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Texture based classification of the severity of mitral regurgitation

Arun Balodi [a,*], M.L. Dewal [a], R.S. Anand [a], Anurag Rawat [b]

[a] Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee 247 667, India
[b] Department of Cardiology, Swami Rama Himalayan University, Dehradun 248 016, India

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ABSTRACT

Clinically, the severity of valvular regurgitation is assessed by manual tracing of the regurgitant jet in the respective chambers. This work presents a computer-aided diagnostic (CAD) system for the assessment of the severity of mitral regurgitation (MR) based on image processing that does not require the intervention of the radiologist or clinician. Eight different texture feature sets from the regurgitant area (selected through an arbitrary criterion) have been used in the present approach. First order statistics have been used initially, however, observing their limitations, the other texture features such as spatial gray level difference matrix, gray level difference statistics, neighborhood gray tone difference matrix, statistical feature matrix, Laws' textures energy measure, fractal dimension texture analysis and Fourier power spectrum have additionally been used. For the classification task a supervised classifier i.e., support vector machine has been used in the present approach. The classification accuracy has been improved significantly by using these texture features in combination, in comparison to when fed individually as input to the classifier. The classification accuracy of 95.65 ± 1.09, 95.65 ± 1.09 and 95.36 ± 1.13 has been obtained in apical two chamber, apical four chamber and parasternal long axis views, respectively. Therefore, the results of this paper indicate that the proposed CAD system may effectively assist the radiologists in establishing (confirming) the MR stages, namely, mild, moderate and severe.

1. Introduction

Valvular heart disease (VHD), one of the noticeable causes of cardiac-related mortality and morbidity, has a ubiquitous presence in the world. The VHD causes stenosis, insufficiency (regurgitation or incompetence), or both. Stenosis is the failure of a valve which prevents it from opening completely, resulting in blocking the forward flow of blood. In contrast, failure of a valve to close completely, thereby allowing backward flow or leakage is known as regurgitation. Echocardiography, an ultrasound (US) based technique, is an extensively used imaging modality in the diagnosis and evaluation of the cardiac diseases. It is cost-effective, non-invasive, un-harmful and portable [1]. Advancement in medical ultrasound imaging technologies has facilitated radiologists to have more number of images for analysis. Hence, automatic analysis of medical images acclaimed popularity among the researchers.

MR is defined as systolic backward flow from the left ventricle (LV) to the left atrium (LA), caused by structural abnormalities of the valve leaflets. This abnormal leakage of blood into the LA increases the blood volume and pressure. This results in heart failure due to gradual dilation of the left ventricle (LV). The mitral valve can be visualized in three views, namely, apical 2 chamber (A2C), apical 4 chamber (A4C) and parasternal long axis (PLAX). The A2C view shows the anterior and inferior walls of the LV. The A4C view, demonstrates all four chambers (left/right ventricle and left/right atrium) of the heart. It is the best view to visualize the apex of the left ventricle and to study the mitral inflow (diastolic function and mitral stenosis). The PLAX view is useful for the measurement of the size of the right and left ventricle and for interpretation of valvular function. It permits us to understand the morphology and motion of the interventricular septum.

Utsunomiya et al. [2] proposed a technique for the estimation of the volume flow rate in valvular regurgitation and shunt lesions, known as proximal isovelocity surface area (PISA). Tribouilloy et al. [3] performed a study for determining the utility of the regurgitant jet width at its origin that is measured by transesophageal Doppler color flow imaging for the assessment of severity of MR. The usefulness of color Doppler for the accurate identification and estimation of mitral regurgitation (MR) is demonstrated by Helmcke et al. [4] in their work. Lee et al. [5] introduced a simple-to-use echocardiographic parameter, left ventricular early inflow–outflow index (LVEIO). This study demonstrates that the LVEIO

* Corresponding author.
E-mail addresses: drbalodi@gmail.com, baloddee@iitr.ac.in (A. Balodi), mld.iitr@gmail.com (M.L. Dewal), anandfee@iitr.ac.in (R.S. Anand), anuragrwt@gmail.com (A. Rawat).

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correlates with severe MR independently, whereas MR jet area, vena contracta width, and effective regurgitant orifice area measured by the PISA method correlate with MR in combination. This tool particularly helps in identifying accurate severe MR of the patients having a normal LV ejection fraction. Quader et al. [6] advocated in their study that 3D echocardiography can overcome some of the limitations of 2D multiplane transesophageal echocardiography (TEE) and thus is decisive in evaluation of patients who are going through mitral valve surgery. As 3D echo is complimentary to 2D, multiple TEE should be utilized as part of the mitral valve preoperative assessment.

At present, available echocardiographic techniques for quantifying valvular regurgitation are confined by various factors, including uncertainties in orifice location and a hemispheric convergence assumption that often results in, over or underestimation of flow rate and regurgitation orifice area [7,8]. Besides these, a number of research studies through quantification methods for the proper evaluation of MR, have been conducted by several researchers, in which manual tracing of the regurgitant area is done by clinical experts [9–13]. However, Grayburn and Bhella [14] reported 60% variation in all the parameters computed by various clinicians. Various studies have been reported on the MR based cases of mitral valve repair or replacement. Further, Ge et al. [15] suggested that transcatheter mitral valve repair (TMVR) is safe and effective for the patients of severe MR. Kaneko et al. [16] conducted an observational panel study to clarify the prevalence and prognosis of functional mitral regurgitation (FMR) and left ventricular systolic dysfunction (LVSD). Kron et al. [17] analyze the prediction of recurrent mitral regurgitation after mitral valve repair. This model used logistic regression to estimate the probability of recurrence or death.

Table 1 summarizes the various proposed CAD systems given by several researchers [18–26] for the characterization and classification of various diseases. These CAD systems have shown their ability with reasonable accuracy based on the texture features extracted from the images of various medical image data sets in combination with different classifiers. Loizou et al. [27] advocate that texture features employed in their study may be used in classification problems. Based on contemporary research, different texture features such as first order statistic (FOS), gray level difference matrix (GLDM), gray level difference statistics (GLDS), neighborhood gray tone difference matrix (NGTDM), statistical feature matrix (SFM), Laws' textures energy measure (Laws' TEM), fractal dimension texture analysis (FDTA) and Fourier power spectrum (FPS) have been extracted. Thereafter, the extracted feature vectors are fed as input to the supervised classifier, SVM for the classification of the severity of MR.

The rest of the paper is organized as follows. Section 2 describes the materials and methods, which give the details of the image data set and the adopted methodology. Section 3 presents the results of the proposed method. Section 4 presents the discussion and Section 5 concludes the paper.

2. Materials and methods

2.1. Image dataset

A data of 115 patients have been used for this study. For each patient, a video has been recorded in three views, namely, A2C, A4C and PLAX. These 345 (115 patients $\times$ 3 views) acquired videos from 115 patients were then converted into frames. Each of the 345 videos have several cardiac cycles. In order to choose three images from each of the videos per patient, three cardiac cycles (one image/cardiac cycle (systole–diastole)) were identified in consultation with the practicing clinicians at the Swami Rama Himalayan University, Dehradun, India. Thus, a total of 1035 (115 patients $\times$ 3 views $\times$ 3 images) images have been acquired considering all three views together. Philips US machine armed with multi-frequency transducers of 2–5 MHz range has been used for the recording. The size of the individual image is 800 $\times$ 600 pixels. In color Doppler echocardiography, the regurgitant area shows the mosaic characteristic. The images shown in Fig. 1 illustrate the mosaic patterns of the MR jet which vary with the severity of the MR mentioned underneath. Table 2 provides the information about the number of images acquired in the different views in three classes of MR used for the purpose of analysis.

2.2. The proposed methodology

The method employed for the classification of the severity of MR is shown in Fig. 2. The three major steps involved in the classification task are, preprocessing, feature extraction and selection and classification. In the preprocessing step, color Doppler echocardiographic images are converted into grayscale images. The region of interest (ROI) in the form of a fixed rectangular window that covers the regurgitant area of all the images under consideration is then selected. In the second step, the texture features of the ROI are extracted using texture feature extraction techniques. Feature selection is the next step which is used to optimize the number of features selected for classification. These selected features are then fed to the multiclass classifier for the classification of MR images in the final step. A supervised classifier, SVM [28,29] has been used in the present study with three kernel

Table 1
Summary of the proposed CAD systems for classification of various diseases.

Authors	Classification technique	Diagnosis	Features used
Christodoulou, 2003 [18]	KNN	Carotid plaques	FOS, SGLDM, GLDS, NGTDM, SFM, LTE, FDTA, FPS
Chen, 2005 [19]	*K*-mean classification	Breast cancer	Fractal feature
Chang, 2010 [20]	SVM	Thyroid nodules	GLCM, SFM, GLRLM, LTE, NGLDM, Wavelet feature, Fourier based features
Cheng, 2010 [21]	Linear classifier, ANN, BP-NN	Breast cancer	Texture feature, Morphological feature, Model based feature, Descriptor features
Nikolaos, 2011 [22]	SVM, PNN	Carotid atherosclerosis	DWT, GT
Mandeep, 2013 [23]	Linear Discriminative Analysis (LDA)	Liver images	SGLCM, GLDS, FOS, FPS, SFM, LTE, Fractal feature
Sudarshan, 2013 [24]	SVM, KNN	Myocardium tissue	FOS, GLCM, LTE, LBP
Virmani, 2013 [25]	SVM	Liver images	GLCM, GLRLM, FPS, LTE
Gao, 2014 [26]	Neural network	Liver images	GLGCM, GLCM

KNN: *K*-nearest neighbors, ANN: artificial neural network, BP-NN: back-propagation neural networks, PNN: probabilistic neural network, FOS: first order statistics, SGLDM: spatial gray level difference matrix, GLDS: gray-level difference statistics, NGTDM: neighborhood gray tone difference matrix, SFM: statistical feature matrix, LTE: Law's texture energy, FDTA: fractal dimension texture analysis, FPS: Fourier power spectrum, GLCM: gray level co-occurrence matrix, GLRLM: gray level run length matrix, NGLDM: neighboring gray level dependence matrix, DWT: discrete wavelet transform, GT: Gabor transform, SGLCM: spatial gray-level co-occurrence matrices, LBP: local binary pattern, GLGCM: gray level-gradient co-occurrence matrix.