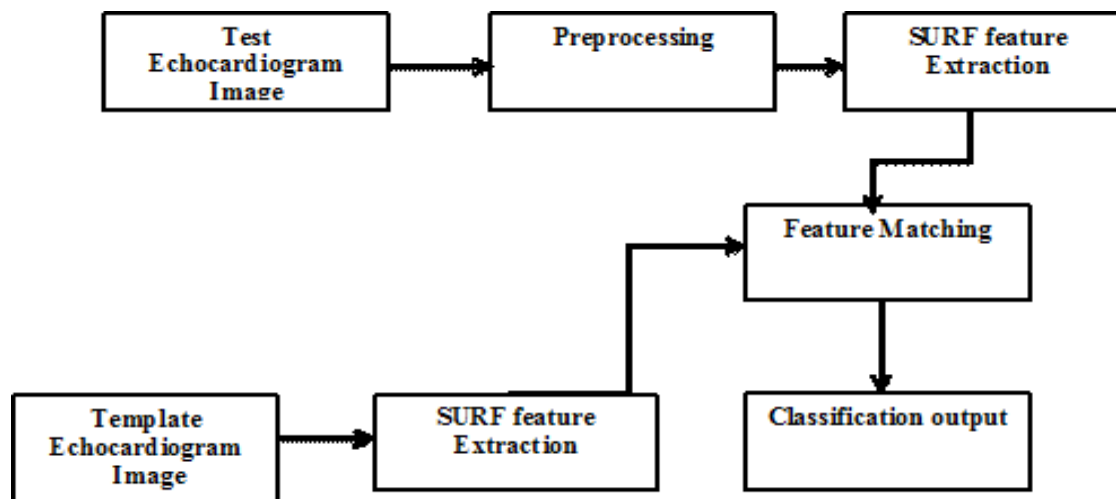


Figure 2. The block diagram of proposed system.

keypoint exists. In SURF, a descriptor vector of length 64 is constructed using a histogram of gradient orientations in the local neighborhood around each keypoint. Our method extracts salient features and descriptors from images using SURF. This extractor is preferred over SIFT due to its concise descriptor length. Whereas the standard SIFT implementation uses a descriptor consisting of 128 floating point values, SURF condenses this descriptor

length to 64 floating point values. The template consists of a sample image (without artifacts) of each view to be classified from which the proposed system extracts knowledge. SURF first detects the interest points and generates corresponding descriptors. The pre-computed SURF descriptors of template images in each category are then used to match with the extracted descriptors of the input echocardiogram image.

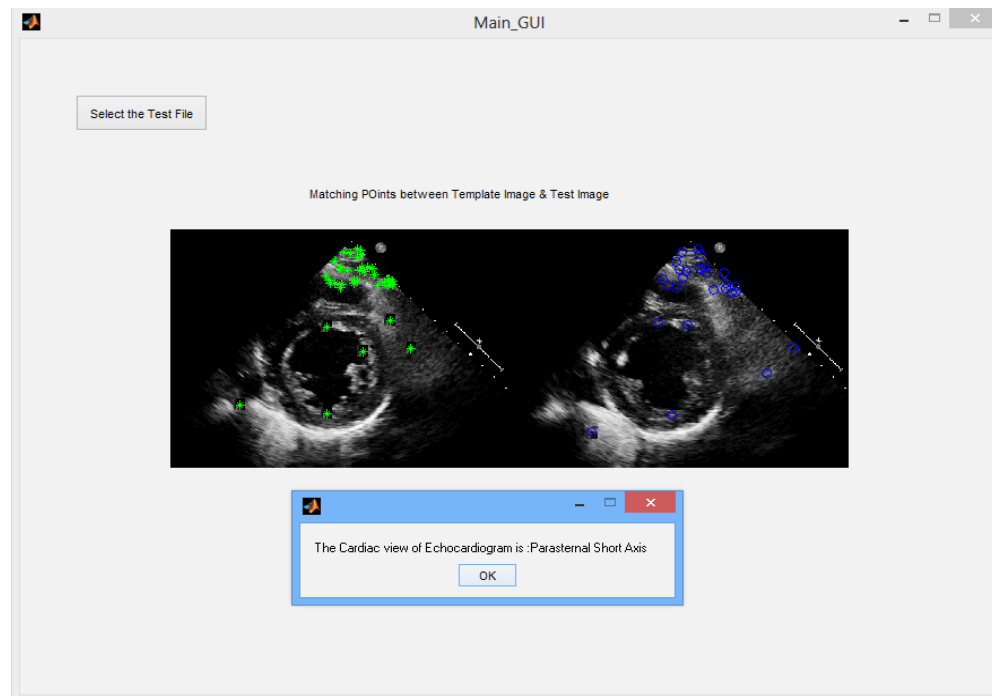


Figure 3. Snap shot of cardiac view classification system.

The number of matched points between the input echocardiogram image and template images of different categories is determined. Then the Euclidean distance between the matched points in the template and the echocardiogram image is calculated and the average is taken. The template image with the shortest distance with the input echocardiogram image is classified as the echocardiogram view and the result is displayed as shown in Figure 3.

3. Data Source

A dataset of 204 patients consisting of 56 PSAX, 46 PLAX, 41 A2C and 61 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 1024×768 pixels.

Table 1. Confusion matrix of cardiac view classification system

Test Image	PSAX	PLAX	A2C	A4C	Correct classification (%)
PSAX (55)	51	0	4	0	92.3
PLAX(45)	0	42	0	3	93.3
A2C (40)	1	2	35	2	87.5
A4C (60)	0	3	3	54	90
Overall Accuracy					90.7

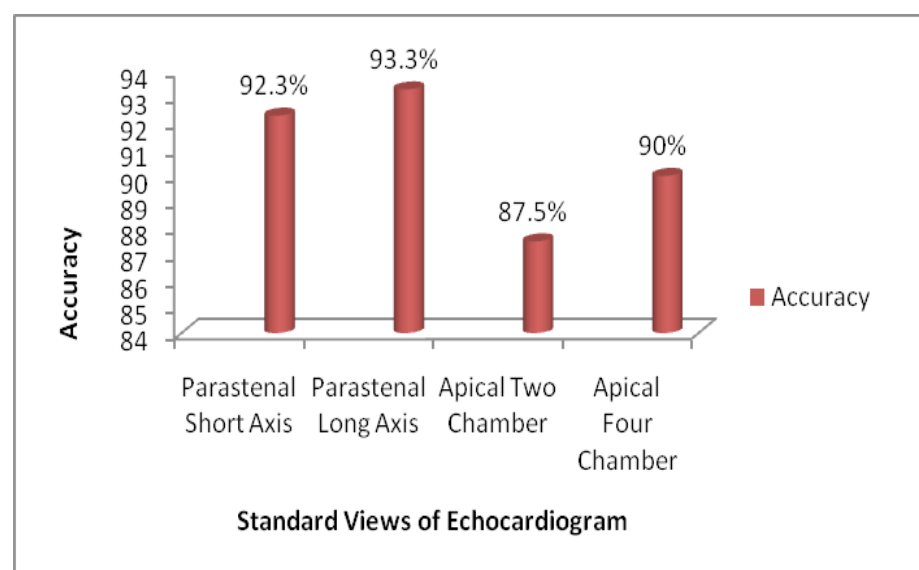


Figure 4. Accuracy of SURF in classifying cardiac views of echocardiogram

4. Experimental Results

In each view one image is chosen randomly and used as a template. The efficiency of the pro-posed system is tested with the remaining 200 images. The proposed system gives an overall accuracy of 90.7% in classifying the cardiac views of echocardiogram. The confusion matrix of the cardiac view classification system is shown in Table 1.

The classification of PLAX view is difficult because of the arrangement of chambers and valves using the appearance based methods. The proposed system gives higher accuracy of 93.3% in classifying Parasternal Long Axis view (PLAX) as shown in Figure 4, however, the other three views were also classified efficiently and the overall accuracy is 90.7%.

5. Conclusion

In this paper standard cardiac views of echocardiogram are automatically classified using Speed Up Robust Features. The evaluation of SURF on echocardiogram dataset validates the effectiveness of SURF to match reference regions with query echocardiogram images. The proposed method performs well on all standard views of echocardiograms considered for classification. The work could be extended to include other views such as sub costal view, Doppler view etc., and also in automating detection and diagnosis of cardiac diseases.

6. References

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