Classification of Segmental Wall Motion in Echocardiography Using Quantified Parametric Images

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Abstract. The interpretation of cine-loops and parametric images to assess regional wall motion in echocardiography requires to acquire an expertise, which is based on training. To overcome the training phase for the interpretation of new parametric images, a quantification based on profiles in the parametric images was attempted. The classification of motion was performed on a training set including 362 segments and tested on a second database including 238 segments. The consensual visual interpretation of two-dimensional sequences by two experienced readers were used as the "gold standard". Mono- and multi-parametric classification approaches were undertaken. Results show an accuracy of 74% for training and 68% for test in case of mono-parametric approach. They are 80% and 67% in case of multi-parametric approach. Moreover, the evaluation protocol enables to understand the limitations of this approach. The in-depth study shows that a large part of false-positive segments are apical segments. This suggests that taking into account the segment location could improve the performances.

1 Introduction

Echocardiography is the modality of choice for the detection and the follow-up of wall motion abnormalities. The global wall motion index which is assessed as the sum of regional wall motion scores (RWMS) has a high predictive value. At the present time, the analysis of the contraction is mainly visual and requires a long training to acquire the necessary expertise. Among the new techniques which provide an additional information to clinicians to evaluate the RWMS, the most cited are: "Color Kinesis", which displays the timing and magnitude of endocardial wall motion [1], the "Tissue Doppler Imaging", which shows the instant velocity of the myocardium [2], and the "Strain-rate Imaging", which displays the radial and longitudinal deformation of the myocardium [3]. These images can be evaluated visually but this evaluation remains subjective. Several indices are currently studied to quantify these images [4][5][6].

A.F. Frangi et al. (Eds.): FIMH 2005, LNCS 3504, pp. 477–486, 2005.

The methods of parametric imaging provide images that represent parameters estimated on the temporal variation of intensity curve of each pixel [7] [8] [9]. These methods do not require specific acquisition or software. In [8], a qualitative validation of parametric images obtained by the Factor Analysis of the Left Ventricle in Echocardiography (FALVE) has already been proposed. In this paper, quantification indices of parametric FALVE images are proposed. A classification methodology based on ROC curves is applied in order to evaluate the power detection of these indices for regional wall motion abnormalities of the left ventricle. Cut-off values are optimized on the training data set and diagnostic performances are studied on a test database.

2 Patients and Methods

2.1 Patients' Databases

Eighty-six apical two dimensional harmonic gray scale sequences were acquired using an HDI system (Philips Medical Systems, Best, The Netherlands) and digitally recorded with the use of HDI Lab software. Four-chamber and two-chamber views were acquired during routine examinations in order to be representative of in-hospital patients in terms of pathology and echogenicity. Fourty-nine patients were enrolled in the study. No patient was excluded. The etiology of the left ventricule dysfunction was coronary artery disease in 28, cardiomyopathy in 7, valvular disease in 5, and other in 9.

Series of three or four cycles were acquired and separated cycles were identified by selecting the onset of QRS complex of ECG, and the associated end-diastolic images. The cycle giving the best superimposed initial and final images was selected automatically, in order to minimize the global motion.

The consensual visual interpretation of two-dimensional sequences by two experienced readers were used as the "gold standard" for comparisons. Each view was segmented as recommended by the American Society of Echocardiography [10]. For each patient, endocardial motion in each segment was examined visually and judged as normal or pathological (hypokinetic, akinetic or dyskinetic).

The patient's database was divided into two groups : a training database and a test database. The training database was constituted by 52 sequences in order to have an equivalent number of normal (n=185) and pathological ($\bar{n}$=177) segments. The test database, constituted by 34 sequences, had normal ($n = 160$) and pathological ($\bar{n}$=78) segments. Only 2 segments were unclassified, due to their extremely bad quality.

2.2 Methods

Parametric Imaging. FALVE is a method used to extract the myocardium contraction information of an image sequence which corresponds to a cardiac cycle [8]. It expresses the time signal amplitude $p(x, y, t)$ of each pixel (x, y) at time t as:

$$p(x,y,t) = f_1(t)I_1(x,y) + f_2(t)I_2(x,y) + e(x,y,t) \quad x = 1,...,M \;\; y = 1,...,N \quad (1)$$

The time functions $f_1(t)$ and $f_2(t)$ are called the factors, and the weighting coefficients $I_1(x,y)$ and $I_2(x,y)$ the factor images; M and N are the row and column numbers and $e(x,y,t)$ is the residual error.

The first factor $f_1(t)$ estimates the continuous component of the curves. The pixels (x,y) which show only small variations of the signal during the cardiac cycle (those which stay inside the myocardium or the left cavity during the whole cycle) present an intensity $I_1(x,y)$ larger than $I_2(x,y)$. The second factor $f_2(t)$ estimates the contraction-relaxation component: it increases during systole, then decreases during diastole. The pixels which have a significant variation in intensity, for example the points located in the cavity and close to the endocardium in the initial image of the cycle, present a larger intensity $I_2(x,y)$. While $I_1(x,y)$ is always positive, $I_2(x,y)$ is either positive or negative.

The three-color superposition of these images (green color for I_1, red color for the positive values and blue color for the negative values of I_2), called parametric FALVE image (see Fig. 1(b)), was interpreted by the clinicians in order to detect the contraction abnormalities [8].

Left Ventricle Segmentation. Parametric FALVE images were partitioned according to the guidelines of the American Heart Association [10]. A fast method of myocardial segmentation was implemented. Three anatomic landmarks P1, P2 and P3 (apical, left and right mitral valves points) and a distance d were manually located on an image of the sequence (see Fig. 1(a)). In the apical two- and four-chamber views, the image was divided into two regions separated by a line (defined as the long axis) connecting the apical point P1 to the the mid-point P4 between the mitral valves points. The long axis was divided into three thirds using two orthogonal lines, dividing the image into apical, medium and basal sections. Intersection points were noted P5 and P6. Apical section was divided into three equiangled regions by two radial lines. Outside points were defined on the orthogonal and radial lines at the distance d.

These points delimit a global mask (ROI_g) located on the left ventricle excluding the mitral valves. This mask was divided into seven regions of interest corresponding to the seven segments of the left ventricle (see Fig. 1(b)). Global mask was applied on images sequence to reduce the influence of the mitral valves motion in the estimation of the factors (see Fig. 1(a)).

Long Axis Distance Map. An image where intensity represented the Euclidian distance between the pixel location and the long axis [P5P6] of the left ventricle was computed (see Fig. 2). Using this coordinate system, inspired by [11], it was assumed that the decomposition of the local motion depended on the pixel location : a pixel belonging to the medium wall contracts towards the long axis, a pixel close to the apex contracts towards the point P5, a pixel close to the base contracts towards the point P6.

Let P5=(x_{P5}, y_{P5}) and P6=(x_{P6}, y_{P6}) be the extreme points on the long axis and $\boldsymbol{n} = (x_n, y_n)$ the perpendicular vector to the $[P5P6]$ segment. The long axis distance map was expressed as follows :

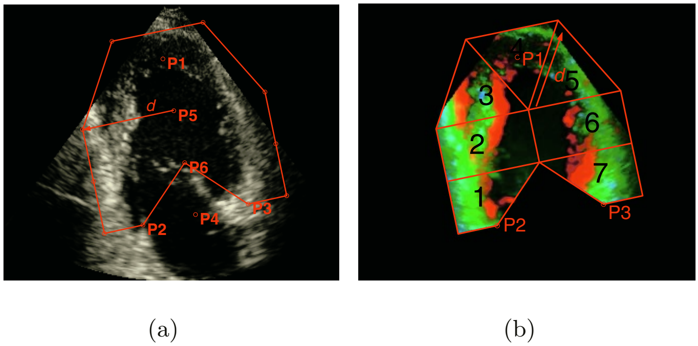


Fig. 1. Points of interest and global mask superimposed on one image of the sequence (a); manual landmarks (P1, P2, P3 and d) and seven segments on the corresponding parametric FALVE image (b)

$$R(x,y) = \begin{cases} \sqrt{(x-x_{P5})^2+(y-y_{P5})^2} & if\; y < \frac{x_n}{y_n}x + \left(y_{P5} - \frac{x_n}{y_n}x_{P5}\right) \\ \sqrt{(x-x_{P6})^2+(y-y_{P6})^2} & if\; y > \frac{x_n}{y_n}x + \left(y_{P6} - \frac{x_n}{y_n}x_{P6}\right) \\ x.x_n + y.y_n & else \end{cases} \quad (2)$$

Finally, the distance values were rounded to integer values.

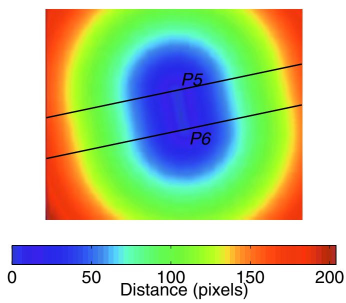


Fig. 2. Long axis distance map

Extraction of Segmental Profiles in Parametric Images. In [8], it has been shown that for a given segment, the color and the width of the band oriented towards the interior of the cavity in the parametric FALVE images were related to the RWMS. The values of the pixels in each parametric FALVE image corresponding to a segmental ROI were transformed into two mean profiles averaging the intensity of pixels located at the same distance. Thus, mean profiles $p_i^1(r)$ and $p_i^2(r)$ corresponding to segment i on factor images $I_1(x,y)$ and $I_2(x,y)$ were computed by formula:

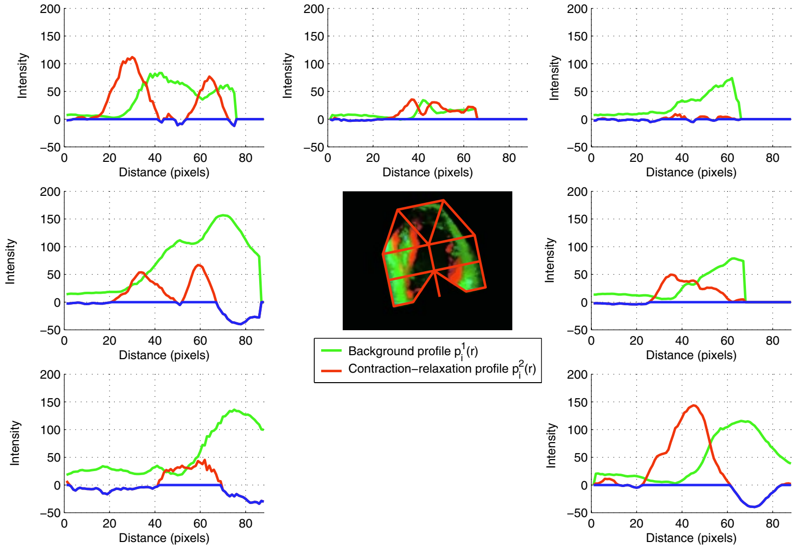


Fig. 3. Parametric FALVE image and contraction-relaxation (red-blue curves) and background (green curves) profiles corresponding to the seven segments

$$p_i^1(r) = \frac{1}{N_r} \sum_{\substack{(x,y)/R(x,y)=r \\ (x,y)\in ROI_i}} I_1(x,y), \qquad p_i^2(r) = \frac{1}{N_r} \sum_{\substack{(x,y)/R(x,y)=r \\ (x,y)\in ROI_i}} I_2(x,y), \quad (3)$$

where $r = 1, ..., R_{max}$, N_r being the number of pixels such as $R(x,y) = r$ and R_{max} the maximal distance in ROI_i. The mean profiles $p_i^1(r)$ and $p_i^2(r)$ were called respectively background and contraction-relaxation profiles. The figure 3 shows the background and the contraction-relaxation profiles associated with a parametric FALVE image.

Two types of parameters per segment were proposed for the classification task:

– A normalized signed area (A_n) was estimated from the profile $p_i^2(r)$ to quantify color and width of the band oriented towards the interior of the cavity from the image corresponding to the contraction-relaxation factor. Distance r_{max} was defined as the distance corresponding to the maximum value in $p_i^1(r)$ profile. Positive and negative areas of contraction-relaxation profile from 0 until r_{max} distance were then computed. The maximum of these areas was normalized by the difference of the maximum value and the cavity value of the background profile to take into account the echogenicity of the segment: $(p_i^1(r_{max}) - p_i^1(r_0))$ (see Fig. 4(b)).
– A composite profile was estimated from the profiles $p_i^1(r)$ and $p_i^2(r)$. As the length of profiles R_{max} depended on the distance d that was different for

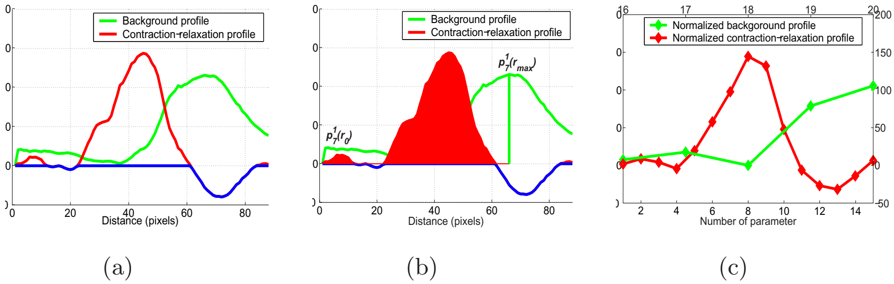


Fig. 4. Mean profiles (a), area and normalization coefficient of contraction-relaxation profile (b) and length-normalized profiles (c) of the segment 7 from the figure 2

each view, two length normalized profiles were computed by changing the sampling rate of the profiles. This was performed in the spectral domain by applying a cascade of three operators: up-sampling (zero padding) by integer factor q_1, filtering by an anti-aliasing (low-pass) FIR filter, and down-sampling by integer factor q_2. A study was performed to determinate the minimal sampling rate : spatial resolution of the factor images $I_1(x, y)$ and $I_2(x, y)$ was reduced similarly in order to keep visible the useful information for the diagnosis of contraction. Five points were retained for the profile $p_i^1(r)$ and fifteen points for the profile $p_i^2(r)$ (see Fig. 4(c)). A composite profile was constructed by juxtaposing the 5 values and the 15 values.

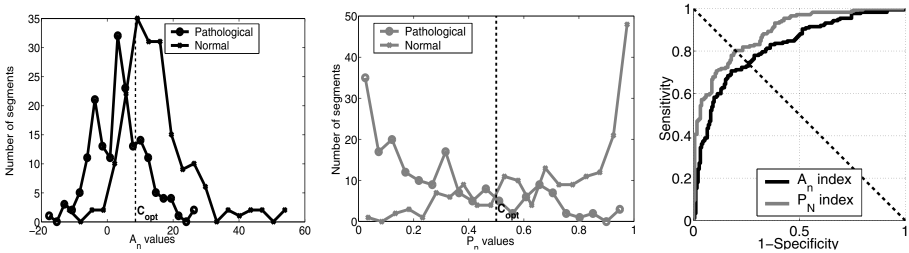
Classification. Two types of classification of segments were then proposed:

– A mono-parametric approach based on A_n index: it was computed for the normal and pathological segments of the training database. The ROC (Receiver Operating Characteristic) curve corresponding to this index was traced (Cut-off, Sensitivity,1-Specificity) [12]. Optimal cut-off was defined as the value of A_n that minimized the difference between the sensitivity and the specificity. Optimal cut-off was finally applied to the classification of the segments of the test database.
– A multi-parametric approach based on logistic regression applied to composite profiles. Logistic regression parameters were estimated from the training database. For each segment, the probability of belonging to the normal (P_N) and pathological class (1-P_N) was computed. The parameters of the logistic regression model were finally applied to the composite profiles of the segments of the test database in order to infer the classification of these segments.

Comparisons of mono-parametric and multi-parametric approaches were performed for the training and the test databases. A non-parametric comparison of the ROC curves was carried out. The sensitivity and the specificity in test of both approaches were compared by McNemar's statistics.

3 Results

The empirical ROC curves corresponding to A_n and P_N indices are shown in Fig. 5(c). The empirical areas under ROC curve (AUC) were respectively 0.82 and 0.89. The difference of AUCs was statistically significantly different from 0 (p=0.001).



(a) (b) (c)

Fig. 5. Distributions of the (a)normalized area and (b) probability of belonging to the normal class for both normal and pathological segments. Corresponding ROC curves (c)

For the optimal cut-offs (A_n=8.6 and P_N=0.5), the sensitivity and the specificity of A_n and P_N indices were respectively 74%, 74% and 80%, 80% on the training database (see Table 1 and Table 2).

Table 1. Training results for A_n

Number of segments	Gold Standard	
Classification	Normal	Pathological
Normal	137	46
Pathological	48	131

Table 2. Training results for P_N

Number of segments	Gold Standard	
Classification	Normal	Pathological
Normal	149	35
Pathological	36	142

For the test database, the sensitivity and the specificity were respectively 67%, 69% for the A_n index and 62%, 70% for the P_N index (see Table 3 and Table 4).

Table 3. Diagnostic test results for A_n

Number of segments	Gold Standard	
Classification	Normal	Pathological
Normal	111	26
Pathological	49	52

Table 4. Diagnostic test results for P_N

Number of segments	Gold Standard	
Classification	Normal	Pathological
Normal	112	30
Pathological	48	48

4 Discussion

Echocardiography is the most widely used imaging modality to assess regional wall motion. The evaluation of RWMS is commonly performed by visual inspection, which is subjective and experience dependent. The use of a consensus of two expert readers seems to be the best "gold standard". This gold standard is conventionally used by clinical evaluation studies [4].

A new quantification method of wall regional left ventricular motion based on profiles derived from parametric FALVE images was presented. To achieve a correct classification, a crucial step is the reduction of the information. This was performed successively as follows : first, using Principal Component Analysis based techniques : FALVE reduces the sequence of images corresponding to one cardiac cycle to 2 factors images; then, by the extraction of 14 mean regional profiles, 2 per segment. Finally, two types of parameters were estimated per segment: one normalized area index, that represented magnitude of the regional wall motion, and two length normalized profiles (20 parameters per segment). The length reduction of the profiles was necessary for the logistic regression because of the reduced number of segments in the training database. Such a reduction avoids learning by heart.

To reduce the inter-patient variability of the area parameter, a normalization was required. Different normalization coefficients were tested : normalization by the length of the profiles, normalization by the maximum value of the contraction-relaxation profile, and normalization by the difference between the maximum value and the cavity value of the background profile. The latter was retained because it gave the best results.

Some regional indices to quantify regional wall motion in echocardiography have been proposed and tested in the literature [4]. Validation of the "color kinesis" index was performed by cut-off determination on a training database. In the cited study, the training database was exclusively composed of normal subjects and the cut-off was defined as one standard deviation around the mean of the normal control group. This provides a specificity greater than the sensibility. In our study, healthy subjects and patients composed training database, presenting a similar number of normal and pathologic segments, and the optimal cut-off was estimated to minimize the sensitivity and specificity difference.

Using the training database, diagnostic performances are significantly better with the index P_N than with the index A_n. But diagnostic performances of P_N and A_n are no more significantly different for the test database. The large difference between training and test performances that is observed for P_N suggests a case of "overtraining" : this could be solved either by reducing the number of parameters or by increasing the number of segments in the training database.

Moreover a large part of the misclassified segments concern the apical segments. These results can be explained by the regional heterogeneity of wall motion amplitude, which has not yet been introduced in the learning phase. Indeed, some major variations of mean indices values could be observed according to the localization of the segment (see Table 5 and Table 6), showing that the motion magnitude is considerably reduced at the apex.

Table 5. Localization effect on A_n

	Mean Values of A_n	
Region	Normal	Pathological
Basal	15.94	4.98
Medium	16.51	7.40
Apical	14.78	3.39
Apex	8.74	-1.38

Table 6. Localization effect on P_N

	Mean Values of P_N	
Region	Normal	Pathological
Basal	0.73	0.35
Medium	0.75	0.31
Apical	0.78	0.26
Apex	0.56	0.16

The modelling of the localization as a covariate factor could improve the performances of the diagnostic test largely [12], but this would require a larger valued database. This is currently under construction, using the same criteria for patients' selection as those presented here. Indeed, the construction of an appropriate database and the collection of medical expertise is a key point of any evaluation approach. Using acquisitions from in-hospital patients enables us to have a good estimate of difficult cases and to be strict with tested indices.

The classification of contraction into four classes is also under study in order to have an approach similar to the clinicians' evaluation. This requires to generalize the ROC approach to 4 classes (normal, hypokinetic, akinetic, dyskinetic) in order to optimize the estimation of thresholds.

5 Conclusion

A methodological approach was developed to test the discrimination power of any quantitative method, aiming at detecting regional wall motion abnormalities. Some encouraging results have been observed for indices derived from a regional analysis based on parametric FALVE images. However the location of the segments being classified should be introduced as an complementary information to improve the performances of the classification. Moreover, several other methods of parametric imaging, such as [7][13] are already planed to be evaluated in the future, using this protocol and an augmented database. Some others methods [1][2][3] could be tested using the same protocol, but would require a modification of the acquisition.

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